Goldsmiths, University of London

Doctoral Thesis

Department of Computing

Designing a Sensor-Based Wearable Computing System for Custom Hand Gesture Recognition Using Machine Learning

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A thesis submitted in fulfilment of the degree of Doctor of Philosophy in Arts & Computational Technology

April 4, 2022

Declaration of Authorship

I, Hadeel D. Ayoub, hereby declare that this thesis and the work presented within it is entirely my own. Where I have consulted the work of others, this is always clearly stated.

Signed:

Date: 04.04.2022

Acknowledgements

First and foremost, I am thankful to God for granting me the opportunity to progress in my career. I am thankful to my country, Saudi Arabia, for sponsoring my post-graduate education.

I am deeply thankful to my supervisor, Professor Mick Grierson, for his valuable guidance and support throughout this journey. I thank my second supervisor, Dr Rebecca Fiebrink, for her insight and advice.

I thank the department of Computing at Goldsmiths, for the unlimited access to the prototyping labs and endless support in using the equipment to build the technology for this research.

I thank Essex County Council, for funding the longitudinal study of this research and supporting the implementation of assistive technology in their schools.

I would like to thank my co-founder and business partner, Ed Hill, for holding the fort in the challenging early days of a tech start-up, while I focused on my research degree.

I would like to thank my parents, who instilled in me a sense of perpetual curiosity and brought me up to become a lifelong learner. I thank my sisters and brother, for sharing the experience of being in the third decade of our lives but still pursuing education.

I would like to thank my partner in life and the father of my children, Fahd, for his many sacrifices so that I could achieve my goals and fulfill my dreams.

I thank my children for their ambitious and creative ideas, in the lab, and after hours, which many of the children I worked with appreciated. Jana, Abid, Amin and Tala, it is to you that I dedicate this work.

Abstract

This thesis investigates how assistive technology can be made to facilitate communication for people that are unable to or have difficulty communicating via vocal speech, and how this technology can be made more universal and compatible with the many different types of sign language that they use. Through this research, a fully customisable and stand-alone wearable device was developed, that employs machine learning techniques to recognise individual hand gestures and translate them into text, images and speech. The device can recognise and translate custom hand gestures by training a personal classifier for each user, relying on a small training sample size, that works offline on an embedded system or mobile device, with a classification accuracy rate of up to 99%. This was achieved through a series of iterative case studies, with user testing carried out by real users in their every day environments and in public spaces.

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Abbreviations

- **3D** - 3-Dimensional
- **ANN** - Artificial Neural Network
- **API** - Application Programming Interface
- **AR** - Augmented Reality
- **ASL** - American Sign Language
- **BLE** - Bluetooth Low Energy
- **DTW** - Dynamic Time Warping
- **ERDF** - European Regional Development Fund
- **HCI** - Human Computer Interaction
- **HMM** - Hidden Markov Model
- **IC** - Integrated Circuit
- **IPN** - National Polytechnic University of Mexico
- **KNN** - K-Nearest Neighbours
- **LCD** - Liquid Crystal Display
- **MIT** - Massachusetts Institute of Technology
- **OLED** - Organic Light-Emitting Diode
- **PCB** - Printed Circuit Board
- **SEN** - Special Educational Needs
- **TVS** - Transient Voltage Suppressor
- **UI** - User Interface
- **UUID** - Universally Unique Identifier

- **VR** - Virtual Reality
- **WAV** - Waveform Audio File

Chapter 1

Introduction

Research currently suggests that sign language is one of the earliest documented methods of communication between primitive hominids. Premaratne et al. suggests that before the development of the highly structured languages we have today, we used hand gestures, facial expressions and body language to express ourselves (Premaratne et al. 2010). Today, the majority of those using sign language for daily communication are either diagnosed with a disability or have a family member who has been. More recently, partly as a result of better diagnosis of a wide range of Autism Spectrum Disorders, children with non-verbal or non-vocal autism use a form of sign language to communicate (Bonvillian et al. 1981).

As technology development is accelerating, new fields of Assistive Technology have emerged. Such technology is directed towards developing innovations to help people considered to have disabilities live better lives and integrate more easily into their communities. As a result, healthcare technology innovations are receiving a great deal of attention from the medical field, and research is being pursued in healthcare innovations relating to assistive technology.

One of the goals of this research project is to help people with limited or no speech abilities interact with technology and use it to communicate in public with those who do not understand sign language. The research focuses on exploring new methods to make this technology more accessible and universal in a number of ways, including adding translation features, and more easily allowing customisation of different sign language libraries and their variations, as well as recognising individual differences in signing, and finally by improving usability through design, making the device unobtrusive to wear and easier to control.

1.1 Background

Hand gesture recognition is perhaps the most significant application of human computer interaction (HCI) research that contributes to innovating technology for sign language users. In such investigations, patterns emerging from hand movement and orientation are classified using sign language segmentation (Han et al. 2009). This can be done using two approaches:

1. Vision-based systems
2. Data Glove-based systems

A Vision-based system is a gesture recognition system that is based on computer vision. Such systems employ the usage of cameras, either individually or in multi-camera systems (C. Vogler and D. Metaxas 1998), to detect the motion of the signer's hands and to translate those motions into segmented gestures. Alternatively, a Data Glove-based system uses a "glove" that is fitted with an array of gyroscopic sensors that measure rotation, flex sensors that measure the bending of the fingers and accelerometers that measure the forces acting on the hand due to its own acceleration. The data is streamed from these sensors in real-time and processed by a computer or micro-controller (a small processing chip). This processing engine interprets the motions of the hand into sign-language gestures. After the gestures have been interpreted, using either system, the meanings of each can be "looked up" and their spoken translations can be played from a speaker.

Vision based systems often require complex programming to isolate the hands from the image backgrounds, making them hard to use in non-controlled environment and almost impossible to use for daily communication or as mobile, wearable devices. Some studies have attempted to improve the output of vision-based systems by adding multiple cameras (C. Vogler and D. Metaxas 1998), using coloured gloves (T. Starner et al. 1998), using a depth camera (Borba 2019) or employing neural network models (F. Zhang et al. 2020). However, the size of the gesture library able to be recognised remains limited.

In contrast, data glove based systems have proven to be more reliable in registering and relaying hand gestures. Data gloves use sensors that can more reliably detect finger flexing, hand movement, and orientation (Anetha K 2014). They can also be simpler than vision based systems. As such, they can offer a wider vocabulary and a higher recognition accuracy. However, such systems are still not robust enough, and in the past 10 years, no significant improvement has been achieved in accuracy rates (Premaratne et al. 2010). This is possibly because researchers currently seem to be more focused on vision based systems.

There are many versions of the Data Glove that translate sign language to text or speech. Most of these gloves rely on a smart device for output and it seems that none have yet moved beyond prototyping. There is almost no published work showing evidence of sign language data gloves being tested by speech-disabled participants for daily communication. This may be due to the low accuracy, complexity and the high cost of the electronic hardware currently required.

1.2 The purpose of the Research

Assistive technology designed to enable communication for non-verbal disabilities is currently available in the form of software. Special communication apps are used to help children with speech disabilities communicate via tablets and smart devices. Throughout this research process, it emerged that parents try to limit access to other features on the tablet by locking the device to be used only with the communication app. Through observation (as detailed in Section 5.3.4) while visiting schools and sitting in classrooms, I noted that this causes frustration to the children although it was designed to make their lives easier. I identified a need for a stand-alone device that serves the purpose of communication without offering any other features.

For these reasons, I have chosen to explore the data glove approach to the translation of sign language for this research, primarily because they have potential to operate independently from a smart device. Additionally, glove based sign language recognition systems have been reported to offer a wider vocabulary and better recognition accuracy than computer vision systems.

It is still important to consider that such systems struggle to find a match as the sign language vocabulary data base grows larger (Premaratne et al. 2010). Another drawback is the limited manoeuvrability due to wires connecting the gloves to the computer. I address these two problems during the iterative cycles of prototyping and identify them as essential criteria for evaluation.

1.3 Location and scope of the Research

In this research, I explore the many opportunities and challenges for the design of a robust, stand-alone Data Glove to translate sign language hand gestures to text and speech. The glove would have sensors to monitor the flexing of fingers and to calculate hand orientation in order to more accurately classify complex hand gestures.

Previous research has shown that many systems have failed because of the vast range of sign language vocabulary they had been manually programmed to process (Dipietro et al. 2008). I propose programming a limited vocabulary of signs and rely primarily on machine learning-driven software to train the glove for new words.

I explore the implementation of machine learning techniques to allow users to train the glove and upload their own sign language gestures and dialects. Importantly, I have chosen not to use approaches that require large amounts of data including some 'deep learning' approaches due to the complexities of deploying and testing such systems using embedded devices for the purposes of improving accessibility and customisation, as well as the fundamental requirement for each user to spend an unreasonable amount of time creating such a dataset. However, some cloud-based systems that require similar methods are tested as part of the research. I move on to adding more features, such as speech translation to different languages and wireless smart-phone communication to make the glove more usable in external environments and more easily integrated into daily technology contexts, in the same way as conventional phones or tablets.

I recruit participants who use sign language as their primary language for communication and conduct a series of usability studies in their natural environments at home, school and public spaces.

People with a various range of abilities, both sensory and physical, were involved in the evaluation cycles of the proposed glove. However, the most important research findings were relevant to school-aged-children, primarily those with speech and/or hearing impairments as well as non-verbal Autism. As such, special considerations were in place to best cater for the chosen user groups.

A big part of the research took place at Special Educational Needs (SEN) schools in the UK with the collaboration of Essex County Council.

1.4 Research Questions

Research Questions:

- RQ1: How can an assistive technology innovation be developed to facilitate communication for people with speech disabilities who use sign language for their daily communication?

- RQ2: How can this innovation be made more universal and compatible with different libraries of sign language?

- RQ3: Can machine learning be employed to extend the applications of this system beyond sign language recognition to enable building a library of custom signs by training a personal classifier for the purpose of recognising individual and unique hand gestures?

1.5 Structure of the Dissertation

I present the research findings through a series of controlled usability studies. I employ interactive user centred design research methods where most of the findings are gained through iterative prototyping. I engage non-verbal participants in the case studies and implement their feedback into the research cycle.

The plan to limit pre-programmed vocabulary and simplify recognition is a novel attempt to reduce the size and number of components required for the hardware and reduce the complexity of the minimum required software to use the system, in order to make the data glove simpler to run, easier to wear and cheaper to produce.

During the research, a great deal of discussion arose around the innovation aspect of the technology used. As the case studies progressed, it was found that the technological development, as guided by the iterative prototyping process, strongly aligned with the progression towards the commercialisation of that technology (Section 9.3). This eventually lead to the development of a fully integrated on-body hand gesture classification system and a patent was filed and ultimately granted (Appendix F.1), documenting this contribution to the field of research.

1.6 Summary

After looking at previous work in this field, I was motivated to introduce a new technology to the assistive wearables and healthcare innovation markets and give a chance to speech disabled individuals to try it and use it.

I showcased the technology developed for this research at multiple tech exhibitions globally, gave talks about it at conferences and won prestigious awards, including IBM Grand Prize for Artificial Intelligence for Social Care and MIT Award for Challenging Minds in Artificial Intelligence Solving Social Issues.

A spin off start-up resulted from this research, after a need for such technology was identified by usability studies participants. The start-up was awarded government grants which funded further development of the data glove and allowed the research to expand to six schools for Special Educational Needs (SEN) in the UK. As of now, more than 30 children are using the data glove, developed as part of this research, in the classroom to overcome daily communication challenges.

On a social and economical level, I have worked closely with councils, assistive technology providers and medical insurance companies in the UK to get the data glove approved on their platforms, as part of a scheme to issue it as a benefit for education and employment, thus sparing the user the cost, and insuring they get the technology they need for communication.

This research is part of a programme to develop and produce an accessible data glove that translates sign language to text and speech, facilitating daily communications between individuals with speech disabilities and the general public.

Some of the work demonstrated in this research was drafted into a patent application titled: "Method and system for gesture recognition", filed to the United Kingdom Intellectual Property Office (UKPTO) on the 20th December 2019, and granted on the 16th November 2021 with patent No. GB2590502 (Appendix F.1).

Chapter 2

Literature Review

2.1 Sign Language Applications of Hand Gesture Recognition in Human Computer Interaction (HCI) Research

In this section I discuss various approaches taken by researchers, over the last two decades, to enhance the accuracy of hand gesture recognition and expand its applications.

Gesture recognition is a research field of computer science that is explored in a number of fields, including robotics, machine learning and Human Computer Interaction (HCI). Gesture recognition focuses on the computer recognition of expressions or motions by humans including hands, body language and facial expressions. HCI has gained a lot of research attention utilizing hand gestures (Chen 2003). There are many applications which employ gestures to control output such as media players, gaming controllers, robots and virtual objects or environments (Mäntyjärvi et al. 2004; Ong and Ranganath 2005). The output of sign language is considered to be "one of the single most prominent applications of hand gesture recognition" (Premaratne et al. 2010).

Researchers have explored the idea that sign language hand gestures can be used to interact with computer interfaces (P. Premaratne and Nguyen 2007). The advancements in sensors, accelerometers and infrared cameras further enhanced the accuracy of recognition modules.

Since the 1990s, there has been lots of research into developing technology for sign language users (T. Starner et al. 1998). Advancements in hand gesture recognition research has helped improve recognition for sign language assistive technology. Sign language hand gestures can be recognized by processing four patterns: "hand shape also known as hand configuration, hand movement, orientation and classification." (X. Zhang et al. 2009).

In his book *Human Computer Interaction Using Hand Gestures*, Dr Prashan Premaratne explores the impact of this kind of technology in depth:

> "Today the focus has shifted again from the mundane use of sign language to the more advanced human-machine interaction. This would, in effect, advance the interactions that disabled people would have with technology as well as make sign languages easily understandable by ordinary users. The technology can also pave way for automatic translation to other languages in other parts of the world making a silent communication revolution for the disability. Yet, the challenges are enormous and the different approaches taken by researchers around the world have shed light on difficulties ahead as well as the progress made so far."
>
> - *Premaratne et al. 2010*

In this section, I start with an overview of the historical development of hand gesture recognition in HCI research, highlighting the invention of data glove-based control interfaces and how that was eventually combined with computer vision, where gloves used markers and colours for finger tracking rather than sensors, leading up to the glove based systems we know today.

2.2 Overview of Hand Gesture Recognition Research in Human Computer Interaction (HCI) Since the 1980s

In this section, I collate a non-exhaustive summary of hand gesture recognition prototypes highlighting elements which relate to this research.

Humans have always used hand gestures as a natural means of non-verbal communication. The field of Human Computer Interaction (HCI) incorporates extensive literature on research for recognizing hand gestures through machine learning, for the purpose of replacing keyboard and mouse interaction with electronic devices (Takahashi and Kishino 1992). For the last few decades, hand gesture recognition research has made significant contributions to interactive human-machine interfaces and virtual environments (Takahashi and Kishino 1992).

Some gesture recognition studies focus on static hand postures (Kılıboz and Güdükbay 2015), while others analyse dynamic hand motions (Rigoll et al. 1997). HCI interpretation of gestures require the posture and movement of hands, arms and sometimes other parts of the body to be measurable by the machine (Pavlovic et al. 1997).

Since the 1980s there have been a number of studies dedicated to developing gesture-based interaction techniques in the domain of HCI (Rautaray and Agrawal 2015). These studies are mainly classified as glove-based or vision-based (Pavlovic et al. 1997; Rautaray and Agrawal 2015).

The first research approach to recognize hand gestures was to measure the bending of finger joints and hand orientation by designing special gloves called "Data Gloves" (Liang and Ouhyoung 1998; Pavlovic et al. 1997; Rautaray and Agrawal 2015; Takahashi and Kishino 1992). Data Gloves are gloves wired with flex sensors, which are used to measure finger bends and joints angles, accelerometers and gyroscopes, which are used to measure hand orientation and direction. Data Gloves have proved to be very reliable in relaying hand gestures' position and motion data (Mitra and Acharya 2007). However, the multiple wires which connected the gloves to the computer limited users' mobility. This led to the development of a wireless approach to gesture recognition defined as "vision-based systems" (Rautaray and Agrawal 2015). Vision-based hand gesture recognition systems employed multiple cameras to classify hand gestures but required complex software for image processing to isolate the hand gestures and deal with finger occlusion (Pavlovic et al. 1997; Shen et al. 2012).

Before flex sensors were available, researchers used light tubes, fibreoptic (Takahashi and Kishino 1992), and resistive ink (LaViola 1999) to detect if fingers were flexed or bent.

The earliest documentation of a sensor-based Data Glove was developed in 1983 by Gary Grimes (Dipietro et al. 2008) commissioned by "Digital Entry Data Glove". This glove was wired with multiple sensors. Touch and proximity sensors were attached to determine if two fingers were making contact with each other. Flex sensors were placed over the knuckles to measure fingers bending, and a tilt sensor was positioned at the wrist to detect hand orientation. This glove was programmed to recognize 80 “alphanumeric characters”. Despite the complex circuitry, this glove had low accuracy rates and had heavy wiring. The development of this glove stopped at the proof of concept phase and never made it to commercialisation.

The “MIT data glove” (Premaratne et al. 2010) was one of the earliest advanced data gloves of the 1980s. It became a commercial product for the gaming industry and was considered an example of pioneering HCI research to replace keyboard input. Registered as AcceleGlove (*Mobile Mag - AcceleGlove* 2020; *WTOL - AcceleGlove* 2020), the glove was wired with an accelerometer to record hand and finger movement in 3D. AcceleGlove has applications in video games, sports training, physical rehabilitation and virtual reality. It costs between $1000 and $5000.[1]

More data gloves started to appear in the industry, designed for motion capture, music applications and animation. I mention below three examples that were considered important commercially: CyberGlove II & III[2], 5th Dimension Technologies' (5DT) Data Glove[3] and P5 Glove[4]. These gloves were highly accurate but very expensive and could only be operated by professionals and in a studio setting.

CyberGlove II and CyberGlove III are two generations of data gloves developed by CyberGlove Systems. They are designed for motion capture for the motion picture, visual effects and animation industries. These gloves are wired with 22 sensors including flex sensors and a WiFi™ chip to send data wirelessly to a controller computer.

5DT Data Glove was also designed specifically for motion capture for the motion picture and animation industries. It is wired with an array of sensors and is Bluetooth™ enabled to allow the provision of a wireless data transfer system, running in real time.

X-IST Data Glove[5] is a motion capture glove with touch sensors placed on the fingertips. It was designed to be used for music related applications. It requires a

[1] Cost is an important consideration for this research. Making an affordable and accessible glove is highlighted as one of the research goals.

[2] CyberGlove - http://www.cyberglovesystems.com/cyberglove-ii

[3] 5th Dimension Technologies - https://5dt.com/5dt-data-glove-ultra/

[4] P5 Glove - http://www.mindflux.com.au/products/essentialreality/p5glove.html

[5] X-IST - https://www.globalsources.com/si/AS/SouVR-International/6008831878791/pdtl/X-IST-Data-Glove/1023350755.htm

connection to the computer via a USB cable.

A great example of a data glove which replaced keyboard and mouse input for gaming is the P5 Glove. The P5 Glove was developed by MindFlux™ as a way to provide a cheaper alternative to many expensive wired gloves available in the market that can be used for gaming. The P5 incorporates a flex sensor as well as remote camera tracking technologies. It provides users intuitive interaction with 3D virtual environments; such as games, websites and educational software.

Data Gloves have come a long way in employing advanced sensor technology resulting in satisfactory hand gesture recognition output. However, they remain heavy in wiring and are still largely extremely expensive to manufacture. Vision based recognition systems proved to be more convenient in terms of hand gestures (Lamberti and Camastra 2012), as they do not constrain the flexibility of hand movements. However, they still retain majour issues, for example hand isolation and lack of mobility, as described below.

Although this research focuses on sensor-based Data Gloves for hand gesture recognition, I will highlight briefly the history of Vision-based systems, how they work and what are the main comparable features to glove-based gesture recognition.

In the early stages of vision based recognition systems, low resolution cameras and limited computer power made it very difficult to isolate gestures. To help the camera in tracking hand gestures, non-wired coloured gloves were sometimes used to enhance recognition (James and Mubarak 1994).

With the advancement of video cameras and greater processing power, researchers have moved towards developing vision based gesture recognition systems employing real-time vision processing software (Pavlovic et al. 1997).

The earliest computer vision gesture recognition system emerged in the 1980s. This was a glove developed by MIT Media Lab where the finger tips were marked with coloured LED which created different "illumination patterns for different gestures" (Sturman and Zeltzer 1994) which could then be segmented and interpreted by the computer.

Occlusion resulted in very poor performance of the glove, especially since there were many variations in hand gestures when performed by different users.

Vision-based recognition modules used multiple layers of feature extraction software, skeletal tracking, sample matching and 3D positioning (Berci and Szolgay 2007). However, researchers were only able to extract static gestures. Extracting dynamic gestures was still not possible with this approach.

More attempts were made at combining coloured gloves with cameras for vision based hand gesture recognition. One of which was reported by Davies et al. (Sturman and Zeltzer 1994) who used gloves with coloured finger tips combined with a grey-scale camera. The system could determine seven hand gestures and was mainly designed as a proof of concept as opposed to being a commercialisable product.

Although these approaches represented progress, the problem of occlusion remained. It was later addressed specifically by multiple studies. The earliest being in 1996 by Iwai et al. (Iwai et al. 1996) who introduced the use of decision tree-based methods to allow the computer to recognize different gestures. The results of this study led to the creation of further research, including the first system to be used for virtual reality applications (Wang and Popović 2009). The late 1990s witnessed a shift in approach for vision based hand gesture recognition systems. Researchers were able to develop hand recognition systems which relied on computer vision but that did not require the use of gloves or markers (Rehg and Kanade 1994). This was due to improvements in camera technology, resulting in enhanced resolution and also more reliable detection and analysis. Researchers added a second and in some instances, a third camera to improve the recognition of hand gestures (Darrell and Pentland 1993; Gennery 1992). Depth cameras were later introduced and proved to be revolutionary.

For the first time, real-time gestural extraction was demonstrated in 1995 (Bobick and Wilson 1995; Utsumi and Ohya 1999) through the use of depth cameras. However, this required a static background to be present behind the subject.

At the turn of the millennium, vision-based hand-gesture recognition systems were finally able to identify a growing number of gestures in real time, but only for static gestures. This encouraged researchers to combine the new multi-layered gesture recognition software with the latest camera technology; in an attempt to decipher dynamic hand gestures using computer vision (T. E. Starner and Benton 1995).

As hardware technologies improved, high resolution cameras became easily available to researchers and at a low cost, compared to the more expensive versions used in previous vision based studies. As a result, researchers "devised new ways to rely on feature extraction from the high quality images available instead of sophisticated multi camera system"(Chen 2003).

A pioneer study in recognizing dynamic hand gestures using computer vision was conducted by Chen et al. in 2003 (Chen 2003). The system was designed to recognize dynamic hand gestured in real time against a static background. Recognition accuracy levels were above 90% in identifying 20 gestures. The system used complex multilayer software employing hand tracking, feature extraction, and Hidden Markov Model (HMM) training for gesture recognition (Chen 2003).

Many studies followed (Berci and Szolgay 2007; Binh et al. 2005; Gastaldi et al. 2005; P. Premaratne and Nguyen 2007) using different approaches for vision based gesture recognition. Results vary but the primary challenge remains in isolating hand gestures from the background and retaining the mobility of the system.

> "The development of the computer vision based gesture recognition will have to go a long way in realizing what has been achieved by glove based systems. No single one prominent strategy in camera setup to feature extraction to classification has been established as the research indicates different trends in myriad of ways. Yet, a powerful application such as sign language stands to challenges the brightest minds to develop the best of approaches in the above areas for a cohesive solution."
>
> - *Premaratne et al. 2010*

It is important to note that computer vision based hand-gesture recognition will never be mobile as it relies on high resolution cameras and powerful computing to be successful. The unfavourable impacts of this on the form factor and cost of the technology mean that glove-based hand-gesture recognition has a better chance on multiple counts to serve as a communication tool for modern sign language users.

In the following section, I narrow the prior research in gesture recognition to focus on sign language translation, and how it evolved with both vision based and glove bases systems. I show examples of translating different standardised libraries of sign language, though they could equally be applied to custom hand gestures and personal libraries of sign language.

Sign language hand gesture recognition research builds on the background research summarized above.

2.3 The Development of Sign Language Recognition Systems to Date

A central goal of Human Computer Interaction research is to explore the use of new types of interfaces that use different kinds of inputs, for example human gesture. By the 1980s, systems had "..already been developed to react to limited hand gestures, especially in gaming and in consumer electronics control." (P. Premaratne and Nguyen 2007).

Since then, hand gesture recognition research has been used to attempt to decipher sign language (Kawai and Tamura 1985). There are a range of different sign language libraries and types, just like any language and these vary from one region to another.

This research focuses on classifying a standardised library of sign language hand gestures using a machine learning software that can then be trained to recognize customized sign language.

I chose to start with a standardised sign language because they are widely used by the hearing impaired and deaf communities around the world. Recent statistics estimate as many as 70 million people around the world use a standardised sign language library including immediate family members of speech disabled individuals[6].

It is important to identify the fundamental features of most standardised sign language libraries' hand gestures to accurately address segmentation and classification research queries. Finger spelling, hand orientation, facial expressions and body language are essential elements to be considered (Kyle et al. 1988). A good example for facial expression is raising the eyebrows to indicate a higher pitch or to ask a question. It is also important to consider that some sign language hand gestures are static, meaning that the hands remain still, while others are dynamic, where hand movement affects the meaning of the sign (Armstrong and Karchmer 2009). In addition, it is crucial to examine the dictionary of hand shapes for sign language to determine whether it is necessary to track two hands in recognition systems or if one hand would be sufficient. Taking American Sign Language (ASL) as an example, in signs using two hands, either both hands are performing identical gestures, or the dominant hand is moving while the passive hand is still (Tennant and Brown 1998).

[6] World Federation of the Deaf - https://wfdeaf.org

It is therefore likely that a recognition system that tracks a single hand, which is the dominant hand, might be reliable in evaluating sign language translation.

Different research approaches employ different classification methods. However, they all use a combination of the elements identified above. Just like hand gesture recognition systems, sign language recognition systems are based on either computer vision or data gloves.

2.4 Computer Vision Based Sign Language Recognition Systems

Computer vision based sign language recognition systems are divided into two categories: static gesture recognition and dynamic gesture recognition (Waldron and Kim 1995) systems. Static gesture recognition is designed to classify isolated hand posture whereas dynamic gesture recognition records and processes continuous hand movement. Both static and dynamic hand gesture recognition systems face the challenge of isolating the hand from the background, not to mention incorporating body movement and facial expression for an accurate translation of sign language.

Depth cameras (Borba 2019) and coloured marker gloves (T. Starner et al. 1998) were used to help the computer isolate hand gestures. This proved to be very difficult in non-controlled environments, limiting recognition to labs and research facilities. As a result, computer based recognition systems were never upgraded to become mobile systems. The size and high cost of the equipment also made it difficult to test outside of the lab.

I mention here, in chronological order, previous research that has attempted to enhance sign language hand gesture recognition using computer vision, mostly utilizing the same methods highlighted in hand gesture recognition research background (Section 2.2).

The earliest accurate system was reported in 1988 by researchers Kawai and Tamura of Osaka University. Kawai and Tamura published a study featuring their attempt at machine recognition of Japanese sign language in real-time (Shinichi Tamura and Kawasaki 1988). In this study, Kawai and Tamura used image processing techniques to recognize 20 Japanese hand gestures. They could isolate hand gestures from the background by “comparing a grey scale intensity of two consecutive image frames" (Shinichi Tamura and Kawasaki 1988).

A decade later, in 1995, MIT researchers Starner and Pentland published research on "dynamic gesture recognition and classification based on coloured gloves and Hidden Makov Model (HMM) classifier" (T. E. Starner and Benton 1995). They reported a 92% success rate in accurate translation of American Sign Language (ASL) without explicitly modelling the fingers, rather, by deciphering hand outlines. Recognition models were based on camera tracking of coloured gloves. Their system used a limited vocabulary of 40 hand postures (T. E. Starner and Benton 1995).

In 1997, Grobel and Assan, researchers at Aachen University of Technology in Germany, utilized HMM classifiers for a video based recognition system of Netherlands sign language (Grobel and Assan 1997). They designed a vision-based system to recognize 262 isolated hand postures. Accuracy level was reported at 94%. They also used coloured gloves but with an improved design to enhance accuracy levels.

By 2000, most vision based recognition systems incorporated both static and dynamic sign language hand gestures. This was referred to as local (hand posture and location) and global (hand movement and path) information (Imagawa et al. 2000).

The first research addressing both local and global gesture information was by Imagawa et al. in Japan (Imagawa et al. 2000). They used a clustering technique to layer multiple images of hands extracted from sign language images. Accuracy was recorded at "...around 94% which was a significant achievement given that they relied on very low resolution images" (Premaratne et al. 2010).

In 2004, researchers Vogler and Metaxas at the University of Pennsylvania also devised both static and dynamic gesture recognition system for ASL but this time relied on HMM and 3D motion analysis" (Christian Vogler and Dimitris Metaxas 2004). Their system was the first to "...break down the signs into their constituent phonemes, modelling simultaneous events in stochastically independent channels" (Christian Vogler and Dimitris Metaxas 2004). They used a vocabulary of 22 signs and three channels to validate their system. Results were recorded at the 96% accuracy mark.

Another breakthrough in 2004 was the employment of neural networks to classify sign language hand gestures by feature extraction.

A pioneering approach using neural networks to recognize sign language hand gestures was attempted by Isaacs and Foo in Florida. Similar to Imagawa et al.

(Imagawa et al. 2000), Issac and Foo also used hand images for attempting video-based sign language recognition. However, they utilize a vector to feed a neural network that recognizes the ASL alphabet (Isaacs and Foo 2004). Their system results in 99% accuracy in the context of finger spelling. According to Premaratne et al., They planned to expand recognition models by designing "algorithms for ASL feature vector recognition" (Isaacs and Foo 2004), however, no record was found of them having achieved that to date.

The above studies suggest that sign language hand gesture segmentation has high accuracy results. More recent research has built on this theory combining it with new emerging computational technologies.

The debut of Kinect had a very strong impact on the sign language recognition community. Kinect offered a real time solution to pose estimation and hand gesture isolation, that was able to run without substantial computational power and could be acquired at a low cost. This presented a "short-cut to real time performance and made recognition possible in different environments" (Cooper et al. 2012).

A study in 2012, conducted by Cooper et al. at University of Surrey presents what they call a "sophisticated sign language recognition system based on Kinect" (Cooper et al. 2012).

For sign language recognition, Cooper et al. used a two-stage recognition system based on linguistic sub-units paired with Kinect 3D hand tracking in real time. The collected data was combined using a sign language classifier. A neural network was then employed to encode the variations in sub-units (Cooper et al. 2012). This approach resulted in recognition rates of 99% based on a 20 sign multi-user data set and 81% on a 40 sign test data set.

Cooper et al.'s research is a culmination of all previous research in the field of gesture recognition based on computer vision and is the most comprehensive effort to date. It was published in many machine learning journals and HCI conferences.

Sign language recognition based on computer vision gives high accuracy rates when it is used with a limited vocabulary of trained signs. As the number of words increase the accuracy rate declines (Fang et al. 2003). Results vary greatly between different users due to the variation in hand shapes, speed, position and orientation. Sign language libraries are enormous with some signs being very similar and difficult to distinguish. Computers still struggle with isolation, depth, classification and segmentation. Sophisticated software and multi-stage processing is required to recognize sign language. As a result, it is unlikely that these systems can exist yet as accessible mobile devices or become available universally to sign language users and deaf communities.

It is for these reasons that I opt to exclude vision based recognition systems from this research and emphasize on data glove based sign language recognition systems.

2.5 Data Glove Based Sign Language Recognition Systems

Data glove based systems have proven to be more reliable in registering and relaying hand gestures than vision based systems. Data gloves use sensors that can more reliably detect finger flexing and bending, as well as hand movement and orientation (Parvini et al. 2009) as well as global and local features. These systems are simpler than vision based systems because they don't have to consider background isolation or hand motion tracking.

There are many versions of the data glove that translate sign language to text and/or speech. I mention here an overview of the prototypes developed to date, and how they progressed to the versions we know today. One of the earliest attempts to translate sign language hand gestures to speech was Fels and Hinton's Glove Talk (Fels and Hinton 1993) in 1992. They used a data glove and a speech synthesizer to translate 66 root words with six different endings and a vocabulary of up to 200 words. Their data glove is wired with sensors to collect finger bending data and hand orientation over 16 parameters which is measured every $1/60^{\text{th}}$ of a second. The data is then sent through a computer which defines the text and sends it to a speech synthesizer to translate it into human-like speech. The computer starts processing when it detected a motion from the glove. A stop in motion gives the computer a message of the end of the gesture and it stops processing. One of the challenges they faced was adjusting the signing speed to tell the system when to start/stop processing. Another challenge was the response delays since three different software were being used at the same time and sharing the same memory. Glove Talk resulted in 1% incorrect output and 5% non-identifiable gestures. The system was not tested with different users to observe system adaptation to user variation.

In 1998, building on Fel's and Hinton's Glove Talk system (Fels and Hinton

1993), researchers Liang and Ouhyoung (Liang and Ouhyoung 1998) from National Taiwan University were able to interpret Taiwanese Sign Language in real time using a data glove and HMM. They first solved the end-point detection problem - a major challenge for Glove Talk - by creating a threshold for gesture time variance. They classified recognition models based on four gesture parameters: "posture, position, orientation and motion" (Liang and Ouhyoung 1998). Their prototype system was programmed to recognize a vocabulary of 250 words with an accuracy rate of 80.04% In 2003, building on both Fel's and Hinton (Fels and Hinton 1993) and Liang and Ouhyoung's (Liang and Ouhyoung 1998) research, Fang et al. (Fang et al. 2003) attempted to develop an advanced sign language recognition system by improving processing speed for a large vocabulary of sign language based on hierarchical decision trees. They acknowledged that output delays were due to the systems being programmed to recognize more words and so their proposal helped the computer prioritize which clusters to look through first. Fang et al's research addressed and solved a major challenge in previous data gloves - how to reduce recognition time without the loss of accuracy. Their testing results showed processing speed was 11 times faster than previous systems and was able to process a vast vocabulary of 5113 words.

In 2011, a different approach to sign language recognition systems was proposed by Oz and Leu (Oz and Leu 2011) who used a motion tracker, an artificial neural network and a sensor glove to translate ASL to speech. Three sets of data were collected and aligned for an improved classification of sign language.

Finger and hand shape data was collected from the sensory glove. Hand motion data was collected from the motion tracker. Both data sets were then classified by the artificial neural network. Gestures feature extraction was continuously being performed in real time. The system was trained to recognize 50 ASL gestures with accuracy results of 90%.

2.6 Current Academic Projects and Early Prototypes of Sign Language Data Gloves

Sign language recognition technology is currently being developed by many research teams at universities and digital technology labs. Recognition systems are still based on either computer vision or data gloves. However, researchers continue to explore solutions that bring them closer to producing a reliable and embedded system which could be integrated into the speech-disabled community and enable them to express themselves more naturally.

In this section, I mention some of the most significant academic research projects in this field and highlight the features and limitations of this work. Many of these projects build on the literature mentioned above and show great promise but have not yet moved beyond the research phase, to taking it outside of a lab environment, testing with real users, or production.

Perhaps one of the earliest academic debuts of a working sign language data glove was AcceleGlove, developed by researcher Jose Hernandez-Rebollar at George Washington University in 2003 (*Mobile Mag - AcceleGlove* 2020). AcceleGlove was presented as an experimental device that translated the hand gestures and body language of ASL into spoken words. It was perceived as a wearable computer with very small electric circuits which was considered revolutionary at the time. AcceleGlove is a right-hand glove with two small armbands, for the wrist and the upper arm. The glove is wired with sensors and a micro-controller attached to the wrist, mapping the placement and movement of the arm and fingers. The collected data from the sensors is processed by the computer and converted into speech spoken out through a speaker or text displayed on a computer screen. This single glove can produce up to 200 words which could be signed using only one hand and a few expressions. As for accuracy, Jose Hernandez-Rebollar stated that "the device usually is accurate, though the precision declines with complicated movements; for example, words that start with the same hand movement or orientation" (*WTOL - AcceleGlove* 2020). This was one of the most powerful data gloves in terms of output to be published in 2003. However, the processing happens on the computer itself as well as the text display, so AcceleGlove could not operate as a mobile device.

In 2012, a data glove was designed and programmed by two Ukrainian students to translate sign language into speech. The glove was called Enable Talk[7] and was part of a competition organized by Microsoft in which it won the first prize. Enable Talk is fitted with "flex sensors, touch sensors, gyroscopes and accelerometers, as well as some solar cells to increase battery life" (*Enable Talk* 2017). The glove has a system that can translate sign language into text and then into spoken words

[7]EnableTalk - http://enabletalk.com

using a text-to-speech engine. The whole system then connects to a smartphone over Bluetooth™. A major drawback is that the Enable Talk system mostly uses Microsoft technology and is not compatible with any other platform.

The team has built a number of prototypes and claim to have tested them with sign language-users in the Ukraine, although no documentation of usability studies have been shared or published. Enable Talk would have been highly competitive if introduced into the market because it was set to cost under $100 and also promised to come equipped with a software the enables the users to teach the system new gestures and eventually build a library of custom gestures. However, no further research has been done on this project since 2012 and it did not move into production.

In 2013, inspired by Jeremy Blum‘s innovation, the Sudo Glove (Blum 2012) which is a sensor data glove for non sign language applications, Roman Kozak[8] set out to create a device that could utilise the same technology (flex sensors, accelerometer and microcontroller) while accomplishing a different task: translating sign language into text and speech. Roman Kozak, a high school student at the time, is probably the youngest programmer who designed a glove-based sign language translator. He was also the first to program an Arduino[9] to read analog data from flex sensors and outputs them as letters matching the sensor data with a series of if-statements. In his own (albeit limited) tests, he encountered no errors. However, it was still limited to letters, specifically, one letter at a time. Letters were not aligned to form sentences. Kozak stated that “distinguishing between similar sign language gestures was very challenging” (Rozak 2017). Processing and display of letters happened on a computer screen or a smart device tablet sent wirelessly via Bluetooth™. Kozak has now stopped working on this glove and instead moved on to create other innovations with different technology[10].

In 2014, Gesture Glove[11] was another project that generated significant press attention. It was designed by two groups of students at Cornell University who have developed a different version of a glove which translated sign language to speech. Designed and built to be worn on the right hand, this glove used a machine learning algorithm to translate sign language into words. The glove hardware is very similar

[8] Roman Kozak - http://www.romanakozak.com/sign-language-translator/

[9] Arduino - https://www.arduino.cc/en/Main/Products/

[10] Verdi - http://www.verdiag.com

[11] Gesture Glove - http://people.ece.cornell.edu/land/courses/ece4760/FinalProjects/f2014/rdv28_mjl256/webpage/

to previous gloves, including most data gloves (Prashan Premaratne et al. 2013). It consisted of five flex sensors, a gyroscope and a micro-controller. The incoming data from the sensors are sent serially to a computer to be analysed in conjunction with a Python script. By collecting a moderate amount of this data for each letter or word and feeding it into a machine learning algorithm, it can train over this dataset and learn to associate a given hand gesture with its corresponding sign. It is interesting that the glove continuously learns from the user. However, there are important features to discuss about this glove, namely the lack of accessibility. First, much of the computation happens on the computer and not the glove itself, which makes the glove heavily reliant on a computer to operate. Secondly, from an accuracy point of view, in some cases, the change in the resistance from the flex sensor will be negligible and the algorithm may be unable to discern the difference between these signs. Thirdly, this glove is only programmed to recognize and output letters, which is not necessarily practical for sign language users. The hardware is also bulky at this early prototype state, making it difficult to wear.

Also in 2014, Anetha K, assistant professor at the Institute of Technology, Coimbatore in India, developed a sign language recognition data glove called Hand Talk (Anetha K 2014). Hand Talk uses an artificial neural network (ANN) to translate ASL alphabet into text and sound. The glove circuit consisted of a controller unit, text to speech conversion module and an LCD display. The glove itself was wired with flex sensors, a 3-axis accelerometer and sEMG sensors to capture gestures (Anetha K 2014). Just like previous data gloves discussed above, the flex sensor produced the change in resistance value depending on the degree of bend in each finger. The corresponding hand movement and orientation was reported by the tri-axial accelerometer. A novel aspect of this technology was its use of sEMG sensors, which are used to measure the muscle activity of the hand while performing gestures in terms of electrical signals. The recognized gestures were then converted and displayed as corresponding text and speech using a text to speech conversion module (Anetha K 2014). This glove builds on all previously discussed glove prototypes. Testing for Hand Talk was published based on its ASL alphabet output only, which again makes it not necessarily practical for sign language users. Hand Talk hardware was not wearable. Output relied on a computer to display letters and to produce sound(Anetha K 2014).

One of the latest sign language translation data glove prototype was developed by researchers at Mexico's National Polytechnic Institute (IPN). This prototype, created by Miguel Felix Mata and Helena Luna Garcia, senses hand movements of the user and identifies them with the 26 letters of the English alphabet (*Mexico's National Polytechnic Institute* 2020). Once the message reaches the device, it plays a voice. Listeners can then understand what their differently-abled companion or acquaintance is trying to say. Presently, the glove can only read letters of the ASL alphabet, but the researchers indicate that Mexican sign language support is a target feature. Smart textiles with conductive features have been used to detect if the fingers are open or closed. A combination of nylon and polyester was used to support the embedded hardware and give the glove better manoeuvrability. "Words and phrases are transmitted by Bluetooth™ to a mobile device with a pre-loaded application that displays and reads the signs", Luna said (*Mexico's National Polytechnic Institute* 2020). This by far is the only sign language data glove that addressed glove materials, appearance and durability. This is also the only glove which designed an application for smart devices to pair with the glove for output. The application is available on the Android platform as Glove Translator but needs the glove to work. The main drawbacks of this prototype are the size of the glove and the output mode. It depends on the app for output and cannot operate as a stand-alone glove. This glove prototype is patent pending with plans to enter manufacturing.

Another feature that was not addressed in prior research is continuous classification of incoming gesture data. A single study was published in 2016 with promising results (Luzhnica et al. 2016). It demonstrated the additional usage of a sliding window to translate a pre-trained list of sign language hand gestures. By recording the minimum, maximum, range, average, and standard deviation of the data glove sensors (bend sensors, accelerometer and gyroscope), and using a KNN classifier, the system achieved continuous recognition of ASL signs in real time, with an accuracy level of 98%.

Most data gloves mentioned above are single gloves, specifically right hand gloves. Further investigation was conducted to explain the lack of literature on using a second data glove, as it seemed that a set of two data gloves should improve accuracy results in recognition modules and could be a potential area to explore in this research.

It was found that there were several attempts to integrate a second glove to sign language recognition systems. The most recent one was published in 2017 by a team of researchers in Montreal (Natesh et al. 2017). They implemented an "intelligent two hand gesture recognition system" by creating a primary system for the right hand glove and sub-system for the second glove. Their system recognised 196 static gestures from eight different sign language libraries with an accuracy range of 80 to 93%. The reported result is lower than some of the previously published projects, discussed above, that use only one data glove. Therefore, the prospect of pairing one right hand glove with a left hand glove and integrate signals from both gloves to form one more accurate output is not a consideration for this research.

2.7 Summary

In summary, all data gloves described above use some form of a standardised sign language library base to process alphabet letters or static gestures, they all use an external device for output and some of them are extremely bulky with little or no consideration of being effectively wearable.

As this research is multidisciplinary and is placed across the fields of art, computation, and technology, issues of hardware, design and software development were explored in iterative action research cycles with an extensive range of user base outside of the lab environment.

The goal is to enhance performance and increase accuracy in comparison with existing data gloves, while making a single stand-alone data glove which is accessible, universal and wearable.

Rather than output letters or words, the aim was to develop a glove and accompanying software which can process full sentences worth of incoming gesture data, in real time.

Instead of relying on a smart device or a computer, a wireless and stand-alone data glove with all required hardware for output would be embedded in the design of the glove which is powered with a battery. The challenge for this approach is to reduce hardware to make it wearable. In order to make this glove as universal as possible, it should be paired with a translation API to output the speech in different spoken languages, regardless of which library is used for sign language.

Considering the vast variations in sign language libraries, the system would be equipped with machine learning software to allow each user to train the glove using customized hand gestures. This would be most useful for users on the Autism

Disorder Spectrum who use the Makaton sign language library[12].

A user interface (UI) would be designed to interact with the glove for training new gestures and building a customized library. This UI could further be used to set the speech language or connect to the internet for future upgrades.

To make this glove accessible to everyone that needs it, it must be affordable by trying to reduce hardware and replace it with software when possible and also integrating all parts onto one circuit board.

To make this glove wearable, smart textiles should be utilized with a customized glove design pattern to house all hardware in correspondence with hand and arm ergonomics. Fabric used should be water resistant, machine washable, fire resistant and employ safety measures to insulate the electrical circuit from contact with skin.

[12] The Makaton Charity - https://www.makaton.org

Chapter 3

Research Methodology

3.1 Research Methods

Human-problem oriented inventions (Cox and Cairns 2008), similar to the proposed design of the data glove, have conventionally employed user-centred design research methods (Bevan and Curson 1999). Rather than starting with an idea for a system based on what technology can do, and then trying to determine whether people will be able and willing to use it, instead I will start with a specific user group's needs and ability; and find a technology that they will be able to use to fulfil that need. This strategy is confirmed in multiple research resources in HCI (Dix et al. 2004) and is referred to as 'Interaction Design'.

The main steps in such a strategy are the following:

1. Identify a problem that requires a solution, which then becomes the research goal. This can be confirmed through surveys, interviews and observation.

2. Find the source of the problem. What is causing the difficulty?

3. Invent, or this case innovate, a solution to help people with their difficulty. This can be done through multiple rounds of testing and developing to prove that the proposed solution is valid. Interaction design research will be used in this phase to develop and test iterations of the designed system, in a build-measure-learn loop.

4. Create a system which incorporates findings and make it available to the people who struggled with the previously identified problem. If the function people wanted to perform but couldn't do well is made more available, chances are

it will be successful, considering of course it is affordable, which is a major consideration in this research.

In this research, interaction design methods will be applied to collect data through a series of usability studies. These studies will mainly consist of iterative case studies followed by a single longitudinal and in-depth case study. I combine this with iterative prototyping as the prototyping cycles are continuous. This will be discussed in detail under evaluation methods (Section 3.2). I chose to integrate two research methods because it is more of a holistic approach to problem-solving, rather than a single method for collecting and analysing data (O'Brien 2001). I propose starting with iterative prototyping rounds for the preliminary case studies to maximise gained feedback while testing multiple features of the proposed system. Finally, a longitudinal user-centred design study will be used to validate the proposed solution through usability testing.

Evaluation criteria in this research as identified in the research question are:

- **Assistive**: Effective in facilitating daily communication between sign language users and the public. This specifically measures the performance of the glove, its durability and comfort and mobility.

- **Adaptable**: Can be used by adults (all genders), children, output different languages, compatible with any platform, translate different libraries of sign language including customized gestures.

- **Accessible**: Can be made available to people who need it, not requiring any external hardware or device, stand alone and wireless.

- **Affordable**: Cost effective - priced at a reasonable point relative to existing solutions (Section 9.2).

As in most research in the HCI field, both text-based information and multimedia-based information will be collected from the participants (Lazar et al. 2010). However, since I will be designing new technology and studying speech-based interaction, I will also need to evaluate a number of issues relating to the recognition rate, which requires comparison between the recorded data and the system output. To evaluate system performance, I will combine with the identified evaluation criteria, the following methods (Rogers et al. 2011):

- **Failure Analysis**: to find out specifically where things go wrong.
- **Individual Difference Analysis**: to identify that certain kinds of users, ones with certain background characteristics or abilities, affect the results of testing the system in different ways. This is directly relevant to the proposed universal design of a sign language data glove to be used by all ages, genders, languages and abilities.
- **Time Profiling**: to measure and analysing how much time is spent on isolated tasks within the system. Time profiling is important in identifying problems in the system and potential areas for improvement (Cox and Cairns 2008).

3.1.1 Interaction Design: Build - Measure - Learn

Drawing on standard methods for research in HCI (Cox and Cairns 2008; Dix et al. 2004; Lazar et al. 2010; Zimmerman et al. 2007), the practice portion of this research will employ interaction design as a research method. The start and focus of any interaction design is the intended user or users (Dix et al. 2004). The user in this case is speech disabled individuals who use sign language for their daily communication.

The research, design and evaluation will be based on their needs. Consequently, testing rounds will employ user-centred design research methods.

In principle, interaction design research is “learning by doing”: researchers identify a problem, design a solution, test and evaluate their proposal, and if not satisfied, try again using the feedback they gained from the research cycle. While this is the essence of the approach, there are other key attributes of interaction design research that differentiate it from other problem-solving research methods. One being its heavy emphasis on scientific study. In interaction design research, the problem is studied systematically, and intervention is informed by theoretical considerations. As such, data is presented on an ongoing basis. All the while, the methodological tools are being refined to suit the demands of the research (O’Brien 2001). Another reason that I chose Interaction Design research, is because it is a user-centred research methodology. Interaction design research focuses on turning the people involved in the studies and testing into researchers, too. “People learn best, and more willingly apply what they have learned, when they do it themselves. It also

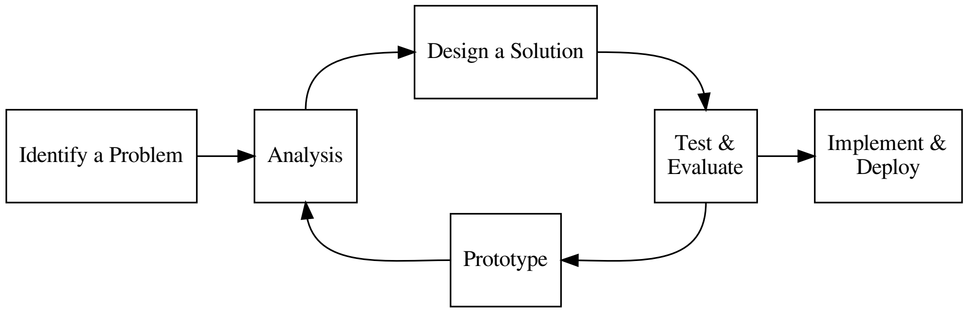


Figure 3.1: Interaction Design Process; based on Figure 5.1 of Dix et al. 2004

has a social dimension - the research takes place in real-world situations, and aims to solve real problems" (O'Brien 2001). This is the exact setting for the proposed research studies, where real participants will test and use the data glove, sometimes over a long period of time and mostly in their own environments. The interaction design process (Dix et al. 2004) of the research will be divided into four main phases plus an iteration loop (feeds evaluations back into the design), focused on the design of interaction, illustrated in Figure 3.1.

Requirements: The first stage is establishing what exactly is needed. As a pioneering study in this field it is necessary to find out what is currently happening. For example, how do individuals with little or no speech abilities currently interact in public using sign language? How does the process of communication work? A number of techniques have been documented for this in HCI (Dix et al. 2004; Zimmerman et al. 2007) including interviews, video documentation and direct observation.

Analysis: Observations and interviews are analysed to highlight how people carry out various tasks in relation to the problem identified. The results are classified in a format to outline key issues resulting in task models. Task analysis methods are then developed and applied to formulate a proposal for a design solution.

Design: Design is at the core of the interaction design process. This phase starts with the data gathered from previous steps and moves from what we need to design, to how we should design. Design loops are then attempted based on user testing and feedback, in compliance with user-centred design principles.

Iteration and prototyping: Evaluation of prototypes will be based on usability testing feedback. Observations will be made in terms of performance and improvement areas. Most user interface designs involve some form of prototyping, producing early versions of systems to try out with real users (Bevan and Curson 1999). This is the approach for the proposed data glove design. Prototyping iteration will be discussed in more detail in Evaluation Methods (Section 3.2).

Implementation and deployment: Finally, when the design gives indications that is successful based on user feedback from testing rounds, the plan is to build it and deploy it. This will involve finalising writing code, concluding hardware design, writing documentation and manuals - everything that goes into a real system that can be given to others in preparation for production.

As the user centred design loop of build-measure-learn is continuous in this research, iterative design through cyclic prototyping (Nielsen 1993) becomes an integral part of the research and is combined with interaction design as a research method.

3.1.2 Iterative Design: Cyclic Prototyping

Cyclic prototyping is also known as "continuous prototyping" and is usually referred to in the context of iterative design; based on a looping process of building a prototype solution, testing it, analyzing its performance, and then refining the design of the solution. The results of the testing phase of the latest iteration of this cycle inform the changes and refinements to be made (Carey 1990).

Much like the Interaction Design methodology described above, using a Build-Measure-Learn loop, this iterative design system utilises a cycle of processes, with the output of each in turn feeding into the next.

In each cycle, a prototype is developed, based on prior knowledge as well as informed by the conclusions drawn from the observation and analysis of the testing of previous prototypes in the process, with an emphasis of course being on the most recently tested design. By incrementally refining each prototype based on the flaws and areas for improvement of the last, the process aims to make the ultimate design more utile and functional for its target users. The study of the interaction between target users and each prototype constitutes the research that in turn informs the next prototype, each time bringing the researcher closer to the end goal of an ideal solution to the central problem that the design process is attempting to solve. The process should conclude once the product has been developed to a level satisfactory to those it exists to serve (Bailey 1993).

While this methodology can be applied at any stage during the process of developing a new project, changes are most often easier and far less expensive, both in terms of monetary expense as well as development time, if they are implemented in the earliest stages of development. The consequence is that if this methodology is applied ideally, the most invasive and substantial changes are made in the first few prototypes, with further prototypes only being subject to increasingly minor refinement (Bailey 1993).

Iterative prototyping and user-centred design are two methodologies that have been successfully integrated in prior research with promising results (Gulliksen et al. 2003) and especially with new technology such as the one proposed in this research.

Specifically, when designing an interface between a user and a machine, the designer of that interface can observe users interacting with that machine, using the prototype of the interface that they have designed. By noting and analysing the mechanisms that users found difficult or frustrating, the designer can produce the next prototype having refined those mechanisms, in turn making the interface more functional and easier to use. While some projects opt to gather much larger amounts of quantitative data on which to base their refinements, sufficient feedback and insight into the issues that users face can often be obtained with a relatively small testing group (Nielsen 1993).

It is important, however, to ensure that this process is continued for a sufficient number of iterations, in order to be confident that the end product is of sufficient quality. Multiple studies show that basing user interface design on iterative user testing methodologies such as this, producing at minimum three prototypes with two testing rounds, can improve the ultimate usability of the interface in a substantial way (Nielsen 1993). It was found to be the case that adding more rounds is likely to further improve the utility of the design.

Finally, in order to ensure that measurements of the effectiveness of user interfaces, particularly wearable ones, do translate into the genuine usability of the final product in the real world, it is important to select the tasks that users complete as a part of the testing process such that they are representative of the goals and environments that users in the real world would experience. By considering the users' usage of such interfaces in terms of the mental models they construct of their actions early on, the interface can be designed and tuned both quicker and more optimally, requiring fewer iterations before feedback converges to a near-optimal product (Smailagic and Siewiorek 1996).

3.2 Evaluation Methods

For the proposed data glove prototype, preliminary iterative case studies will be conducted followed by one in-depth longitudinal case study.

Evaluation methods will be divided into two overlapping sets (Fallman and Waterworth 2005):

1. Formative evaluation and iterative testing - for the preliminary case studies
2. Full-scale evaluation studies - for the longitudinal and in-depth case study

Two main groups of users will be recruited for this research: adults with speech disabilities and children who are non-verbal. Testing will be conducted in a natural environment where participants spend their day time, like a workplace or school. There are several factors to consider when conducting case studies with participants with different abilities:

- Due to the nature of the participants' disabilities, it is not feasible to conduct studies in a group setting or with large numbers of participants.
- One-on-one time will be needed with study participants to train them on how to use the new technology, keeping in mind that disabilities will vary between users.
- It is common for testing with participants who have disabilities to gain feedback through a care giver, a therapist or a family member (Lazar et al. 2010)

3.2.1 Formative Evaluation and Iterative Testing

Cost is an important factor to consider when building hardware for an ongoing research such as this. Therefore, it is essential to justify why conducting multiple rounds of prototype building and testing is required. Designing multiple prototypes each performing an isolated task and testing a single particular feature is more effective than prototyping a fully executed system and testing multiple features at once.

> "The best strategy for good design is to try various options (suggested, of course, by experience with previous similar systems, guidelines, and available principles), test them, and be guided by the failures, successes and comments garnered in watching their use, redesign trying new options, and iterate. This is called formative evaluation or developmental evaluation. The idea is simple enough. The barriers to its more frequent use are largely lack of will (organizational resistance), lack of time, or lack of ingenuity."
>
> - *Dix et al. 2004*

It is documented in previous HCI research (Cox and Cairns 2008; Lazar et al. 2010) that formative testing can be both extremely effective and quite economical. Although a single test is not sufficient, multiple iterations of the whole system are not required to evaluate it. "There are many reports in the literature, of dramatic improvements in usability in cases where two or three iterations were made on each important interface design problem, each requiring about a dozen hours of human testing and an equivalent amount of reprogramming" (Georges and Romme 2004).

HCI researchers (Cox and Cairns 2008; Lazar et al. 2010) have strongly recommended that user testing begin as early in the development cycle as possible, so that improvements can be made before design processes and coding become complex. For this to become feasible, it is advised to keep the system development flexible and easily modified to be able to conduct continuous user testing. This is known as "rapid prototyping, and consists of first developing a system specifically designed to be easily modifiable" (Wania et al. 2006). It is done through segmenting performance and postponing the launch of the full system to a later stage in the study (Dix et al. 2004; Georges and Romme 2004).

An exemplary case study and rational account of the iterative testing and rapid prototyping approach is given in an article by Good et al. (Cox and Cairns 2008) in which they describe the process as "User derived interface design".

In this way, a series of prototypes of the data glove will be designed and iterative prototyping becomes the pillar of the research method, following the same structure illustrated in Figure 3.2. First prototype will be a proof of concept, to prove that the system works with minimal hardware and software. Testing will be conducted and feedback will be applied to the development cycle of the next prototype.

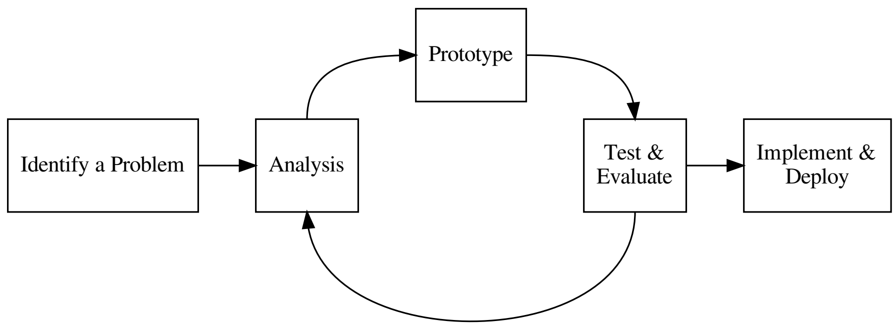


Figure 3.2: Iterative Prototyping; based on Figure 5.14 of Dix et al. 2004

The consequent prototypes' features will be upgraded gradually based on usability testing, always considering the four main elements of this research: affordable, accessible, adaptable and most importantly effective in facilitating daily communication between speech disabled individuals and the public.

As an example, when designing an interface for a prototype voice store and forward system, a first attempt-by an expert human factors team at a set of user procedures produced around 50% unrecoverable errors in attempts to use the service. After four weeks of testing and three revisions in the protocol, field tests found the procedure to result in less than one error for every hundred uses (Landauer 1988). The voice message system demonstrated by IBM at the 1984 Olympics in Los Angeles (Gould 1988) was developed by a team of programmers and behavioural scientists who continuously tried new versions of the system and its protocol and made revisions for several months. Despite what would ordinarily be considered a rather small-scale development effort, usability in the initial full-scale trial was extraordinarily good. The development of the much acclaimed user interface for the Apple Lisa computer (including design lessons later incorporated into the Macintosh) was accomplished by almost continuous formative testing during system and interface development. In this case the testing was done by the manager of the interface programming group, named Larry Tesler, himself (Blackwell 2009). The tests were relatively informal. Tesler selected a particular issue, for example where to put an "exit" icon on the screen, for semi-formal evaluation, (i.e. for some subjects it was in one place and for others in another), for each small experiment. Then he would have a handful of subjects try each of the two options. Most of the gain was not, however, from the comparison of the options but merely from observing the difficulties experienced by the users, and from the participants' comments and suggestions.

According to Tesler the formal comparison served primarily to help in the discipline of systematizing observations. Difficulties were then either taken back to the design team for immediate alterations and retest, placed on a wish list for later solution, or ignored for practical reasons. Iterating this step every time an interesting design question arose, and after every significant milestone in the interface development, required running only about two dozen subjects per week through trials of the system, and caused almost no delay in the total development process since the fixes were made concurrently with the normal course of programming. This whole procedure strikes me as exemplary, as do the somewhat more elaborate and ingenious techniques utilized by Gould, Boies, Levy, Richards and Schoonard (Cox and Cairns 2008).

3.2.2 Full-Scale Evaluation Studies

HCI studies have used full scale evaluation to compare the performance of different systems (Wania et al. 2006). Full scale evaluations are also known to have been used to examine specific features of existing systems for the purpose of further development. In full scale evaluation studies "A group of representative subjects are recruited to learn and use each of the systems and compare them on a pertinent set of performance measures" (Cox and Cairns 2008).

The aim of the longitudinal case study in this research is to observe how the adoption of the proposed data glove impacts participants who use it for communication over an extended period of time. These studies will only be feasible by doing direct experiments with real users participating on a full time basis for at least six months.

Evaluation criteria will be classified under two main categories:

- **Performance Metrics**: Isolating performance features and setting them as evaluation criteria is key to identifying why a system works better than another. One proposal (Roberts and Moran 1983) is to use a set of "benchmark" tests that are chosen to represent the important functions performed with a system.

- **Usability issues**: In users' feedback I will be keen to observe and discover possible trouble-spots in the use of the prototypes, so that solutions can be proposed in the next cycle of prototype design (Klasnja et al. 2011). To be valuable, evaluations of this kind must look at the details of use (such as time, errors or user reactions) for isolated functions rather than overall performance. Lessons learned from such studies provide important foundation for the development of future systems designs (Cox and Cairns 2008).

3.3 Literature Relating to Chosen Methods

In this section I present a number of case studies that implement the same research methods chosen for this research, as evidence for how and why they were selected, and for the reference of other researchers looking to undertake similar work.

This research is user-centred. It is therefore based entirely on case studies. It is important to highlight the goals of HCI case studies (Cox and Cairns 2008; Lazar et al. 2010) and the role they play feeding straight into interaction design research:

- **Exploration**: Case studies provide valuable feedback in understanding novel problems especially in the early phases of the research. Results often set the foundation for further investigation to inform new system design.

- **Explanation**: Case studies of tools are used to understand a context of the proposed technology. It is very common in computer systems that study participants use the technology in unexpected ways that were not considered in the initial design which impacts the iterative design loop (Klasnja et al. 2011). "As HCI researchers often use a case study as a tool for understanding the technology usage and needs of populations of potential users, HCI case studies often largely draw upon representative users and use cases, omitting extreme cases" (Lazar et al. 2010).

- **Description**: Descriptive case studies are longitudinal and in-depth case studies. They contribute to documenting a system, a context of technology use, and the process that led to a proposed design. They are particularly useful for technology involving new design methodologies. In interaction research, the process behind the design is usually the focus of the case study. "Case studies that describe design processes and results have been written for a wide variety of topics in HCI, specifically for participants with impairments." (Cox and Cairns 2008; Lazar et al. 2010).

- **Demonstration**: Demonstrative case studies are shorter and less in-depth than descriptive case studies. Their purpose is to show how a new tool was successfully used. Participants demonstrate the effective use of a new tool to complete one or more assigned tasks.

Case studies in this research will be of two types: The first set are a series of demonstrative case studies where iterative prototyping evolves into a final product. Those are followed by a final descriptive longitudinal and in-depth case study to evaluate the system over an extended period of time.

3.3.1 Demonstrative Case Study

A good example is a case study conducted by Shinohara and Tenenberg (Shinohara and Tenenberg 2009) of a blind person's (Sara) use of assistive technology. Sara's case study focused on one person's use of technology. How a blind person might use a variety of assistive technologies to achieve tasks, user interactions, including failures and response to those failures. In this case study, Shinohara and Tenenberg (Shinohara and Tenenberg 2009) used three types of technology biography (Blythe et al. 2002): "demonstrations of devices (technology tours), reflections on memories of early use of and reactions to devices (personal histories), and wishful thinking about possible technological innovations (guided speculation)" (Shinohara and Tenenberg 2009). Data sources used in this study demonstrate three types of case study data: "artefacts, observation, and interviews" (Shinohara and Tenenberg 2009).

A total of 12 hours was recorded in Sara's home, broken down into six, two hour sessions. Raw data consisted of written notes, audio recordings, inter- views and photo documentation. Twelve tasks were defined and recorded in terms of their goals. The insights from the individual tasks guided the design of improved tools (Shinohara and Tenenberg 2009).

Although Sara does not provide a comprehensive picture of the needs and concerns of all blind people, the investigations of her needs and goals led to valuable insights that might apply to many other blind people. The Shinohara and Tenenberg

(Shinohara and Tenenberg 2009) case study helped the researchers to understand how Sara used a variety of technologies to accomplish multiple tasks. They were specifically interested in understanding "what technologies were most valued and used, when they were used and for what purpose" (Shinohara and Tenenberg 2009). Conducting the study in Sara's home helped the investigators gain insights into how she actually addressed real challenges, as opposed to the more engineered results that might have been seen in the lab.

Sara's case study demonstrates four key aspects used to describe case studies for users with impairments. These points align with the chosen research methods and will be followed as guidelines in the case studies of the research:

- **In-depth investigation of a small number of cases**: In-depth, broad examinations of a small number of cases are used to address a vast range of concerns.

- **Examination in context**: Labs have the advantage of removing undesired external influences which is not a realistic or credible environment to show how the technology would work. On the other hand, single case studies conducted in a realistic context give meaningful results which are applicable in the real world and are more informative than large scale case studies conducted in a lab.

- **Multiple data sources**: Known as data triangulation and is especially important in single case studies. Multiple data sources are combined to validate the evidence and the quality of the data. Contradictions are important too because they compel the researcher to dig deeper, consulting new data sources, which is the essence of action research.

- **Emphasis on qualitative data and analysis**: Question of how the technology was used to achieve an assigned task are more important than how long it took to complete it. Researchers focus on the quality of the system in successfully delivering what is was designed for rather than the system speed. It is important to highlight that although single case studies can be very informative about the success of a system, results cannot be generalized to include all members of user criteria especially in disability. The real value of single case studies lie in creating realistic insights into design challenges which can

> be applied to a broader scale of users. "Sara's case study led to some suggestions for the design of assistive devices that would help Sara with her daily challenges, but could go further, to influence insights that apply to many blind people. As a result, designs might be useful to a much broader range of blind users." (Shinohara and Tenenberg 2009)

The goal of Sara's case study was: a deeper understanding of a blind user's use of assistive technology in her home. Similarly, usability case studies in this research will have a centre goal of understanding speech disabled participants' use of the data glove and how effective it is in facilitating their daily communication and interaction within a public setup.

3.3.2 Descriptive Longitudinal and In-Depth Case Study

In depth case studies executed in-context, in realistic environments, present credible and valuable evidence. Careful consideration is given to the selection criteria of case study participants. Analyzing the data from the case studies and further interpretation is of the upmost importance (Yin et al. 2008).

In these studies, the process of developing a new system or interaction technique is more important than the end product, especially for innovations that tackle new challenges in the context of use (Cohene et al. 2007).

A study at the University of Toronto (Cohene et al. 2007) provided the base for a very interesting single in-depth case study involving the design of an assistive technology tool to help people with Alzheimer's disease. "This project was based in a body of prior work that firmly established the importance of reminiscences for people with Alzheimer's disease." (Cohene et al. 2007). The goal of the case study was to develop a multimedia tool to help people with Alzheimer's disease recall and relive old memories. The sole participant of the case study was a 91 year old woman named Laura. Laura and her two daughters were fundamental in the study which focused on developing a system to help Laura with her memory (Cohene et al. 2007).

The study started with an exploratory phase to understand Alzheimer's disease challenges faced by patients and their families. A broad understating of the disease was necessary even though the study was aimed to develop a tool specifically tailored to the needs and abilities of Laura. Researchers' observations resulted in a comprehensive understanding of the "abilities and impairments of the participants, leading to a set of design principles" (Cohene et al. 2007). The study also included feedback from caretakers and therapists which acted as a basis in outlining a set of guidelines to assist with memory recollection. As part of the study, family members were required to complete a "family workbook" accumulating stories in the form of pictures, videos and music. The collected media was to be included in the tool the researchers were working on developing, with the main purpose of helping the study participants with Alzheimer's disease remember. The tool was developed through a series of prototypes which lead to an interactive multimedia device informed by the system with output displayed on a screen. The prototypes were refined based on the feedback of the study participants during eight testing sessions over a period of four weeks (Cohene et al. 2007).

The research team conducted follow-up interviews with family members which confirmed that the system contributed in enhancing the memory of the participants.

"This project as a whole is an exploratory case study. As relatively little work has been done on user interfaces for people with Alzheimer's disease, the description of a successful process is valuable in and of itself" (Cohene et al. 2007). The proposed design served to generate further investigations rather than as a solution.

It is very hard to generalize when it comes to disability and especially a cognitive one like Alzheimer's disease. Researchers on this case study aimed at extending the applicability of this work by scaling the design process to include more participants to improve the tool (Cohene et al. 2007).

This research required serious time commitment from all parties involved: participants with Alzheimer's disease, their family members, and research team members. This, combined with the emotional strain, required intensive resources. Even though the result could not be generalized to other users, the documentation of the design process and the resulting designed tool were considered important contributions (Cohene et al. 2007).

"The most broadly applicable results from this story lie in the lessons learned. The authors concluded that new design methods and principles were needed for working with individuals with Alzheimer's disease, that active participation was more stimulating than passive, and that working with both the patients and their family members throughout the entire design process was necessary. Practical concerns included the resource-intensive nature of the research, the emotional commitment required of the family members, the need to make the approach practical for larger numbers of families, and the need for standards for evaluation" (Cohene et al. 2007).

Although drawn from this particular project, these insights might be extremely valuable to others interested in conducting related research. Similar to this study, the research presented here requires working directly with speech disabled participants and children with non-verbal autism. The research dictates interacting with family members, therapists and caregivers of case study participants. Also, through the process of testing and collecting information, a lot can be learnt about the nature of the disability and how the design of an assistive tool can help not only the participants but also the broad spectrum of users with similar disabilities making the technology developed for this research potentially universal and accessible to many people.

3.4 Special Considerations Relating to Testing with Vulnerable Participants

In order to collect credible usability data and effectively evaluate the proposed technology, particularly while being used as a tool for daily communication in public, we plan to conduct case studies with real users in their natural environments. This means that most of the users will have a speech disability that renders them non-verbal, with the expectation that a number of them will have that condition combined with either a cognitive disability and may additionally or alternatively have physical limitations. As such, we looked at previous research in HCI conducted with users with disabilities (Long et al. 1995), and considered their needs in all phases of the research.

Due to the nature of the user groups, stricter protection measures are expected to be in place to ensure the safety of the participates while taking part in the case studies. Ethics approvals will be more comprehensive with supplementary granted permission by the local council and participating school's board of governance. In addition, access to user data will be highly scrutinised and the storage of testing data will only be permitted locally on the technological devices being evaluated. These challenges are discussed in far more detail under the section detailing limitations (Section 6.4).

There are multiple additional factors to consider when testing with young users or users with disabilities. In previous HCI research, it has been reported that the most common issues related to study duration and user feedback (Newell et al. 1995). In this research, we have allotted more time than one usually might for study sessions and have accounted for the majority of the feedback to be gained through a carer or a parent rather than directly from the user. As such, the evaluation methods described above have been chosen to best cater for these special user groups (Subsection 3.2).

Additionally, some of the technology features are required to be modified in order to provide different types of system feedback, so as to accommodate the diverse range of cognitive and sensory abilities of the selected user group, with especial regard to the younger participants. Prior research with children documents that emoticons, the smiley face in particular, were used successfully as communicative symbols to reflect the children's feedback and for evaluation (Hall et al. 2016).

As a direct implementation of this practise, in the last case study (Chapter 5), a smiley face was introduced as a form of system feedback to reflect the successful completion of the training task – that being the recording of gestures. We documented that the children found it easy to understand, especially for the participants who were not yet able to read. The smiley face was alternatively used as a design feature of the glove used in the first case study (Chapter 4). It was printed as a sticker and placed on the back of the glove, to cover the wires, in an attempt to make the glove appear more user friendly, and less intimidating, which was indeed successful in encouraging the children to wear it.

Chapter 4

Data Collection, Analysis & Evaluation: Preliminary Case Studies

In this research, data was collected primarily through case studies. As described in Chapter 3, an interaction design research methodology (Dix et al. 2004), specifically iterative prototyping, was used for the design and implementation of the activities performed in all of the case studies described in this chapter. Due to its inherent role in this methodology of research, user feedback necessarily played a highly important role in the evaluation of the design, and informed the design changes applied to each of the subsequent iterations of the design-research loop.

Iterative testing (Cox and Cairns 2008) was used to evaluate the different data glove prototypes developed for each case study. This testing system, explained in far more detail in Section 3.1.1, allows the researcher to begin testing as early as possible in the design and development process and to make changes to the product being tested, in response to user feedback from usage in constrained as well as real world environments, as making alterations can become increasingly costly, time consuming and convoluted as the complexity of the system increases, particularly when approaching the final iterations of the design.

In total, three glove prototypes were developed over the course of this research. Each of these prototypes went through the build-measure-learn cycle as described in Section 3.1.2. Each of the case studies was constructed to evaluate its respective glove prototype and to inform the development of the subsequent improved versions through user feedback. In each of the following case studies, the stages of development every prototype went through, are described under the following three categories: software, hardware and design. As the studies progressed, the data glove prototypes developed into different and increasingly enhanced versions based on observed user needs and user feedback as documented below.

As described in Section 3.2 a set of preliminary case studies were conducted, starting with a short, initial pilot study, followed by a more substantial 3-stage iterative case study. The results from each of those studies in turn informed a final in-depth, longitudinal case study, based on the refined prototype developed through the iterative studies.

The pilot case study (Section 4.1) was a controlled study in which two students at the Jeddah Autism Centre, selected by their teachers and therapists, were engaged to perform specific tasks while wearing the data glove. This study acted as an important early proof of concept, and set the scene for the research questions to begin to be explored while validating the scope for further investigation and refinement.

In the 3-stage-iterative case study (Section 4.2), a series of user-centred design studies were carried out at public exhibitions, in which iterative prototyping was employed as the primary research methodology. Small tasks were isolated to be evaluated independently in each study. The majority of design changes emerged from user feedback, which motivated the outline for following study, in turn continuing the design-research cycle.

The final longitudinal and in-depth case study (Chapter 5), documented and discussed in Chapter 5, took place over a period of six months and engaged fifteen students across six Special Educational Needs (SEN) schools. The results from this study conclude the research findings for this research and answer the research questions. It lastly paves the way for future research as well as a route to commercialisation for the data glove developed during this research.

4.1 Pilot case study, Jeddah Autism Centre 2016

4.1.1 Introduction

The focus of this study was to design a hand gesture recognition system to translate the Makaton sign language to text and speech (as mentioned in Section 2.7).

The study took place at the Jeddah Autism Centre, in Jeddah, Saudi Arabia, and engaged two students diagnosed with non-verbal autism and who use Makaton to communicate as their primary language.

For this study, a limited vocabulary of ten Makaton sign language hand gestures were selected and pre-trained by the researcher (in advance) using a wireless and standalone data glove, with sensors placed and affixed to the glove to monitor the flexing of fingers in order to provide accurate input corresponding to each of the hand gestures. Recognition modules were based on fixed, unmoving, hand shapes and orientations (static signs) rather than changing hand position, orientation or movement through time (dynamic signs). Sign recognition was simplified in an attempt to reduce the hardware and processing requirements (see the section below), in turn making the data glove simpler to run and lighter to wear. In this study, issues derived from these modifications were explored through feedback gathered from the carers of the non-verbal, autistic participants, when consulted about the participants' use of the data glove and how it affected their daily communication.

4.1.2 Prototyping and Development

The glove prototype used for this first study was developed as part of a masters degree in Computational Arts, conducted by the researcher at Goldsmiths College at the University of London in 2015.

The primary aim when designing this prototype was to produce a data glove, which was standalone and wireless, so that it could be easily wearable without substantial impedance to the movement of the user, and could be operated independently from any other device, such as a smartphone or laptop. As such, the goal was to achieve the development of an accurate data glove with on-board, on-body processing being performed using minimal hardware for the input and computation of sensor data.

Hardware

In order to achieve a wireless glove, an Arduino Lilypad[1], a sewable microcontroller chip, was used as the main computing and I/O assembly. Once the code was uploaded to the Lilypad board, and with an external battery attached, the data glove

[1] Arduino Lilypad - https://www.arduino.cc/en/Main/ArduinoBoardLilyPad/

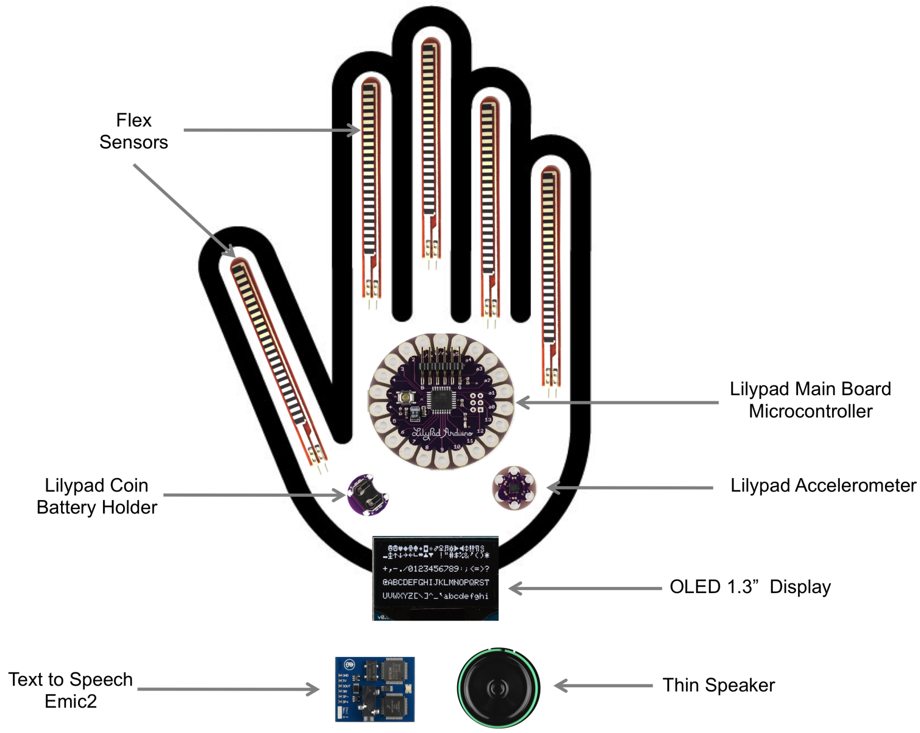


Figure 4.1: Glove schematic

did not need to be connected to an external device in order to operate. A speech synthesis chip (Emic2) was added to support the generation of English speech corresponding to the recognised signs' labels. A small screen and miniature speaker were also connected to the assembly in order to provide textual and audio output, specifically the label of the recognised sign as well as speech synthesised by the aforementioned chip corresponding to that label. To record the shape of the fingers, flex (bend) sensors were placed in correspondence with the five fingers of the glove (see Figure 4.1) along the back of the fingers. These sensors served to register the exact position of each finger relative to the hand and detect its level of flex or bend (see Figure 4.3). Finally, a 3-axis accelerometer chip was placed on the back of the hand to gather accurate orientation data, in the form of the forces acting on the hand in the X, Y and Z directions – the primary one of which being gravity, thus indicating the "down" direction. This force data can be trivially converted into rotation angles describing the orientation of the hand, using trigonometry.

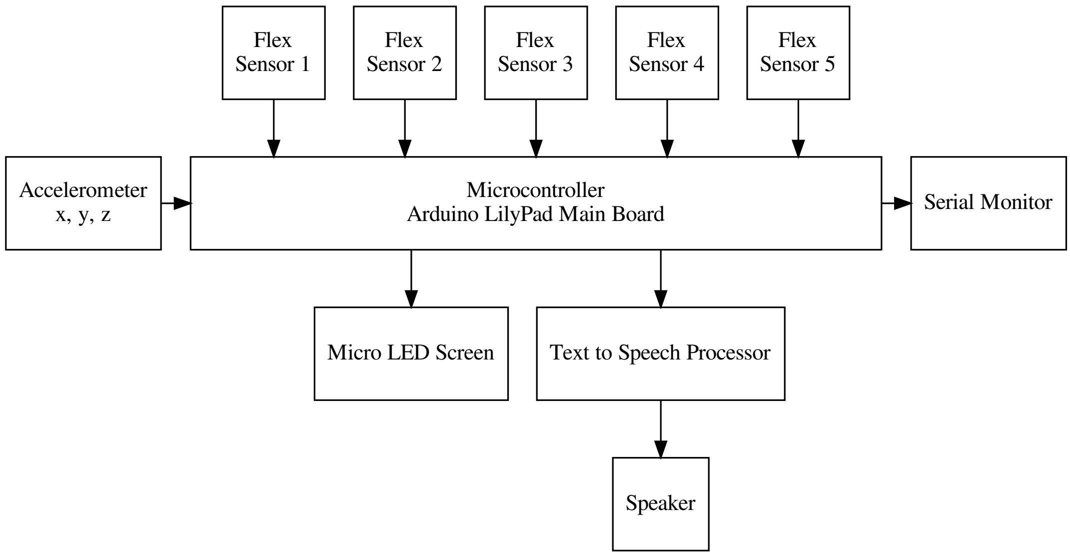


Figure 4.2: Software Block Diagram

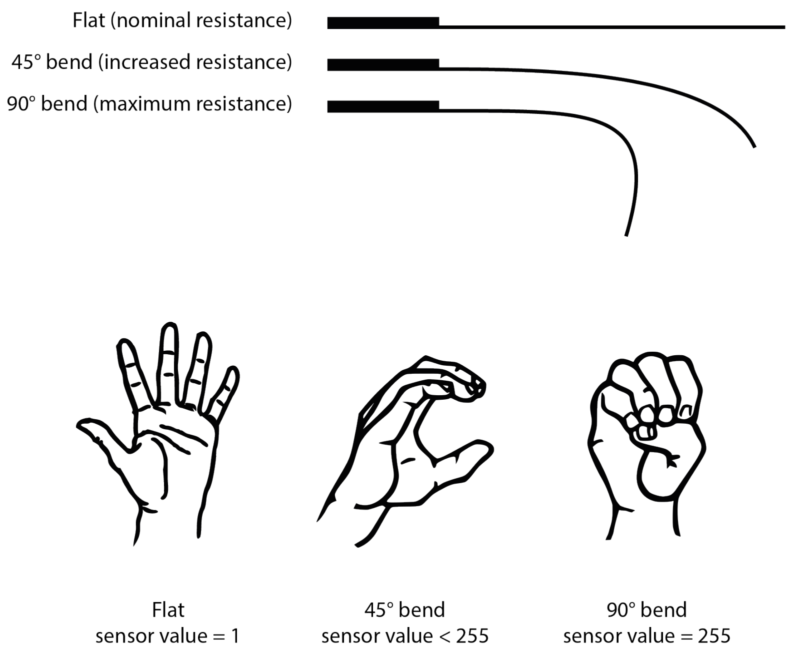


Figure 4.3: Flex Sensor Values and Positions

Software

The signs that were selected to be included in this study were pre-trained and hard-coded by the researcher. Any static sign can be programmed, by defining acceptable ranges of sensor values and orientation angles within which to successfully recognise the relevant hand gesture. By monitoring the sensor data in real time using an external display, while holding the position of the gesture, an ideal value for each sensor and orientation angle was calculated, corresponding to the specific hand configuration for that sign. Exemplar values, calculated in this way, for seven different signs, can be seen in Figure 4.4.

Raw sensor values were linearly mapped between 0 and 255, with values clamped to this range, according to the following rules. Only three distinct positions were required for classification (see Figure 4.3). A fully straightened finger position does not generate any resistance in the flex sensor and so should return a value of 0. A 45° finger bend will cause the sensor to exhibit an increased electrical resistance between its two terminals, which is defined as a value greater than 0 but less than 255. A 90° bend should increase the resistance to the maximum mapped sensor value of 255. To accommodate for different motor abilities and thus some variation in the input sensor values, as well as variability due to inconsistencies in sensor alignment with the fingers as well as manufacturing inconsistencies, when classifying finger positions, any value between 0 and 10 was interpreted as a straight finger, any value between 10 and 250 as a 45° bend, and any value greater than 250 as a 90° bend. Similarly, for accelerometer values, indicating the overall rotation of the glove, a margin of error was added, to ensure that variations in orientation were still classified correctly. As an example, a block of sample code illustrating the assertions made to attempt to recognise the word "Hello", can be seen in Figure 4.5.

Flex Sensors					Accelerometer		
1	2	3	4	5	X	Y	Z
1	1	1	1	1	87	0	-1
1	1	1	1	1	90	-1	-1
1	1	1	1	1	89	0	-1

Table 4.1: Sample sensor values for three separate recordings of the sign for "Hello"

FLEX SENSOR VALUES (0, 255)					AXXELEROMETRE ANGLES (-180, 180)		
1	2	3	4	5	X	Y	Z

```
//--------------------------------Hello-----------------------------

if (sensorValueTHUMB < 10 && sensorValueINDEX < 10 && sensorValueMIDDLE < 10 && sensorValueRING < 10  &&
sensorValuePINKY < 10 && accelerationX > 75 ) {
```

1	1	1	1	1	87	0	-1
1	1	1	1	1	90	-1	-1
1	1	1	1	1	89	0	-1

```
//--------------------------------ThankYou-----------------------------

if (sensorValueTHUMB < 10 && sensorValueINDEX < 10 && sensorValueMIDDLE < 10 && sensorValueRING < 10  &&
sensorValuePINKY < 10 && accelerationX < 0 && accelerationY < -100 ) {
```

3	1	1	1	1	-73	-178	0
3	1	1	1	1	-73	-180	-1
2	1	1	1	1	-72	-179	0

```
//--------------------------------Please-----------------------------

if (sensorValueTHUMB < 10 && sensorValueINDEX < 10 && sensorValueMIDDLE < 10 && sensorValueRING < 10  &&
sensorValuePINKY < 10 && 110 > accelerationX >75 && 110 > accelerationZ > 75 ) {
```

2	1	2	2	1	88	1	90
2	1	1	2	1	89	2	90
1	1	2	2	1	90	1	89

```
//--------------------------------Play-----------------------------

if (sensorValueTHUMB < 10  && sensorValueINDEX > 200 &&   sensorValueMIDDLE > 200  && sensorValueRING > 200 &&
sensorValueRING < 10) {
```

6	249	251	248	4	-178	0	-1
2	249	251	249	2	-176	1	-1
1	250	251	248	1	-180	0	0

```
//--------------------------------Quiet-----------------------------

if (sensorValueTHUMB < 10 && sensorValueINDEX < 10 && sensorValueMIDDLE < 10 && sensorValueRING < 10 &&
sensorValuePINKY < 10 && accelerationX > 75) {
```

2	3	1	1	1	89	-1	-1
1	1	2	1	1	88	0	-1
2	1	1	1	1	89	1	0

```
//--------------------------------OK-----------------------------

if (sensorValueTHUMB < 10 && sensorValueINDEX > 200 && sensorValueMIDDLE > 200 && sensorValueRING > 200 &&
sensorValuePINKY > 200 && accelerationX > 75 && accelerationY > 75) {
```

1	255	255	255	255	90	87	0
1	255	255	255	255	90	88	-1
1	255	255	255	255	89	89	-1

```
//--------------------------------HELP-----------------------------

if (sensorValueTHUMB < 10 && sensorValueINDEX > 200 && sensorValueMIDDLE > 200 && sensorValueRING > 200 &&
sensorValuePINKY > 200 && accelerationX < 0 && accelerationY > 75) {
```

5	255	255	255	255	-88	89	-1
4	255	255	255	255	-87	89	0
1	255	255	255	255	-88	89	0

Figure 4.4: Sample sensor values for seven different gestures

```
if (sensorValueTHUMB < 10 && sensorValueINDEX < 10 &&
 sensorValueMIDDLE < 10 && sensorValueRING < 10  &&
 sensorValuePINKY < 10 && accelerationX > 75 ) {

 // Print word Hello to serial
 Serial.println("Hello");
 Serial.println("          ");

 // Moves all the text one space to the left each time a letter is added
 display.autoscroll();

 // Print 'hello' on graphic display screen
 display.println("Hello");
 display.display();

 // This character represents the beginning of the package of the five values
 Serial.write("<");

 // The values are sent via the Tx pin
 Serial.write("Hello");

 // Send the desired string to convert to speech
 emicSerial.print("Hello");
 emicSerial.print('\n');

 // Turn on LED while Emic is outputting audio
 digitalWrite(ledPin, HIGH);

 // Wait here until the Emic 2 responds with a ":" indicating that it's ready to accept the next command
 while (emicSerial.read() != ':');

 digitalWrite(ledPin, LOW);

 // 500 millisecond delay
 delay(500);
}
```

Figure 4.5: Sample Code: Classification of Hello sign

To enable complete gesture control for the system, negating the need for an external display or device to be attached, a hand position corresponding to a space character and another to clear the screen of the previously recognised signs were defined, to be recognised using the same mechanism as signs corresponding to words. To be able to build up a fuller conversation, an automatic scrolling feature was added to stack the incoming words vertically and to align them to the left, allowing the users and researcher to see a record of a few of the most recently recognised words, rather than only showing the last word detected.

Design

As this was the first prototype data glove, it was designed to be a proof of concept rather than a finished product, meaning that relative to functionality and speed of development, aesthetics was not a substantial priority. However, a sticker with a smiley face was placed on the back of the data glove, to cover the main board and circuitry, and make it more visually appealing and less intimidating for the study participants (Figure 4.6).

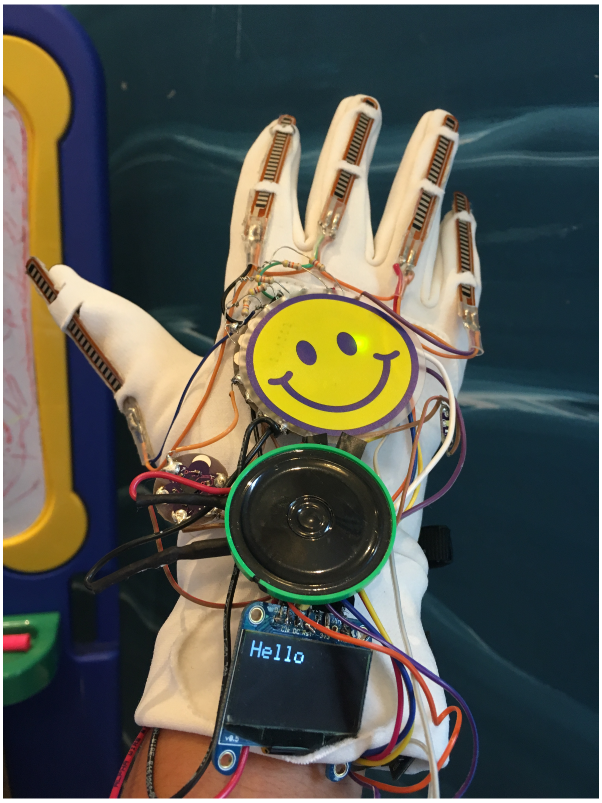


Figure 4.6: Participant A making the sign for “Hello”

4.1.3 Study Method

The system was programmed to identify a limited vocabulary of ten signs selected from the Makaton sign language, based on ten right hand postures and three hand orientations, using the first data glove prototype (as described above) to get accurate input information. In the situation in which the data received from the flex sensors and accelerometer did not fit one of the ranges pre-defined for the trained signs, this constituted a failure to detect any gesture. Failure to detect or correctly identify the gesture was programmed to result in no words being spoken. The accelerometer was used to differentiate between when the glove was being used to sign, or merely worn during play. Only when the glove was in an upright position did it begin processing input data, in an attempt to recognise any sign. In Makaton signs that would usually use both hands, only the right hand was measured in this study. This was still effective because in the signs from our vocabulary that use both hands, in the vast majority of cases, both hands perform the same action simultaneously, or the non dominant hand stays motionless in holding a single fixed position, while the dominant hand makes the shape and movement of the sign. A good example, that illustrates this property, is the sign for "dance", in which the left hand remains completely static while the right hand performs the movement for the sign. Alternative examples include the signs for "play" and "happy". In both of these signs, the right and left hand perform the same gesture, albeit mirrored laterally.

Two different conversation scenarios were written for the participants of the study, during which they could communicate exclusively using the ten gestures previously programmed by the researcher.

Five participants with non-verbal autism were recruited for this research, however, ultimately only two of them, a pair of boys aged 9 and 12 years old respectively, were able to continue the study and commit to all of the required sessions. Selection criteria and eligibility for a student's participation in the study was based on the participant's familiarity with the Makaton sign language as well as according to the attending speech therapist's recommendations. The initial training session consisted of a 2 hour long task (described in detail below), broken into four, 15 minute segments. Each participant was shown videos of each of the signs, and practiced performing them with the researcher and their speech therapist. The speech therapist's primary role was to help the researcher communicate effectively with the participants and provide important feedback and insight into the user's usage of the data glove, based on their expert observations. Participants began to become increasingly familiar with how the glove worked, within approximately half an hour of their first introduction to it. Video documentation of the participants using the glove during this study was recorded [2]. Usability feedback from the participants, parents and therapists was noted by the researcher for later reference.

Task outline

A short, natural conversational dialogue was drafted between the therapist and the participant corresponding to two simple scenarios. In these scenarios, the therapist would ask simple questions to the participant, and the participant would sign the reply while wearing the data glove. Words, corresponding to signs performed by the participant, would in turn appear on the small screen and would be spoken from the miniature speaker on the data glove as in Figure 4.7. The therapist would then proceed on to read the next line in the dialogue. This dialogue is an example of a conversation that the participants might engage in every day.

The data glove had the following Makaton sign language gestures programmed in advance as an available vocabulary by the researcher (as well as the additional gestures for clearing the screen and adding a space, as previously described): *Yes, No, Okay, Play, Dance, Colour, Happy, Hungry, Eat, Drink*

Task I - Participant A - Playtime Dialogue

Therapist: Hello! So what are you doing? How was your day so far?
...Conversation progresses...
Therapist: Let's do something else? What would you like to do?
Participant: [Replies with an activity]
Therapist: Really, you like to [insert activity]?! Do you have any ideas?
Participant: [Mimes one of the sign language activities]
Therapist: And how does that make you feel?
Participant: [Replies with an emotion]

[2] Access video of study session at the following URL - https://resources.brightsignglove.com/pilot_study

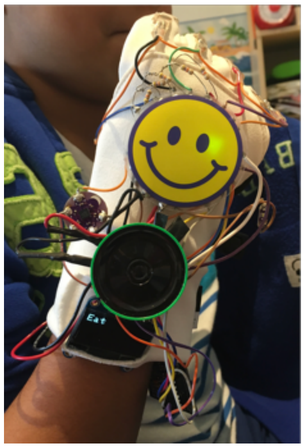
Task II - Participant B - Restaurant Dialogue

Therapist: Hey, do you want to go to a restaurant?
Participant: [Yes/No]
Therapist: Cool, let's get going! What will you order?
Participant: [Replies with a food item]
Therapist: Do you want to use the bathroom before we go?
Participant: [Yes/No]

(a) Play

(b) Hungry

(c) Dance



(d) Eat

Figure 4.7: Participants A & B making hand signs, with translated outputs on the screen

4.1.4 Results and Discussion

After testing, results showed that 4 out of 5 of the participants' attempts to perform a sign resulted in accurate classification of that sign and corresponding textual and audible output from the data glove. Testing with the participants demonstrated that the system was capable of translating sign language to text and speech with an accuracy rate of 80-85% with about 15% of the total number of attempts to translate a sign resulting in no words being spoken, due to a failure of the glove to detect any gesture (i.e. the sensor values recorded fell outside of the acceptable range of trained values for any sign).

The primary reason for these failures is that it is possible for signs to vary meaningfully in position and speed when performed multiple times, even by the same user, particularly when that user is less familiar with the sign language that they use (Premaratne et al. 2010). In this specific case, the glove was initially programmed based on the sensor values reported by the researcher's hand size and position, both of which differed substantially from the those of the participants, in turn affecting the input ranges of sensor values received. The fact that the glove was being used by the participants while they were engaging in other activities, not just signing, and so was processing a continuous stream of data rather than short segments – something that it was not designed to do, also contributed to some of the issues observed.

Another factor that had an effect on the results, was that the second of the two participants had somewhat decreased motor abilities, meaning that he therefore was not able to bend his fingers all the way into a fist. This caused the received sensor values to appear as if the fingers were far less bent, even when he was attempting to close his hand, in turn causing issues in a number of cases with the pre-programmed ranges defined to recognise each sign for some gestures.

Feedback from the participants was conveyed through observation of them, and communicated to the researcher by their therapist. This method of gathering feedback from a third party, usually very familiar with the specific participants, is generally used in academic studies in which the participants are unable to communicate themselves, or where they are unable to process information due to their impairment (Lazar et al. 2010), in which case, caregivers and family members may alternatively act as the primary information source, as opposed to direct feedback from the user themselves.

The majority of feedback related primarily to power issues, where the data glove sometimes appeared to freeze and cease providing any output or where the glove did not respond when the battery was running low on charge. Occasionally, the glove exhibited substantial delays while processing the incoming data, before providing

(a) Playing with blocks

(b) Arranging letters on a board

Figure 4.8: Participants often wanted to use the glove for other activities

any output. It was observed that under these near-continuous usage conditions, the glove's battery lasted for about two and a half hours of use between each charging cycle.

The participants' feedback was largely related to the design of the glove and of the hardware enclosure. Both participants expressed that the glove was overly bulky and that they felt a little intimidated by the exposed wires running along the back of the hand and into the enclosure on the wrist. They further felt that the glove was too uncomfortable to wear for any prolonged periods of time and reported that it caused them some difficulties and restrictions when attempting to bend their fingers. In several situations, it was noted that issues and delays when using the glove due to technical problems caused frustration amongst the participants, because they thought the issues were their fault, or somehow caused by their actions. As a result, video documentation took much longer than the time which had been allocated for it, which extended the duration of the study.

The researcher's observation was that the participants wanted to use the glove for various other activities while wearing it, such as playing or holding things (see Figure 4.8) rather than just perform the task. This unexpected change of usage somewhat affected the output of the glove meaning that programming had to be revisited during the testing phase of the study. A quick solution that was found to allow the researcher to rapidly progress through the testing session without undue disruption was to make changes to the software running on the glove to cause it to process gestures only when the accelerometer registered an upright position. Other potential solutions are discussed in the below sections.

4.1.5 Conclusion

A revised design was proposed based on the feedback of this study in which improvements were to be made including the refinement of the design and hardware used as well as reconfiguration of the software.

Design

Exposed electronic hardware was found to be intimidating for the children participating in the study and discouraged them from using the data glove at times. Inadvertent tugging on external wires while the participants were performing other tasks, as well as subsequently while simply trying to sign, also caused substantial issues throughout the study due to the damaged connections between the sensors and the processor. It was decided that the glove design would have to be revised to be more approachable and user friendly, particularly for younger users, as well as to be made more robust to resist any stresses that it would undergo as a part of normal usage.

To address this, the hardware enclosure would need to be redesigned, with sensors embedded between two layers of the glove textiles as opposed to affixed to the outside of the glove material, along the back of each finger. It was suggested that a custom textile pattern should be designed for the glove to contain the sensors in channels and to enclose the electronic hardware in the inner lining of an improved glove design, leaving only the bare minimum of the screen and the speaker externally visible. This new design would ensure that the circuit would be far better protected while keeping it insulated from any form of skin contact with the participant, thereby retaining the negation of any risk of electric shock or discomfort due to the electronics increasing in temperature.

In addition, stretchable fabric could further be used to make finger movement more flexible, with less resistance, and ensure easier bending of the fingers for small children and those with any form of decreased motor ability, which is common in those with autism. To ensure the complete safety of any future users, fireproof, non-conductive material should always be used to house the circuit and insulate the glove electronics from the user and from the environment.

Hardware

To resolve other key issues, such as the slow processing and short battery life caused by power-hungry but computationally insubstantial components, the hardware would need to be further reduced and enhanced. It was suggested that the Arduino Lilypad micro-controller should be replaced by the Raspberry Pi Zero[3]. This change would reduce the cost of the hardware by a half, as well as increase the computational performance and battery life of the system. The Raspberry Pi also features a built-in software based text-to-speech synthesizer, which would allow the removal of the external Emic2 text-to-speech chip from the circuit, in turn making the glove lighter to wear and reducing excess demand on the battery. This change would also further reduce the cost of the hardware by a third.

The accelerometer could be replaced with a gyroscope in order to allow more accurate classification. The usage of a gyroscope as opposed to an accelerometer would provide more detailed input data for the orientation of the glove covering the full range of gesture motions in space, and thus improve its ability to recognise more dynamic gestures as opposed to the entirely static positions recognised to date.

It was further proposed that a button could be added to the glove, on the back of the hand, to instruct the glove when to start processing. This would be particularly useful for those who want to keep wearing the glove when they are not immediately signing, as the existing mechanism of requiring the hand to be held vertically to trigger the start of classification was deemed to be too inconvenient for regular usage. A second button could also be added to switch between a newly created training mode and classification mode, proposed in the software development section below. Equipping the glove with a BLE (Bluetooth™ Low Energy) chip could, in addition, provide the option to connect the data glove with a smart device or to connect to a separate external network for purpose of training new gestures. A final refinement would be to make all of the electronic hardware removable from the glove in an easy manner, to enable the washing of the glove textiles, as the glove was soiled and heavily stained during the participants usage for the duration of the study sessions. For that, different options to encapsulate the circuit in a removable manner, or alternatively to properly waterproof the electronics and sensors, would have to be explored.

[3] The Raspberry Pi Zero - https://www.raspberrypi.org/products/raspberry-pi-zero/

Software

Delays in processing were largely due to the substantial variance in hand gestures, exhibited in the form of material differences between the values encoded in the form of the pre-programmed signs and those subsequently generated as a result of the signer's abilities. Errors often occurred because the glove was being used for other activities by the participants and did not have a meaningful and reliable indication of when to start or stop processing.

It was proposed that the software could be developed in such a way that it could be personalised to each user, in order to increase the accuracy of gesture classification, through the addition of a new training mode, separate to the existing classification functionality. Such a training mode would enable users to upload the gestures and labels corresponding to signs in their own sign language, adapted according to their individual specific motor abilities and signs. To support this, the glove would need to be paired with machine learning software to train and classify the gestures, using an individual machine learning classifier, trained for each user based on their uploaded sign data. Enabling users to upload their own version of each of their signs would make this data glove accessible to everyone who needs it regardless of which sign language library they use, as well as to those that use common languages but with decreased motor abilities (such as those that are unable to fully bend one or more fingers, or those that have restriction in the angles through which they can rotate their wrist). It would also allow users who do not follow any single standard sign language library to customise their hand gestures and be able to communicate with those who are unfamiliar with their specific sign language.

Lastly, the glove could be paired with a pre-existing translation API, such as those provided by numerous cloud platforms, to allow for translation of the output speech into other spoken languages either ahead of time, or, in real time, if the glove could maintain a continuous connection to the intent. This would make the glove far more widely usable, able to communicate with those speaking any of the supported languages in any country, rather than just the users native language (or the language of their family), breaking yet another language barrier.

4.2 A three-stage iterative case study

4.2.1 Introduction

The first study (as described above) existed as a proof of concept, to illustrate the potential for the technology to be further developed and refined through design iterations (see Section 3.2). It was conducted in a controlled testing environment with a carefully selected group of participants, the results of which laid out the plan for this second iterative case study. To further test the usability of the data glove and improve the underlying technology, this study took place in a public setting, with participants that had differing speech abilities due to various sensory impairments, which in some cases were further combined with additional physical limitations and disabilities.

As such, a three-stage iterative case study was set up, with each phase taking place during a number of exhibitions, each attached to a conference that the early (promising) results of this research were being presented at. The three stages of iterative study each took place at the following conference exhibitions respectively:

- IBM Artificial Intelligence for Social Care in Seoul, South Korea in December 2016
- No Barriers Summit's Innovation Village in Lake Tahoe, USA in June 2017
- CENMAC Assistive Technology for Education in London, UK in May 2018

The studies' primary aim was to engage a range of users of a number of existing hand gesture and sign language translation systems and acquire their feedback about the proposed data glove solution. The same data glove prototype was developed and used for testing at all three of the exhibitions listed above, however, some minor changes were made between each of them, based on the users' experiences in each of the studies, and in response to their feedback.

Bearing the conclusions from the previous study in mind as a starting point, in which low accuracy levels when recognising signs were largely the result of differences in the performance of signs between the person training the classifier and the person using the glove for translation, development for this study was instead focused towards generating a personalised individual classifier that could be trained by each of the user's themselves rather than in advance by the researcher. Consequently, the primary goal for this study was to evaluate the performance of a gesture recognition classifier when allowing individual users to train it for their own individual hand signs, and whilst accommodating their differences in motor abilities and range of movement, as used in a more realistic, public environment.

4.2.2 Prototyping and Development

The data glove that was used for this study followed largely the same structure as the previous pilot study's prototype in terms of design, hardware and software, but was modified in a number of ways after having added a consideration for the manufacturing and component cost of the system, given that it was developed with a plan for future commercialisation in mind.

Relatively major changes to the prototype were required to be made in order to minimise the external size of the electronic hardware and its enclosure, and maximise overall system performance, while making it more wearable and able to support the proposed enhancements to the software (as detailed in the section below).

Hardware

The LilyPad Arduino micro processor was replaced by a Raspberry Pi Zero system-on-a-chip, as the main microcontroller board. Migrating the circuit from an Arduino-based system to a Raspberry Pi board posed many challenges due to the different configuration of pins as well as due to the different software requirements. Raspberry Pi boards, for example, only have digital input pins, whereas the flex sensors as used in the previous prototype usually require analogue pins to report variance in resistance values. For their continued usage to be possible, an analogue to digital converter (an MCP3008) was added to perform the conversion of the raw analogue sensor outputs into digital values that were readable by the digital pins on the Raspberry Pi board (Figure 4.9). This made the connections difficult to group and so a complete redesign of the circuit board was necessary to host all components of the new circuit, including the wearable flex sensors, gyroscope (as detailed below), speaker, OLED screen and power supply (Figure 4.10). This development required substantially more wiring than the previous version, however, hosting all the electronic components onto a single circuit breadboard minimised the size of the hardware significantly, allowing the design of a wrist band to house it.

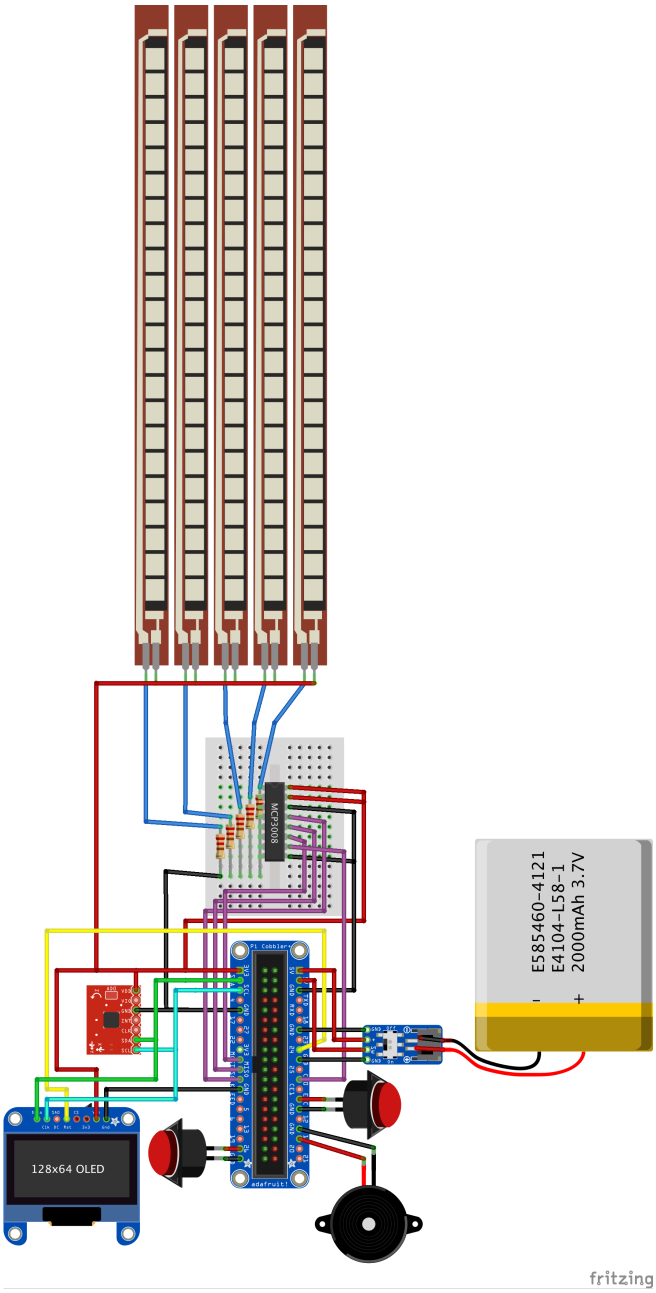


Figure 4.9: Circuit schematic diagram

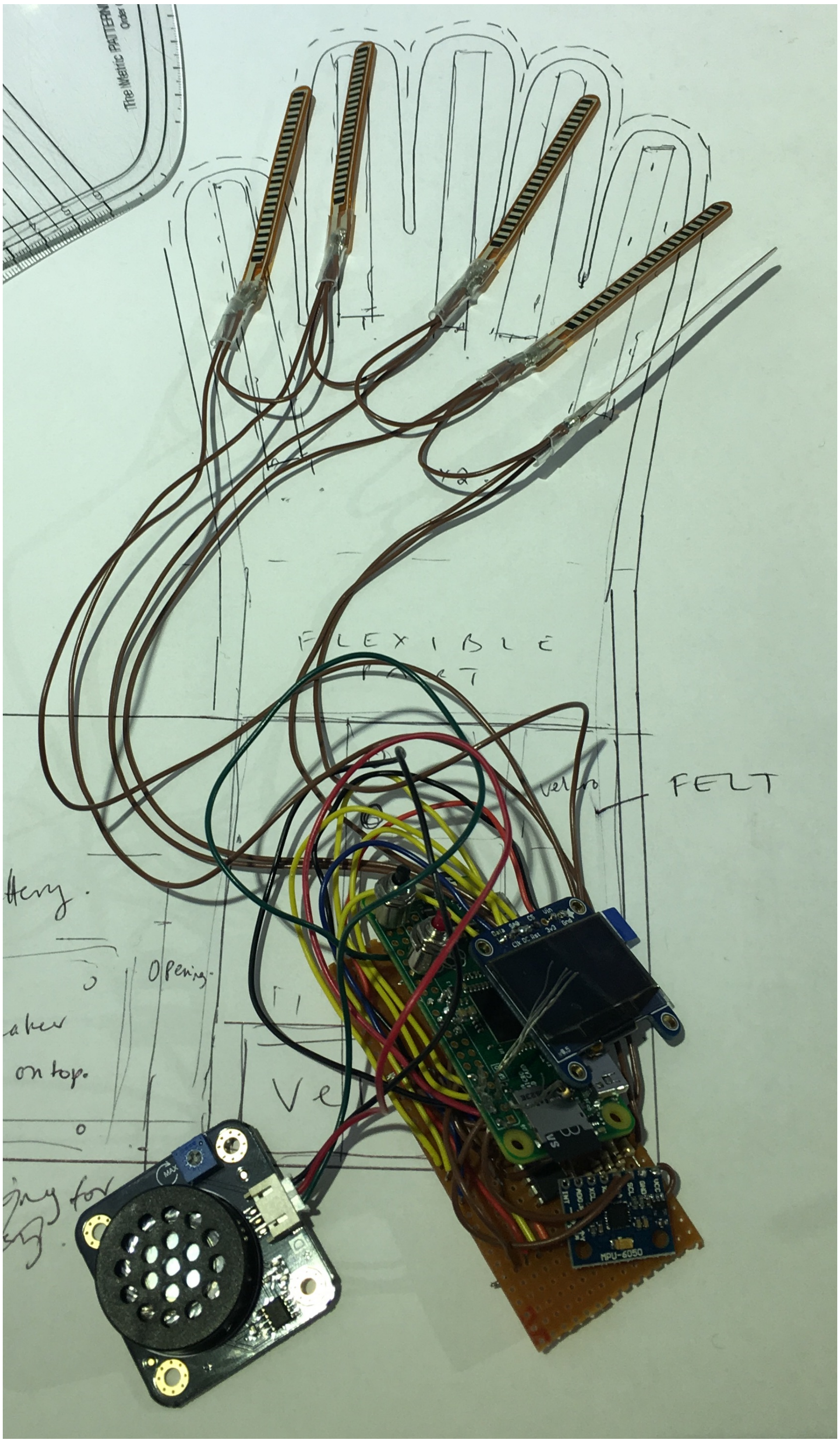


Figure 4.10: Circuit hardware

The circuit was further reduced due to the elimination of the text-to-speech chip used in the previous circuit to generate the audio to be outputted for each sign, since the Raspberry Pi board has a built-in audio processor and output system, as well as more advanced, software based text-to-speech support built in. A final change made to the circuit was to replace the existing three axis accelerometer with a gyroscope. The usage of a gyroscope has the primary key advantage that it measures the orientation of the sensor itself directly, rather than measuring the forces on the glove due to gravity as in the case of the accelerometer. This means that it is able to accurately capture changes in orientation throughout time, in the plane perpendicular to the action of any gravitational force, allowing the capture and processing of dynamic (moving) instead of static (still) gestures, as was a limitation of the previous study's prototype.

Performance-wise, running a full Linux-based operating system, the Raspberry Pi Zero additionally provides a far superior platform for processing the updated software with its additional proposed enhancements - the additional processing power required for running a machine learning algorithm to train individual personalised classifiers for each user. Raspberry Pi boards such as the Pi Zero are also able to connect to a cloud service, where the new classifier was to be hosted, utilising its on-board Wi-Fi™ network chip.

Software

In multiple studies, machine learning algorithms have been implemented and used successfully in prior research for the classification of sign language hand gestures (Fang et al. 2003; Parvini et al. 2009; Takahashi and Kishino 1992). The most common ones, such as Hidden Markov Models (HMMs) and Artificial Neural Networks (ANNs), require far more complex computations to process data, as well as requiring intensive training in advance, usually on very large, sanitised data sets. There is however, a third option that can be used. K-nearest neighbours (KNN), using Dynamic Time Warping (DTW) (Berndt and Clifford 1994) as a distance measure has been shown to be both versatile and accurate when producing time series classification models, while also being highly computationally efficient, particularly with the usage of faster approximations such as FastDTW (Salvador and Chan 2007) or PrunedDTW (Silva et al. 2018), as well as with the addition of lower bounding methods. It also has the key advantage of working well with far less training data than many other machine learning models, functioning accurately with down to only a few samples per trained class, provided the classes are situated relatively far apart within the feature space.

Therefore, Dynamic Time Warping (DTW) and K-nearest neighbours (KNN), were employed in the updated data glove prototype to allow each individual user to train the glove on their own signs and according to their personal motor ability. A cloud translation API was added as a plug in, with calls made to the API at classification time, to allow speech output to be set to any one of a large number of listed spoken languages. The new enhanced software was designed to enable each user to build their own library of gestures, which they were able to label and then select the language of speech they wanted that gesture to be translated into. A detailed description of user tasks and their corresponding software actions and mechanisms are explained later in this section.

A web based platform was created to facilitate the storage of sign data and labels, text-to-speech conversion and language translation. A front end user interface (UI) (see Figure 4.13) was also designed as a web app to allow users to interact with the system through a web browser, specify the labels for the gestures that they had recorded, and select their desired options for speech output, such as the language, gender and voice of the generated speech, which would be passed as parameters when making calls to to the text to speech system.

The system requirements were as follows:

- The minimisation of computational strain on the embedded system by moving crucial computation to remote servers.
- The ability to create, update and modify a persistent dictionary of gesture-word mappings in real time.
- The improvement language accessibility by using a cloud based language translation API.
- The use of IBM Bluemix™ and Watson[4] APIs including CloudFoundry application hosting, Cloudant™ CouchDB DBaaS (Database as a Service) and the Watson text-to-speech and translation APIs. Bluemix™ is a well-suited

[4] IBM Watson - https://www.ibm.com/uk-en/watson

platform for rapid prototyping of real-time web applications due to the integration of each system component in a single environment with a single set of credentials. Figure 4.11 shows the integration of Bluemix™ with the glove system.

- Text-to-speech and language translation: In order to substantially reduce the burden of computation to be performed on the data glove's embedded system, the RESTful IBM™ Watson APIs were used to facilitate text to speech generation for the labels of classified gestures, as well as the translation of those labels from English into other spoken languages prior to output. The language translation API simply returns a translated string for a provided input string and the language code of the desired destination language. The text to speech API accepts a string to synthesize audio for, as well as a voice parameter, and returns a WAV file of the generated speech (MIME type `audio/wav`). The voice parameter specifies which voice to use for the synthesis from a list of options provided by the API based on the selected language, with many languages offering both male and female voices.

The core CloudFoundry application used a simple NodeJS server running Express[5] to expose an API and simple web app. It served a single-page web app, "BrightSign Collection", which provided a way to inspect and modify a set of gesture-word mappings created in the embedded system and stored in the Cloudant™ CouchDB instance. Real-time communication between the server and connected web clients (including the embedded system) is facilitated by SocketIO[6].

SocketIO uses an underlying WebSockets protocol to send small amounts of data asynchronously between clients connected to a server. The web platform used the following set of messages:

- `gesture` is sent to the server by the embedded system on the glove when a new gesture has been defined. It contains a unique ID generated on the glove as well as the raw sensor data for that gesture. This gesture is saved to the database on the server, and kept in a "detached" state until the user associates a word with it.

[5]Express.js - http://expressjs.com/

[6]Socket.io - http://socket.io/

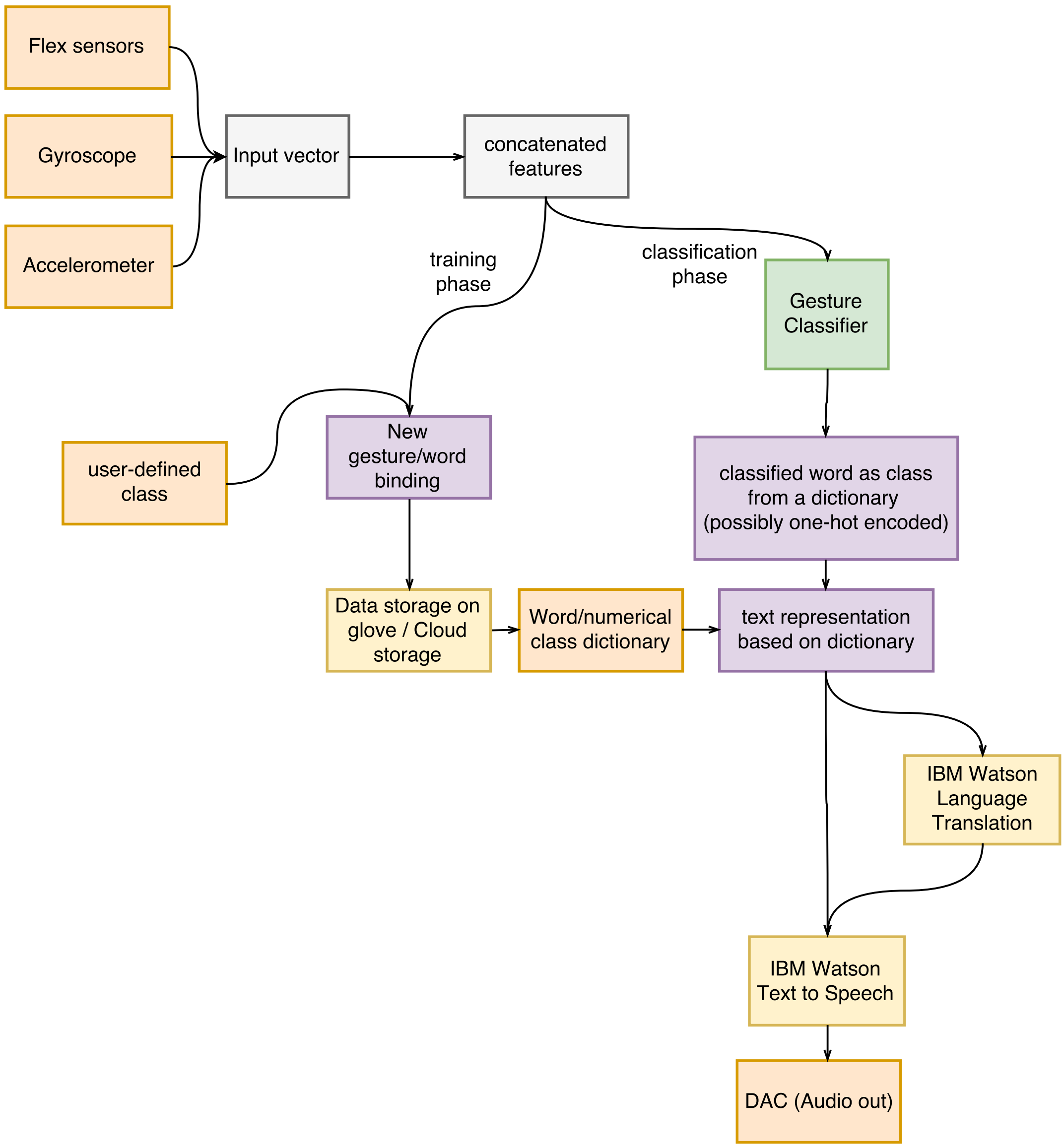


Figure 4.11: End-to-End flow diagram for gesture training and classification

- `updateName` is sent to the server by a web client when the user associates a word with a gesture, or overwrites an existing gesture-word mapping. The server then updates all connected clients with the new dictionary.
- `state` is sent by the server to all clients (including the embedded system) when a change to the gesture dictionary has occurred

To control the system, a file was created to run call-back functions in response to changes in the gloves state (referred to hereafter as `state.py`). This file ran callbacks, if defined, based on state changes such as starting recording sensor data, ending a recording of sensor data, each frame while sensor data was being recorded and when the buttons were pressed (long and short presses, for each of the red and black buttons). This file also tracked whether the glove was currently in its training or classification mode.

The main file featured a loop controlled by a timer that locked the glove to a certain number of frames per second, to keep the sample rate of the sensor data at a consistent, arbitrary rate. Each iteration of this loop made a call to the `state.py` file, in turn running any appropriate call-back functions based on the state of the glove. For example, a call-back was defined such that when the red button was pressed for a short duration, the glove would write the incoming sensor data each frame to a file.

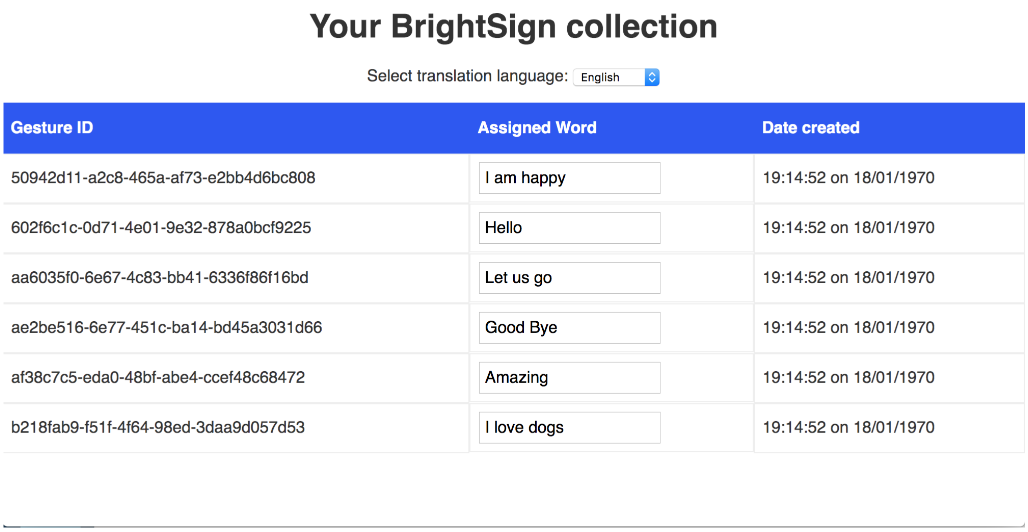
Training and classifying task software description

In training mode, when one button on the glove was pressed, data from the bend sensors and gyroscope was recorded into a buffer. Recording ceased when the button was pressed for a second time. The device then made an API request to the gesture endpoint of the web backend, which added a newly generated Universally Unique Identifier (UUID) to the cloud database, but with the raw gesture data remaining on the glove. This API function sent an update message using a persistent WebSocket connection to any currently connected web app frontends, notifying them of the change to the database, as well as a standard response to the glove, confirming that the request had been fulfilled successfully.

Any web app frontend currently connected to the server would refresh its displayed list of gesture UUIDs and corresponding phrases based on this notification. The user could then use the web app to assign a word or phrase, corresponding to

```
def get_label(all_gestures, all_labels, query_gesture):
    """
    Get the label for the nearest neighbour of a given
    query gesture in a list of recorded gestures,
    using DTW.

    all_gestures: a list of gesture samples' data
    all_labels: a list of labels corresponding to each
        data item
    query_gesture: the gesture data we are attempting
        to classify

    return - the label of the closest gesture from all_gestures
    """

    # Initialise empty list of distances
    distances = []

    for current_gesture, label in
        zip(all_gestures, all_labels):
        # Convert current and query gesture from lists
        # into NumPy arrays
        current_gesture_series =
            np.array(current_gesture, dtype='float')
        query_gesture_series =
            np.array(query_gesture, dtype='float')

        # Calculate the DTW distance and path between
        # both series, using euclidean distance
        distance, path = fastdtw(current_gesture_series,
                                 query_gesture_series,
                                 dist=euc)

        distances.append(label, distance)

    # Return the label with the shortest DTW distance
    distances.sort(key=lamda tup: tup[1])
    return distances[0][0]
```

Figure 4.12: Sample Code: Dynamic time warping nearest neighbour



Gesture ID	Assigned Word	Date created
50942d11-a2c8-465a-af73-e2bb4d6bc808	I am happy	19:14:52 on 18/01/1970
602f6c1c-0d71-4e01-9e32-878a0bcf9225	Hello	19:14:52 on 18/01/1970
aa6035f0-6e67-4c83-bb41-6336f86f16bd	Let us go	19:14:52 on 18/01/1970
ae2be516-6e77-451c-ba14-bd45a3031d66	Good Bye	19:14:52 on 18/01/1970
af38c7c5-eda0-48bf-abe4-ccef48c68472	Amazing	19:14:52 on 18/01/1970
b218fab9-f51f-4f64-98ed-3daa9d057d53	I love dogs	19:14:52 on 18/01/1970

Figure 4.13: IBM Bluemix™ hosted web app interface

the gesture data that had just been recorded. The web app, once a new or updated phrase had been input by the user, made a request to the updateName endpoint of the backend API. This endpoint updated the entry in the cloud database for that UUID, adding or updating the specified phrase, and then again sent a response confirming the successful update as well as notifications to all connected web apps and devices.

When in classification mode, the glove similarly allowed the user to start and stop recording gesture data with the press of a button, however, when recording was ceased, rather than saving the data as when training, the glove instead used it to find a closest match based on the already saved gestures in the database. This was done using a k-Nearest Neighbours (k-NN) classifier, using Dynamic Time Warping (DTW) as a distance measure. In order to allow gestures of varying lengths to be compared without bias, array interpolation was used to increase the length of all gesture data buffers to the same number of frames. This classifier output the corresponding UUID of the closest matched gesture that had previously been saved during training.

A request was then made to the API to provide output for the corresponding phrase, based on that UUID. This API function queried the cloud database for the provided UUID to retrieve the corresponding phrase. Based on options specified in the web app frontend by the user, including language and voice selection, this phrase was then sent to the IBM Watson Translation API, along with the desired ISO language code for the language and dialect to which the phrase would be translated.

The translated response from the Translation API was then sent to the IBM Watson Text-to-Speech API, again specifying the language, but also the specific voice to use to generate speech output. This API provided as its response a lossless WAV file, containing the audio of the generated speech for the requested phrase, based on the language and voice options provided. This audio was then sent using the WebSocket connection to the web app frontend, which in turn played the audio to the user. The classified phrase was also displayed in large text on the screen, overlaid on top of the web app interface.

Design

A custom pattern was designed for the textiles of this glove prototype (see Figure 4.14) in which all wearable sensors were embedded and fully enclosed within special channels sewn into a separate inner lining of the glove. The circuit board was encapsulated in a plastic wrist band casing and was fully insulated with non-conductive and fire resistant fabric to ensure the complete safety of the user at all times. The addition of the channels for the flex sensors, as well as the single enclosed electronics casing, made the circuit removable, which enabled the washing of the textile portion of the glove - an important hygiene point as this prototype would be used by a number of different users in a public setting. The glove fabric was selected after testing a number of potential options, to be stretchable but still soft, in order to accommodate the many different sized hands of its potential users, as well as to add sufficient durability for long term use and to increase the comfort of the wearer.

Furthermore, by grouping all of the components onto a single circuit breadboard and by placing the bulky parts of the electronic circuitry on the wrist rather than sewn into the glove on the back of the hand, the glove was able to withstand much longer and more numerous testing sessions without breaking, and did not have issues when pressure was applied to the connections to the wires at the base of each flex sensor – something that was reported as a major issue with the previous design and that limited the results of the pilot study.

Cost

The component cost of this prototype was reduced by over a half, compared to the previous iteration, as some hardware components were replaced by cloud based

Figure 4.14: Updated glove design, with wearable sensors embedded in channels in an inner lining

software APIs (such as the text to speech chip). However, the design cost increased due to the necessity of commissioning a custom pattern for the glove's textiles. In addition, the software had to be paired with a capable cloud computing platform to host the previously described web application, which required an expensive, continuous, ongoing subscription, hindering the long term cost effectiveness of the final solution.

4.2.3 Method

A series of usability testing sessions were set up at three conferences (IBM Artificial Intelligence for Social Care, No Barriers Summit's Innovation Village and CENMAC Assistive Technology for Education), all of which exist specifically to discuss and address issues directly relevant to the core purpose of this research. Attendees who were invited to participate in the studies had a range of different disabilities and were all at the time using various forms of assistive technology to communicate with those around them day to day.

Study sessions were able to be reserved by attendees on the conference portal or by using a sign up sheet in person at the exhibition. A study session of thirty minutes was allocated for each participant to test the new data glove prototype and for their experiences to be documented. For participants below the age of eighteen, it was stipulated that an accompanying adult was required to be in attendance.

Only one glove prototype was able to be made available for the first of the three case studies, which greatly limited the number of participants able to test it, and required substantial recovery time between the sessions to reset any damage that had occurred to the glove while wearing, using, and then removing it, as well as time to clear the saved gesture library in preparation for the next participant's session. This eventually triggered a number of changes to the study schedule, first to extend the testing sessions for an additional 15 minutes per user, and also to allow for a short break between each of the sessions to allow the researcher to reset the cloud based system and the glove, which further reduced the number of study participants that could be seen over the course of the exhibition days. A second glove prototype was made for the second and third studies with the specifications implied by feedback from the first group of sessions at the first conference.

A computer screen was used with the testing glove to display the web application with the user interface designed for participants to label personalised signs in order to build individual gesture libraries and to select preferred language and voice output. At exhibitions that used public networks, it was challenging to keep a reliable connection between the glove and the server, where the classifier was hosted, so a physical wire was used to connect the glove to the computer; although it was originally designed to operate as a stand-alone device. This affected the mobility of the glove and the range of motion within which the users could perform their signs.

All study sessions were held one-to-one with the participant and the researcher. Sessions started with a demonstration of how to use the glove to record and then classify custom sign language hand gestures. The participant then put on the glove, with the help of the researcher if required, and followed the steps as demonstrated, often guided by the researcher. To record a new gesture, the participant presses the record button (red) on the glove, makes a dynamic hand gesture, then releases the button. Up to three samples could be recorded for each sign. Once a sign was trained, the participant pressed the red button again (short press) to send the data to the web application. A new gesture ID appeared on the computer screen (see Figure 4.13) with an empty text field in the user interface. The participant inputs the word they wanted to correspond to that sign by typing it into the text field. The gesture was then saved with that corresponding label. The same process was repeated to record multiple signs. When the participant had trained five gestures (which was the minimum requirement to consider a study session complete) they could choose to stop and test the system recognition.

To set their speech output preferences, the participant chose a language and a voice from the drop-down menus on the interface. To classify signs, the participant pressed the black button on the glove, and then performed any of the hand gestures they had previously recorded. If the system found a match, the corresponding label was displayed on the screen and spoken out through the speaker in the language and voice selected. If no match was found, an error message appeared on the screen. If the displayed label did not correspond to the performed sign, then the system failed to recognise the gesture and the sign was retrained. The data from the new training samples always replaced the old ones. At the end of the session, gesture data was saved on the cloud server and the gesture library was cleared on the user interface ready for the next user. A simple user guide was printed for participants who wished to operate the glove independently.

To train the glove:

1. Open the web application for BrightSign[7]
2. Wear BrightSign glove
3. Press the on button (red button)
4. Record a sign by pressing and holding the record button (black button) while making the hand gesture for a specific sign / word
5. Release the record button and a pop up window will appear on the web app
6. Type in the word you wish to classify the sign you just made
7. Pick a language for speech from the drop-down menu (English, French, etc)
8. Pick a voice from the drop-down menu (male, female, child)
9. Press enter
10. The sign/hand gesture has now been saved and classified

Notes:

- Use this method to build your personal library of sign language.
- You can record and classify multiple signs at a time by recording the gestures one after the other then classifying them in the web application, given that they are in the same order.

To translate the signs into speech:

1. Wear BrightSign glove
2. Press the on button (red button)
3. Press and hold the black button and make the hand gesture/sign
4. Words/speech will be spoken out through the speaker in the voice and language that you have previously specified.

Notes:

[7] BrightSign is the name used to refer to the data glove developed for this research

- To preserve battery power, the glove has been set to go into sleep mode if it remains still for more than 5 minutes.
- To turn it back on, just press the on button (red button)
- To reset the glove or recover from errors, press and hold the red button until the screen is turned off.

4.2.4 Results and Discussion

This 3-stage-iterative case study engaged twenty-seven participants in total. Gesture data was collected from twenty fully executed testing sessions with a total of 130 trained hand gestures. A wide range of users participated in this study varying in age, needs and abilities. Some extreme cases were included to ensure that the testing of the proposed system was comprehensive and addressed all user requirements.

The outcomes of each study iteration, and the various factors that influenced them, are discussed in detail, under their respective sections below.

Although the method for study sessions was unified across the exhibitions, there was some variation due to the difference in conference scope and the nature of participants in each attendance demographic. In addition, minor changes to the prototype and session outlines were made based on research reflections between study stages. Therefore, the discussion has been categorised below per study:

Usability Study A - IBM Artificial Intelligence for Social Care Conference, Seoul, South Korea, December 2016

This conference started with a global AI Hackathon that ran in parallel, during which the prototype hardware and software was created. IBM software was initially used for this prototype due to being granted free access to IBM Watson APIs and cloud services. The hackathon was followed by an exhibition which hosted the first of the iterative usability studies for the second glove prototype of this research.

For this conference only, I lead a team of two members (Leon Fedden and Jakub Fiala), who assisted with the testing sessions carried out at the exhibition, and helped with troubleshooting system performance as well as provided support to resolve connectivity and arising technical challenges. These team members accompanied me on stage for the final presentation of the data glove at the end of the hackathon (Figure 4.15). As part of this presentation, I gave a demonstration illustrating how the full system works[8], winning my team, and Goldsmiths University of London, the hackathon's grand prize.

Figure 4.15: Presentation of the data glove at the end of the hackathon, by team members Leon Fedden[9] and Jakub Fiala[10].

The exhibition ran over two days, for six hours per day. Initially, 25 participants signed up for the testing sessions. However, due to technical difficulties while connecting the glove to the wireless network and having to reset the libraries between users, only 18 could secure slots. From those, 11 completed the full study session tasks of building a library of five gestures or more. That was due to the fact that most sessions ran over the scheduled time of 30 minutes and some of the participants were not able to stay longer. Participants age range was between 16 and 28 and most were attending the exhibition to explore emerging technology for social care.

All participants were at the time of the study using software solutions for communication, mostly in the form of an app on their phones. 35% of them did not learn sign language when they were young and therefore never used it. Testing a hardware prototype to translate sign language was the first experience for all participants.

The system collected the data for 72 trained gestures, with an average of 6 trained signs per participant and 2 samples per sign. 92% of participants completed the task within 20 minutes. 30% were able to do so independently, and without the

[8] Video of my presentation is accessible at the following URL - https://resources.brightsignglove.com/ibm_study

[9] Leon Fedden - https://leonfedden.co.uk

[10] Jakub Fiala - https://fiala.uk

researcher's help. The system was able to recognise 100% of the signs accurately within a library of 5 signs. This is because the glove was trained and tested by the same person, so the high number of errors that previously occurred because of hand gesture variations in the previous study were eliminated in this instance.

For the few participants who trained a library with more than 5 gestures, the system mismatched 13% of the signs performed. Lower accuracy levels were specifically observed with participants who had smaller hands, mostly females, due to the large size of the glove which meant that the flex sensors were often placed out of alignment along the fingers. It was also noted that participants who did not know a formal sign language struggled to remember exactly how they trained the signs as the library size grew.

Most participants struggled to remember which mode the glove was in, training, classifying or processing, as there was no visual feedback on the glove that informed the participant of the current mode. Furthermore, the majority of participants did not keep track of which button they had pressed and for how long. This was particularly a problem for participants who were constantly switching between training/recording and classifying as opposed to doing one phase at a time.

Direct feedback from several participants suggested that once they trained a library of gestures, they preferred to keep eye contact while signing and didn't have a use for the on-board screen attached to the glove. The screen displayed the word for the recognised hand gesture in the original text input language which is English. Although the screen was not essential for communication, it confirmed to the hearing-impaired signers that what was being signed was indeed what was being output through the speaker. This feature was especially useful while using the glove in a non-English speaking country, such as South Korea, where this study took place, since all users set the speech output to Korean – which is a language that some didn't actually understand themselves.

Reflecting on this study, a duplicate glove was made for the next study to allow more users to participate and to minimise the turnover time between sessions. This glove was slightly smaller in size to accommodate participants with smaller hands, especially children. In addition, a dedicated device with a 4G chip was acquired to provide a reliable internet connection in order to avoid troubleshooting venue networks which proved to be challenging at times and further delayed the sessions. The on-board screen was also updated to display the mode the glove was in while

(a) Participant A

(b) Participant B

Figure 4.16: Participants at the No Barriers Summit in Lake Tahoe

training/classifying and showed sample numbers of the signs while recording them.

Usability Study B - No Barriers Summit: Innovation Village, Lake Tahoe, USA, June 2017

No Barriers Summit[11] is an annual conference bringing together assistive technology and individuals with different disabilities to interact with the technology in an open four-day exhibition. Testing sessions were set on the second and fourth days of the conference. Users who participated in the study had different speech disabilities, some combined with hearing and/or visual impairment (Figure 4.16).

Seven participants completed the testing sessions in the same format described above. Study sessions exceeded one hour at times due to difficulty in communication with the participants who spoke a different version of American Sign Language, which the researcher was unfamiliar with. That required hands-on guidance from the researcher with every task. Accuracy rate was 100% with no errors in matching gestures even with a gesture library of more than 5 signs. This was likely due to the close supervision of the researcher when recording gesture samples, and the consistency of the performance of signs by the participants, as they were all proficient users of sign language, unlike a third of the group from the previous study. Numerous participants recorded multiple gestures forming a sentence or phrase rather than a

[11] No Barriers - https://nobarriersusa.org

single word, such as “I love dogs” (see Figure 4.13). Others created shortcuts by recording the gesture for just one sign but assigning a full sentence to it as a label.

Participant reactions varied between amazement at the technology, and feeling enabled. They had a sense of achievement when they trained the glove and the output was accurate[12].

Observation revealed that the participant with visual impairment did not know which buttons to press, since buttons were colour coded (red and black), had the same shape and provided no haptic feedback. The on-site solution was to guide them to feel the buttons and determine the position of the top button which is the record button.

Reflecting on this study and in preparation for the next one, one major change was identified as necessary in the future – to make the glove run offline. This was, however, not immediately able to be implemented, as running more computationally intensive processes such as the speech generation on the glove itself required an increase in the available processing power, which in turn would necessitate a change of hardware. Although this was the ultimate plan for the third and final glove prototype of this research, a temporary solution was found to allow the training to occur when connected to the cloud API but the classification to happen offline. Under this method, the user would assign the label to each gesture using the web UI, however, rather than waiting for classification-time to generate each speech audio sample, the cloud back-end immediately used the Watson API to pre-generate the required audio files and then transmitted those files to the glove, to be stored on the a microSD card attached to the Raspberry Pi board and then played back by the glove itself when corresponding signs were classified. As such, a library of signs could be built while connected to the cloud system and web app, however, the glove could then be taken offline while being used for classification, meaning that it could be used in public without the need to connect to a network or other external device.

Usability Study C - CENMAC Assistive Technology for Education Conference, London UK, May 2018

CENMAC one of the primary providers of assistive technology for education in schools in the UK since 1969 (*CENMAC* 2020). They organise an annual conference

[12] Video of a participant testing the system during the exhibition can be accessed at the following URL - https://resources.brightsignglove.com/no_barriers_study

Figure 4.17: Participant using the glove to perform the sign for "Fish" at the CENMAC Assistive Technology for Education Conference, 2018

at Charlton Park Academy in Blackheath every year.

Charlton Park Academy is an inclusive school for children with Special Educational Needs (SEN). Most of the students in the school use assistive technology to communicate. This ongoing research project of the data glove was presented in a talk, and the latest prototype was showcased in their 2018 exhibition for assistive technology called "Communication Works" amongst a wide range of assistive technology designed to enable communication[13].

The impact of the talk was positive and a queue of parents formed to sign up their children for the case study, many of which also expressed an interest to acquire a data glove if possible.

As all children with non-verbal disabilities in the school used special tablets with communication apps, I was keen to get direct feedback about their experience with this type of technology.

I was specifically interested in parents' reflection and so a small focus group was formed to discuss the advantages and drawbacks of such systems. Most parents had similar input, with their main concerns summarised here. They universally felt that they had to limit the use of tablets by their children, resorting to locking the tablet to restrict its usage to only the communication app, which caused frustration to the children. Another disadvantage was that children often didn't learn how to sign or keep eye contact while interacting with the public. They hid behind the screen and

[13]Video of a student testing the glove prototype (as an excerpt from a documentary video produced by CENMAC) is accessible at the following URL - https://resources.brightsignglove.com/cenmac_study

often kept their eyes low or fixated on the tablet. Cost was highlighted by many, as at the time (and is still the case to date) available solutions for communication started at £2000 for standard devices and could go up to £9000 when customised. Although the devices used were provided by CENMAC, the process to get them granted was a lengthy one, with a minimum of six years usage to qualify for a device upgrade, when needed.

With that in mind, and to move forward with the research, five study sessions were scheduled. Three sessions were conclusive, two of which testing was conducted with the same user.

The first session was with a seven year old student who had very limited limb movement, a common symptom of cerebral palsy, a condition with which they were born. The participant usually used a plush toy with sensors which they pressed to communicate when they required attention. When pressed, the toy produced a low beep sound and lit up. Their attending teacher and the researcher replaced the toy with the glove and recorded the same gesture performed when using the toy to ask for help. The attending teacher assigned "I need help" as the identifying word for that gesture. The system successfully classified that gesture 100% of the time when it was the only gesture in the library. Training additional gestures proved to be very difficult as the participant did not have the range of movement required for a distinguishable difference to be reported by the glove sensors.

The conclusion was made by the team of teachers and the researcher that although the participant is not benefiting from the full extent of the data glove technology, they can still use it for the same purpose their primary plush toy serves, with the additional feature of assigning custom words/speech output. From the perspective of this research, however, this session proves that users with restricted motor abilities may not be the best candidates for this study, or the data glove, as they do not test the limitations of the system or benefit from the wider range of communication library the system was designed to provide for them.

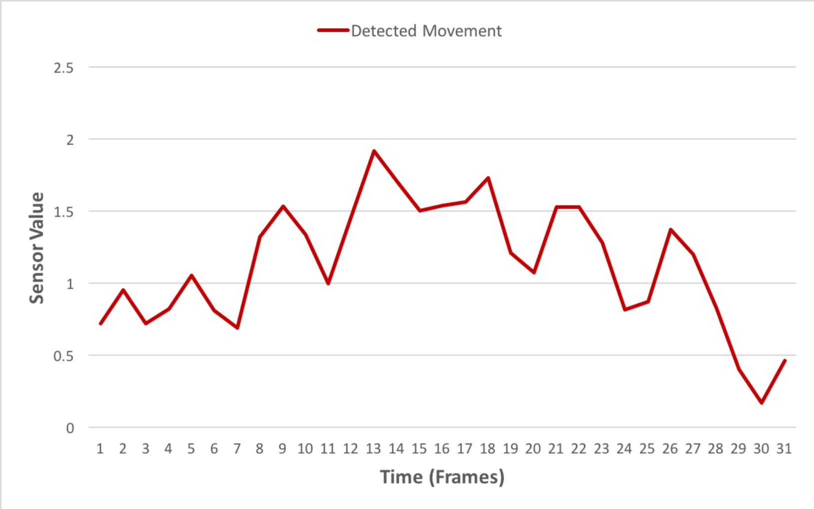
The second session was with a 13 year old student who used Makaton sign language in school and at home, but not in public. They were proficient in signing but had a neurological condition that caused their hands to shake involuntarily. They managed to put the glove on unassisted and followed the researcher's instructions largely accurately to complete all of the study tasks. Five gestures were trained but only one was ever classified accurately, and that is the sign for "slowly". As you can

Figure 4.18: Graphic demonstrating the sign for "Slowly"[14]

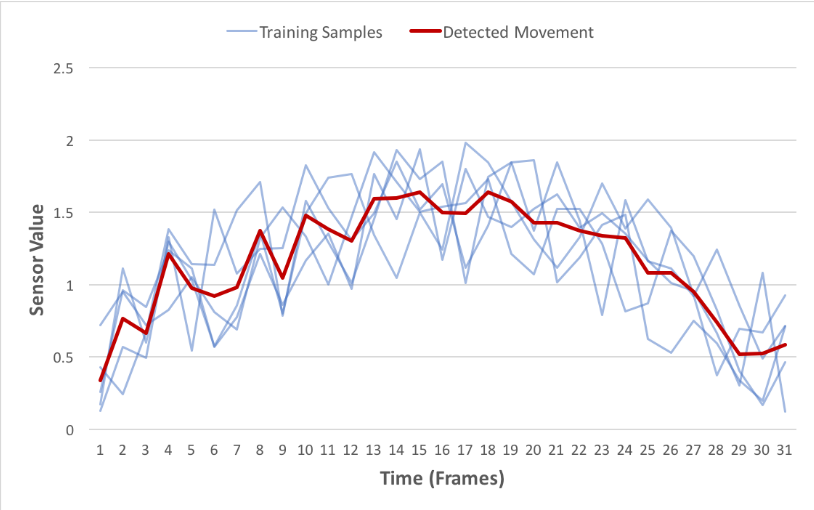
see in Figure 4.18, the gesture for "slowly" requires the signing hand to rest on the opposite elbow then slides along the length of the arm. This provided additional support for the signing hand and greatly reduced the shaking of the participants hand when training the gesture.

Analysing the trained gesture data received, considerable noise was detected, enough to substantially distort the underlying form of the gesture such that the recognition system could not distinguish it. That prompted an update in the method with an increased number of samples required to train gestures. A second session was booked with the same participant. This time ten samples were recorded to train each of the five gestures. With this updated method, the system was able to classify three out of five gestures accurately. This indicates that the supplementary gesture data improved the system's recognition as it enabled it to better generalise the motion from the surrounding noise, identify the patterns of movement, and gradually disregarded the extra motion coming from the individual sensors. This is shown in Figure 4.19, where the progressive smoothing of the detected motion can be observed as more training samples are recorded.

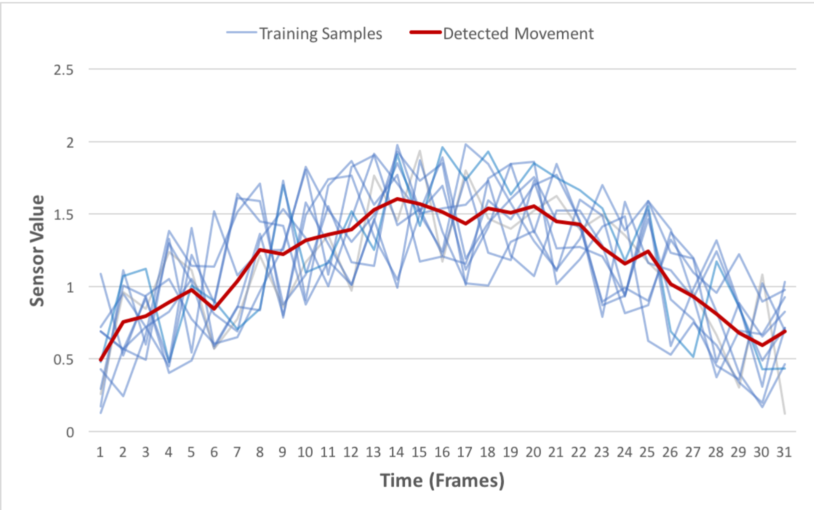
[14]https://british-sign.co.uk



(a) Detected motion with a single training sample



(b) Detected motion with 5 training samples



(c) Detected motion with 10 training samples

Figure 4.19: Charts showing the reduction of noise in detected motion with increasing numbers of training samples

The attending teacher strongly recommended having a set of two data gloves, instead of one, suggesting that getting feedback from two hands rather than one will maximise the chances of classification accuracy. As I did not have a second glove synchronised with this one, I was unable to test that suggestion. While it is plausible and worth exploring, it conflicts with the goal of reducing the cost of assistive technology, which was a primary concern expressed by most of the parents interviewed, as the usage of two gloves would necessarily double the acquisition cost. However, once a commercial route is in place, it is likely that such a decision will fall to the end user whether to acquire one or two gloves. The system would have to be designed to support two gloves, so users who start with one glove could upgrade to two gloves if needed.

4.2.5 Conclusion

The system performed well within the boundaries it was designed for. However, a more inclusive and advanced system is required to address special cases which do not conform to the usual expected usage.

Collating feedback from the three usability case studies, an outline for the next prototype has emerged employing solutions suggested by the users, their parents, and attending teachers. The primary issues to be addressed were as follows:

Design

In order to consistently retrieve accurate data from the sensors, it is important that a correctly-sized, form-fitting glove is provided for each user. With a sufficiently stretchable textile, two sizes (small and large) should be enough to cater for the vast majority of users. However, if the glove is to feel sufficiently unobtrusive to be worn in public and on a regular basis, there should be fewer thick wires contained inside the glove, and the enclosure containing the Raspberry Pi should be minimised in size. Portability and discreetness was flagged by many users and parents as a key driver in their adoption of any assistive technology. It was specifically important to them that any new technology should serve to aid in communication, but not act as a barrier between the user and the person that they are communicating with, as in the case of their current tablet-based solutions.

Hardware

As described above, the key motivator for change in hardware was to allow the classification system to be moved entirely offline, such that no external connection to the cloud would be needed, either during training or during daily use.

Simultaneously, the battery life should be further increased, such that a full day of usage can be extracted from a single glove, as well as decreasing the bulkiness of the sensors and their accompanying wiring. A proposed solution was to design a custom flexible Printed Circuit Board (PCB), connecting the flex sensors and gyroscope to a separate, wrist-mounted enclosure via a ribbon cable. This hand PCB would also include the necessary analogue to digital converters to provide the sensor values to the processor. A Raspberry Pi based platform would still be used, but with the addition of a second custom expansion board providing a port for connecting and charging a larger battery (to be housed within the enclosure) as well as hosting a small speaker for audio output, an OLED screen to display text, two capacitive touch buttons and a ribbon connector with which to connect the flexible PCB. The individual channels in this ribbon connector would pass through to the digital input pins of the Raspberry Pi board, with the speaker connected to the Pi's audio output.

Software

The software would be updated such that training and classification would both occur on the device, rather than using an external, cloud-based solution. An offline, software-based, text-to-speech system would be used to generate the audio corresponding to each label and save it on an SD card within the enclosure. The user would use the buttons on the device to select a label for which to train a sign and record the corresponding gesture. Rather than this data being transmitted to the cloud-based server, it would instead be saved on the aforementioned SD card. When being used for classification, the glove would use a similar, but more efficient DTW and KNN based classifier as ran on the cloud server, running offline. The glove would then display the corresponding label on the on-board screen and output the previously generated audio from the speaker, after reading it from the SD card. A settings menu would also be added, similarly controllable using the two touch buttons, which would allow the user to control the output volume and to select the voice used to generate speech.

Chapter 5

Longitudinal and In-Depth Case Study

5.1 Introduction

In the first study, a basic data glove was hard-coded with a pre-programmed hand gesture library to translate a limited vocabulary of Makaton sign language to English text and speech. This design was a proof of concept and verified that the proposed technology was potentially effective. However, following analysis of the first study it was decided that the design should be augmented to allow users to individually train the device in order to increase the accuracy of the results, and making the device more customisable.

Augmentation of the device was followed by a three-stage iterative study that evaluated the new design. Users were able to train personal classifiers which were then stored on a cloud platform. This enabled users to build their own personal libraries of sign language hand gestures by performing them interactively with the device. Gestures were translated to speech in different languages and voices to match individual user needs. This was possible by pairing the glove with a user interface (UI) that allowed them to choose their preferred output options. The aim of the proposed system was to make the technology more accessible to a wider range of users. The study demonstrated that a personal classifier is more successful in translating hand gestures than a pre-defined generalised classifier (with a single library, shared by all users), and plans were made to upgrade this system to permit offline use, as well as to make the technology as customisable as possible to give the users full control over the features and the appearance of the gloves.

By implementing the recommendations from the previous case study, alterations were made to accommodate participants with different abilities. Gesture classification was enhanced to recognise variations in signing and consistency, and to add structure and feedback when training samples. The new prototype was therefore developed with different user needs in mind. This included changing the output to images for younger participants who could not yet read, and creating shortcuts to bypass features that are not used frequently for users who found it difficult to follow or remember the operation sequence.

This final study was more in-depth than the previous studies and took part over a period of six months, during which three periods of evaluation were performed. This study was conducted in collaboration with Essex County Council and engaged six Special Educational Needs (SEN) schools, who required the use of assistive technology in the classroom to help their students overcome communication challenges. This required a higher-level clearance from University of London Ethics Committee to ensure that participants from vulnerable groups (Appendix A.1), such as children or individuals with disabilities, remained safe and protected during their role in this research study. In addition, public liability insurance was in place to cover all participating children (Appendix A.5).

When designing the prototype for this study, the aim was to develop a bespoke and user-friendly, wireless and standalone data glove which could track hand shapes, orientation, position and dynamic hand movement of children with non-verbal disabilities, for the purpose of translating custom sign language hand gestures to speech. The software was created to operate offline by applying recorded sensor data to train a personal K-Nearest Neighbours classifier, using Dynamic Time Warping (DTW), for each user. A comparison was made between personal classifiers and general classifiers when trained by individual and group gesture data collected over the duration of the study.

To comply with the ethical approval for this study, all testing data was stored locally on the glove and was not accessible remotely or communicated wirelessly at any time. Measures were implemented to ensure the safety of the wearable device, discussed in more detail in the hardware section.

Throughout this study, the iterative design cycle became increasingly shorter, with the prototype rapidly being developed between study sessions, to fulfil the ongoing needs of the participants. During this process, a lot of discussion arose around the innovation aspect of the technology used. As the case study progressed, innovation became part of the research and the user's feedback aligned with the industrial progression of the technology being evaluated. This eventually led to the development of a fully integrated, on-body hand gesture classification system, and a patent was filed to and granted by the UK Intellectual Property Office (UKIPO) titled “Method for Gesture Recognition”, patent No. GB2590502 (Appendix F.1). The aim of this study was to evaluate an offline personal hand gesture classification system and by extension, to explore the different applications of such a system.

5.2 Prototyping and Development

A more child-friendly, wearable device was designed which implements dynamic time warping, in order to build an on-body system for custom hand signal translation. Some alterations in hardware, software and design were required in consideration to the obtained ethics clearance guidelines, discussed in detail under the relevant sections.

Prototype features were updated constantly during this study. I show in this section the final version produced after implementing the last evaluation phase of this study. Glove prototypes were eventually handed over to participants to keep after the conclusion of this study.

5.2.1 Hardware

The hardware for the glove consisted of three primary units; a micro-controller (a Raspberry Pi Zero W[1]), a custom circuit board featuring the speaker and display, and a hand-shaped, flexible Printed Circuit Board (PCB) that contained the various sensors used. The board and Pi were soldered together, on top of one another, with the flexible PCB connected to the main assembly via a short ribbon cable (see Figure 5.1).

The flexible PCB featured 5 flex sensors, one per finger, one accelerometer and one gyroscope. The accelerometer and gyroscope were on the same physical integrated circuit in the centre of the back of the hand (see Figure 5.2). The values from

[1]Raspberry Pi Zero W - https://www.raspberrypi.org/products/raspberry-pi-zero-w/

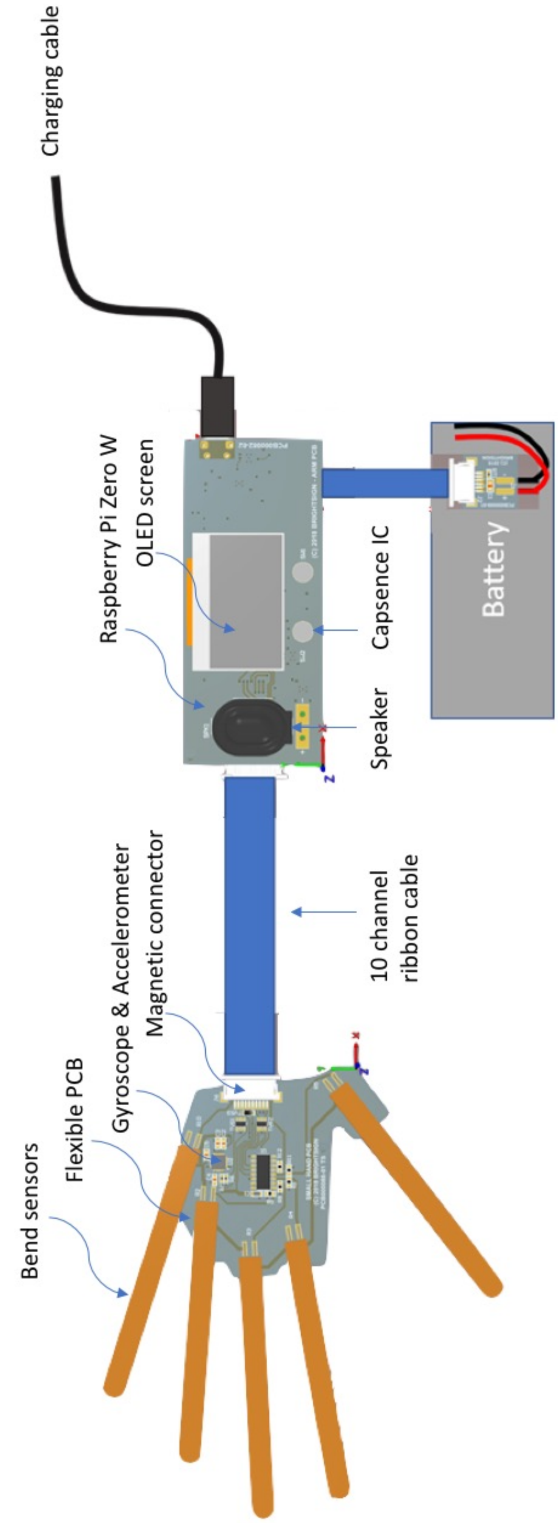


Figure 5.1: Glove hardware circuit design

the flex sensors were transmitted to the Pi in raw form, with the accelerometer and gyroscope unit connected via an I2C bus, as seen on schematics Figure 5.3.

As per the school's request and to conform with the ethical clearance for this study, some measures were taken to ensure that hardware was not accessible by the children while using the gloves. All electronic components were encapsulated and sealed inside a wearable enclosure, secured via an adjustable wrist band (see Figure 5.11). An opening was placed to allow charging the battery internally, rather than replacing it, as in the previous prototype. A fail-safe switch was added to turn the battery off while charging. A battery risk assessment was carried out to ensure the safety of the wearable circuit:

- **Short circuit to the battery:** The battery has short circuit protection built-in

- **Over-voltage charging of the battery:** The battery is permanently connected to the hand PCB and can only be charged by the battery charger on the hand PCB. The charger selected is designed to charge to a maximum voltage of 4.2V which is below the maximum safe charge voltage of the battery. The Input of the battery charger IC also has a Transient Voltage Suppressor (TVS), designed to protect against ESD and also limit the input voltage to 5V (within the safe input voltage range of the battery charger IC). If a higher voltage is connected, then it will clamp and if present for too long, short the TVS. This in turn will cause the 1.5A input fuse to blow, stopping the battery encountering the high voltage. The battery also has over-voltage protection built-in so if the charger failed then the battery would still be protected. The connector to the battery charger is a micro USB at the standard nominal 5V (min/max 4.5-5.5V), all within specification of the battery charger.

- **Over-discharge of the battery:** The battery has over-discharge protection, currently set at 2.75V.

- **Over-charging - Charging the battery above its maximum charge rate:** The maximum charge rate for the battery is 0.5C, C=2Ah, so the max charge current is 1A. The battery charger on the PCB is set to charge at its maximum of 1A; the power supply provided also being 5W (5V, 1A). There is

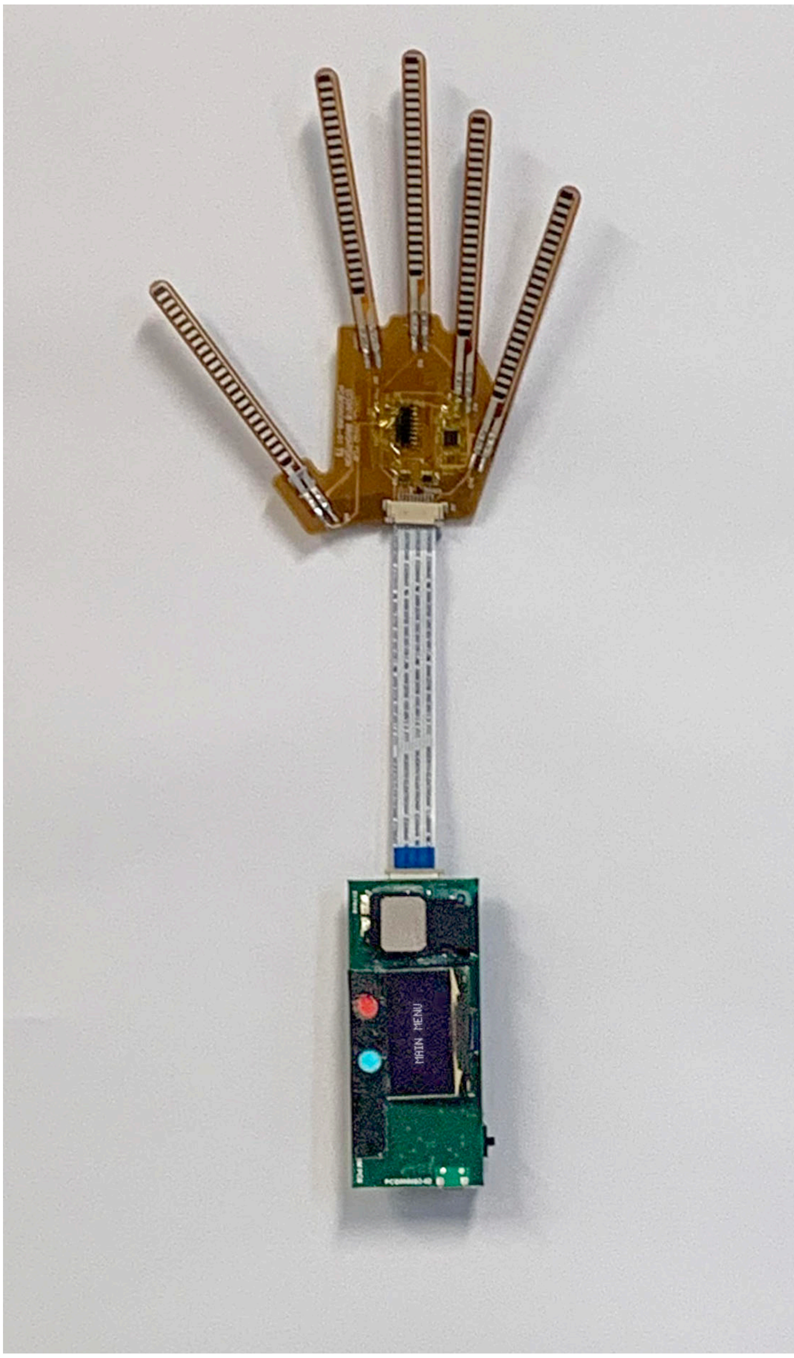


Figure 5.2: Final glove circuit design

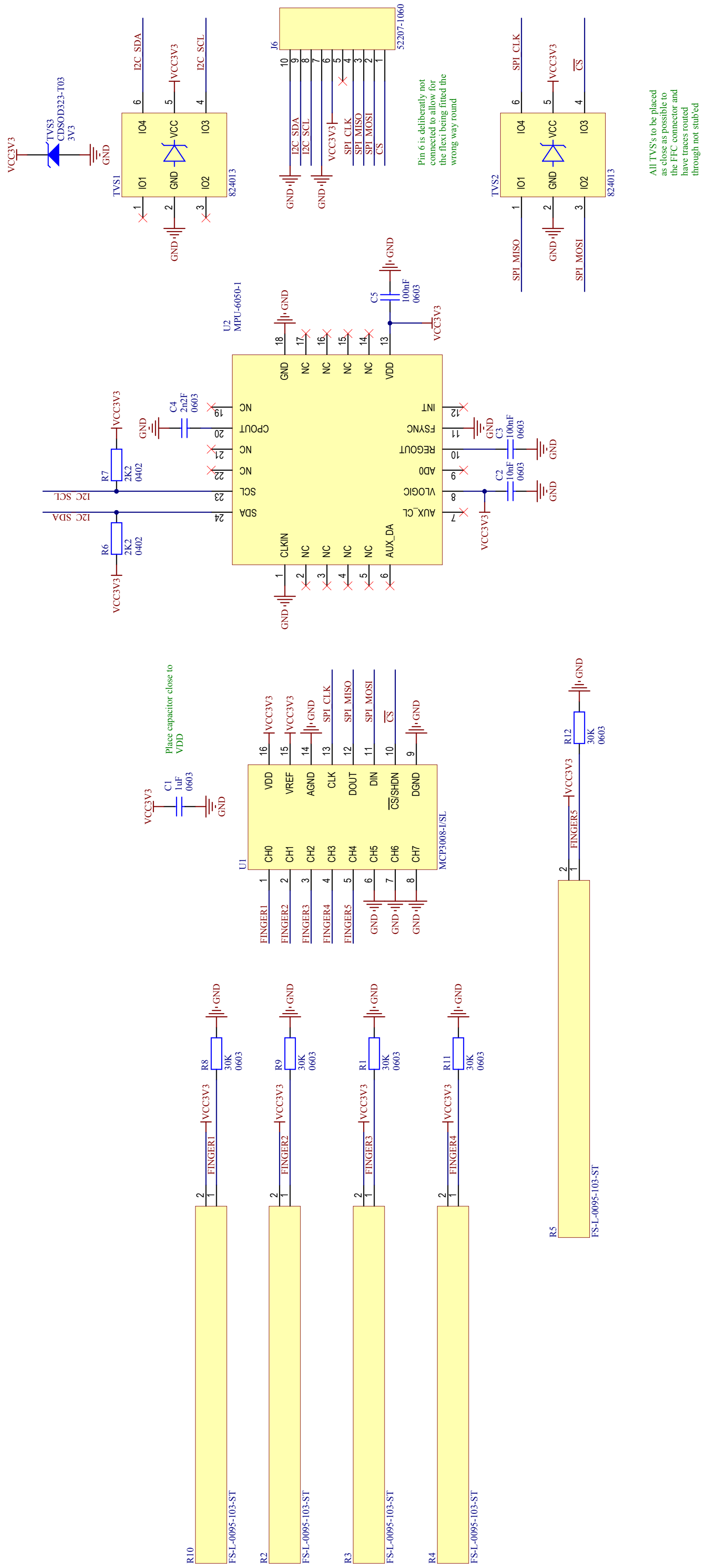


Figure 5.3: Glove hardware circuit schematic

a 1A series fuse onto the battery to restrict the charging current and discharge current. The battery also has over-current protection built-in

- **Over-current - Discharging the battery above its maximum discharge rate:** The maximum discharge rate for the battery is 1C, C=2Ah, so the max discharge current is 2A. There is a 1A series fuse on to the battery to restrict the discharge current. The battery also has over-current protection built-in

- **Over-charging - Due to trickle charge over a long time:** The battery charge has a built-in timeout of 4hrs for charging the battery, this cannot be disabled. The battery also has overcharging protection built-in.

- **Over-temperature:** The battery charger has a NTC temperature sensor to mnitor the battery temperature whilst charging. The battery also has built-in over-temperature protection.

5.2.2 Software

The crucial development towards the prototype for this study was to make it stand-alone, able to run independently from any external device and to fully operate offline. Therefore, the primary software upgrade from the previous prototype was for the classifier to work offline and to run locally on the glove. To enable user interaction with the system, a simple User Interface (UI) was designed to be displayed on the on-board screen with capacitive (touch) buttons to allow the users to scroll between menu options, seen in Figure 5.4.

When the children trained the glove, recordings for all sensors were stored for each sign, with multiple examples of each sign being recorded. These recordings were labelled with the name of their corresponding sign, for example “Please” or “Thank You”.

Children selected the label of the sign for which they wished to record a new sample, while wearing the glove, using the glove’s on-screen display, and pressed a button to start the recording of sensor data. They then performed the sign, before pressing the button again to cease recording.

The system, after receiving the raw data from the sensors embedded in the glove, normalised them between 0 and 1, based on values that were recorded from each sensor as the maximum and minimum possible readings during normal use. This

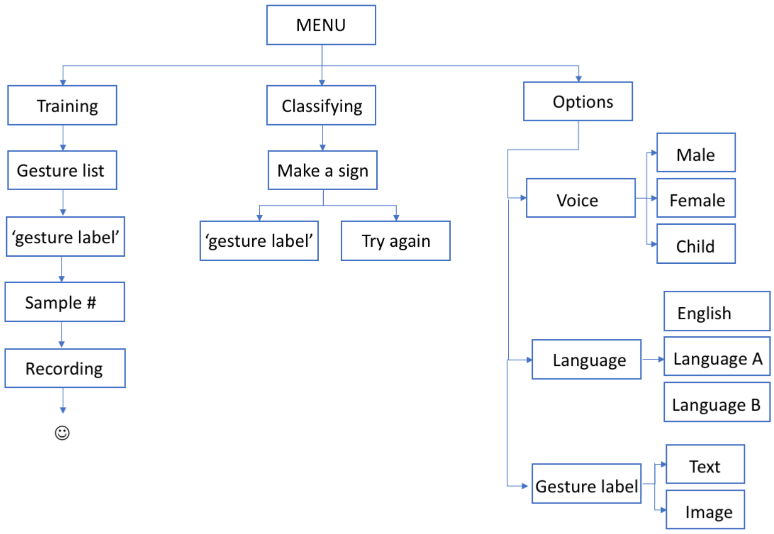


Figure 5.4: Glove UI Flowchart

prevented any sensor from overly weighting the classification result. The sensor values were stored after normalisation.

After pressing another button to begin recording a sign for classification, each child again performed the sign, and pressed the same button to cease recording. As during training, sensor values were immediately normalised to provide values between 0 and 1.

A DTW algorithm, explained in detail below, was then applied to each of the pre-recorded training samples in turn, with the new recording for classification. This provided the distance between each sample (and therefore its label) and the new recorded gesture.

A K-Nearest-Neighbours algorithm, explained in the following section, was then used to select the output audio and text, based on the distances calculated in the previous step. K was set to different values to test its impact on classification accuracy.

The label for the classified sign was ultimately displayed on the screen, with corresponding audio being output from the on-board speaker. While this is fundamentally the same classifier used in the prototype developed for the second case study (see sample code in Figure 4.12), the key difference is that the audio and label output of the system is now hosted on the local board and can be used offline instead of connecting to a cloud based system like the previous prototype used in the previous chapter for the iterative case study of Section 4.1.

Figure 5.5 explains the classification process and Figure 5.6 the training process in the form of flow charts.

The classification software was based on a K-Nearest Neighbours classifier using Dynamic Time Warping (DTW), to calculate a distance measure between time series recordings.

Dynamic Time Warping is an algorithm that enables the calculation of similarity between temporal sequences while allowing for variations in speed and position in time. In this case, this means that the similarity measurements are largely invariant to differences in the speed of signs being performed, and small variations in the delay when recording, prior to the user performing each sign.

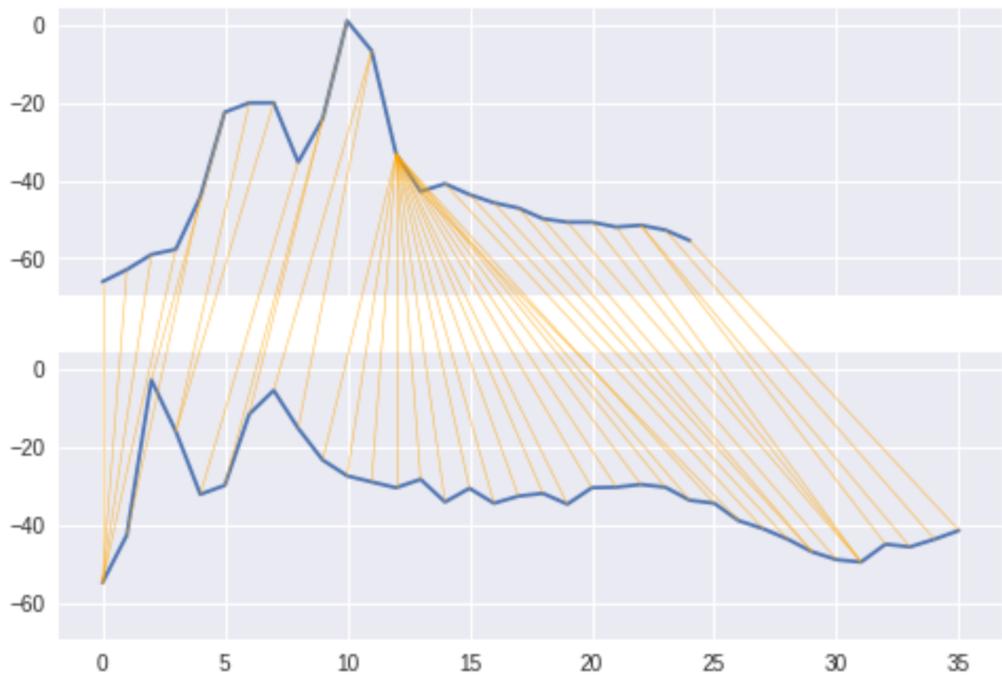


Figure 5.7: Example of Dynamic Time Warping to measure distance between two time series for the hand sign for “Please”.

An example of this can be seen in Figure 5.7. Recordings of the value of one axis of the accelerometer on the glove were taken as a user performed the sign for “Please” multiple times at different speeds. This value is graphed over time (with the raw value of the sensor on the vertical axis, and time on the horizontal axis) in the below chart in the form of two dark blue line plots. The orange lines represent the mapping between the points in the two series as dictated by the DTW algorithm. In this example, the algorithm has largely correctly identified the mapping between the macroscopic features of each series (namely the two consecutive spikes towards

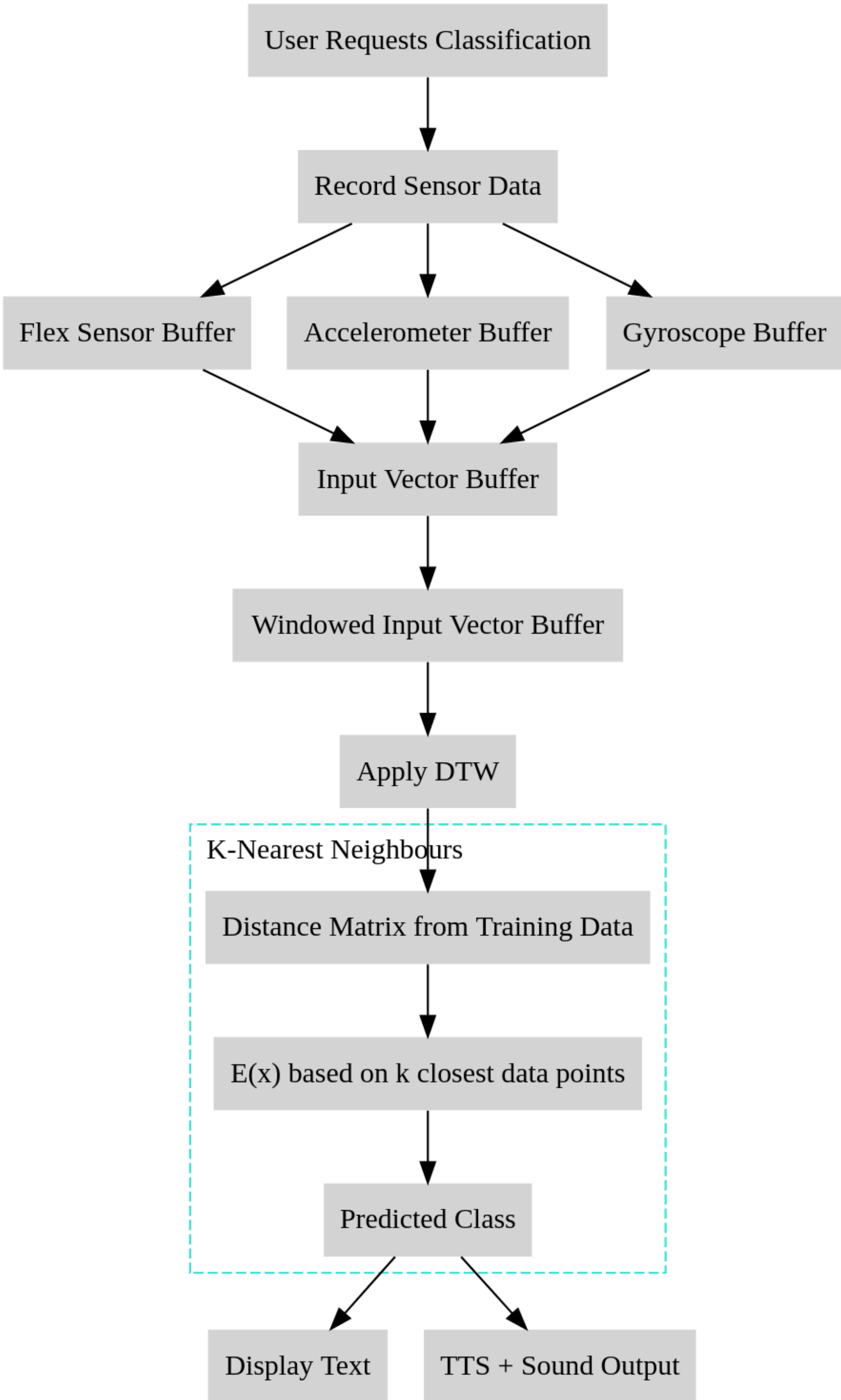


Figure 5.5: Classification task flow chart

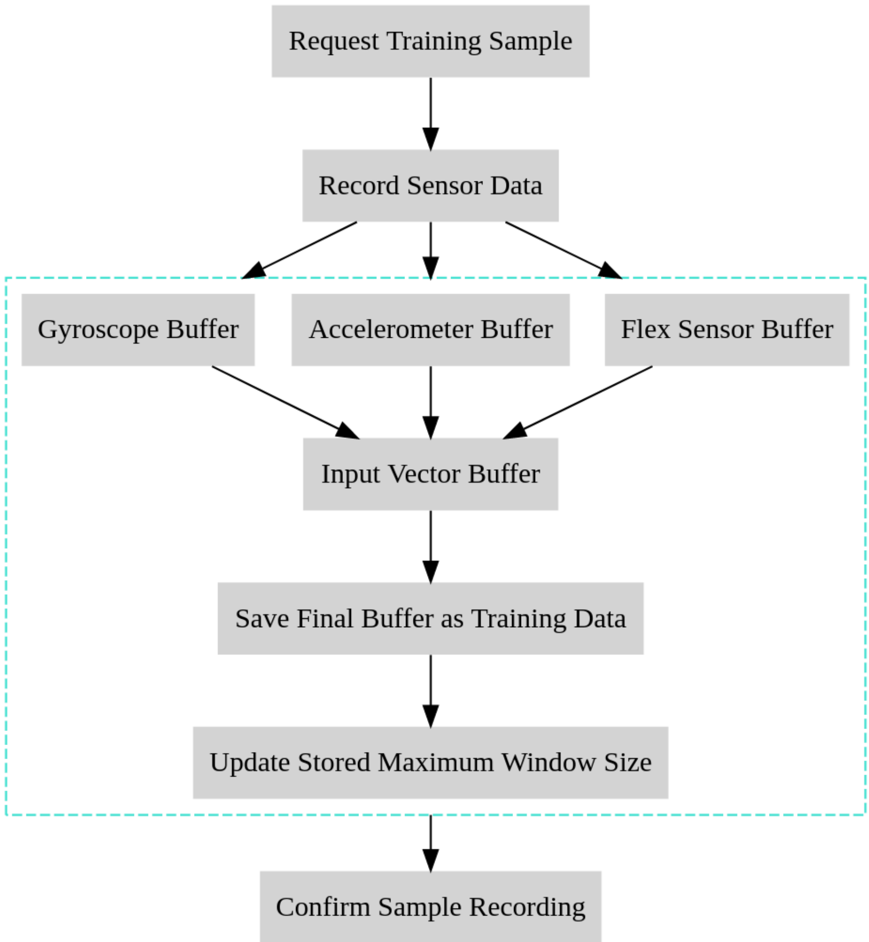


Figure 5.6: Training task flow chart

the start of the time series, followed by a slow decrease in value).

Implementations of the DTW algorithm that guarantee the optimal match have at best quadratic ($O(n^2)$) time complexity of computation. As such, alternative algorithms that will find good approximations of the optimum, such as FastDTW (Salvador and Chan 2007) and SparseDTW (Al-Naymat et al. 2012), can be used instead, some of which run in linear ($O(n)$) time. The FastDTW algorithm was selected to be used for this prototype's system.

When DTW is used in situations where time-series data is multi-dimensional for each frame, two different variations are possible (Shokoohi-Yekta et al. 2015) - the dependent variant ($\mathrm{DTW_D}$) and the independent variant ($\mathrm{DTW_I}$). $\mathrm{DTW_I}$ calculates a separate minimal warping path (and therefore distance) for each dimension of the data, which is then summed (either linearly or as a Euclidean distance) whereas $\mathrm{DTW_D}$ finds a single shared optimal match between points for all dimensions simultaneously, with distance calculated per frame. $\mathrm{DTW_I}$ can be used when the dimensions are only loosely coupled in time. $\mathrm{DTW_D}$ is most appropriate when the values for each dimension are either mutually dependent or strongly coupled in some way. In this case, it is appropriate as the sensor data is physically coupled - corresponding to the real-world configuration of the user's hand.

5.2.3 Design & Enclosure

As the council granted the participants ownership of the glove prototypes after the completion of the study, it was possible to personalise the size (two different sizes of PCB were created to accommodate smaller and larger gloves - see Figure 5.8), colour and design of each prototype as per the each child's preference (see Figures 5.9 and 5.10). This was particularly useful in making the participants more comfortable using the technology, so that they did not feel intimidated by it, as well as to help them treat it as a personal item.

To ensure the safety of the children wearing the technology and to comply with the ethical approval, all sensors were embedded within an inner lining of each glove. Insulating the sensors was a necessary design and safety solution to prevent direct contact with the children's skin and to make the glove appearance discreet for participants who did not wish to wear an obvious assistive technology device. The children were invited to communicate their desired glove designs. Each child received a right

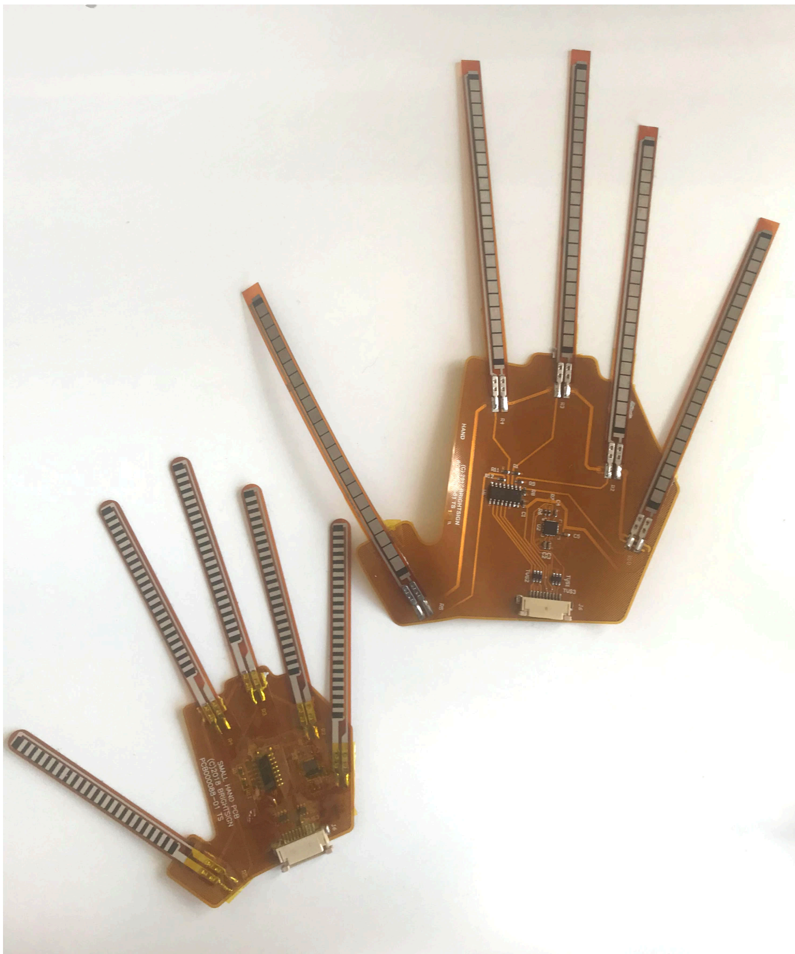


Figure 5.8: Flexible PCB size options: small with 2.2” flex sensors and large with 4.5” flex sensors

Figure 5.9: Personalised glove designs

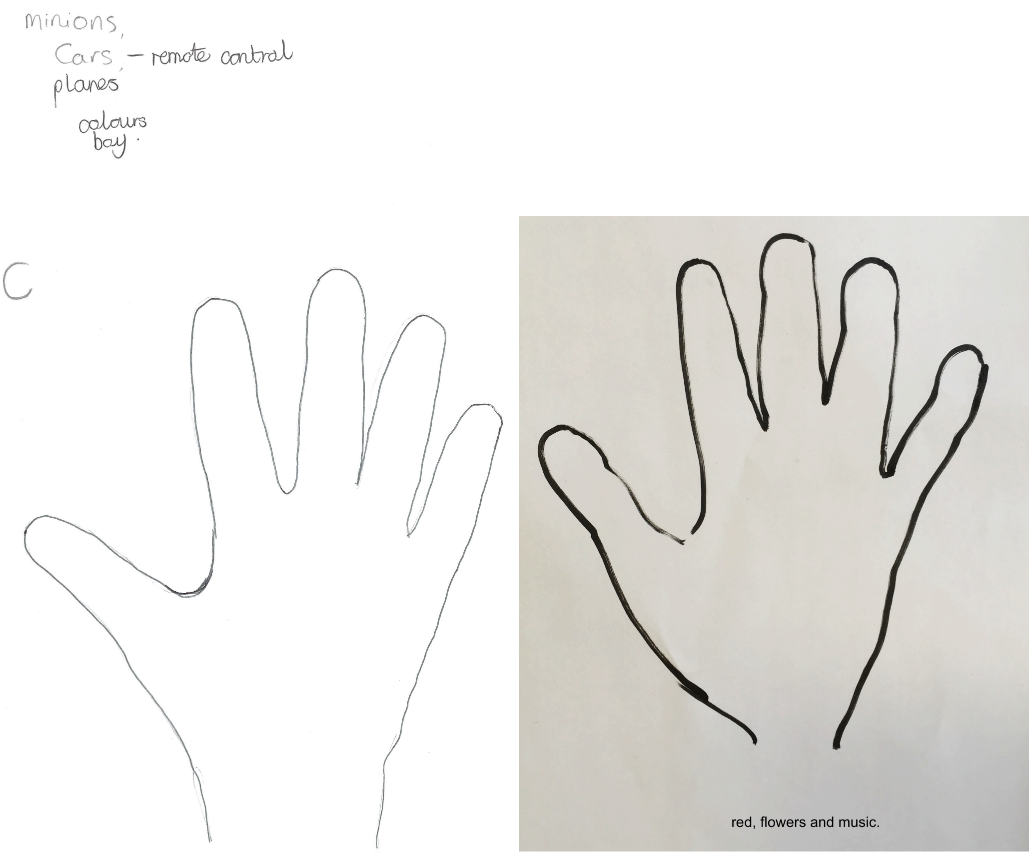


Figure 5.10: Exemplar scans of participant hand outlines

or left hand glove (corresponding to their dominant hand when signing) that was personalised to their preference, in terms of size, colour, and design. A plain glove is shown (Figure 5.11) to preserve anonymity, as gloves also had the children's initials and/or names embroidered. Involving the children in designing their own gloves proved to help them in overcoming their initial intimidation by the technology, that was observed in previous studies, where the gloves were more obtrusive and the design was unified across participants.

A hard-case wrist band was designed to house the micro-controller, a custom circuit board featuring the speaker, screen and two buttons, and a battery (Figure 5.11). The case was sealed to insure children were not able to access any of the electronic components. The two buttons were added to allow children to interact with the glove and use it for sign language training and translation; a red button for training (record a new gesture) and a blue button for translation (recognise a gesture and output the corresponding audio). The battery was charged using a USB port without opening the case. An automatic fail-safe switch was added to disable the operation of the glove while charging as an additional safety feature.

(a) Winter glove option

(b) Summer glove option

Figure 5.11: The assembled glove, flexible PCB and hard enclosure with a winter and summer textile option

5.3 Method

5.3.1 Setting-up the study with relevant parties: schools, teachers and parents

This study recruited fifteen participants aged between five and sixteen, registered in primary Special Educational Needs (SEN) schools in Essex. Speech therapists at participating schools selected children who were non-verbal and used sign language as their primary means of communication. Children gave consent by nodding or making the hand sign for "Yes" when asked if they wanted to wear the glove. All testing sessions were supervised by a member of school staff and with a guardian present, both of whom also provided consent. Participating schools were required to sign a consent form allowing the study sessions to be run on campus. Minimal disruption was promised by the researcher to school's daily operations. An initial meeting was conducted with the parents and teachers of selected students to present the study proposal. A detailed document outlining the timeline, progress and evaluation contribution required of parents and teachers was distributed (see Appendix C).

Three evaluation periods were suggested to take place during the six-month duration of the study, scheduled at two-month intervals. Teachers were asked to evaluate participant's experience with the prototypes in school, and parents when at home. Evaluation forms were explained in detail to both teachers and parents, discussed in more detail in the section entitled "Evaluation".

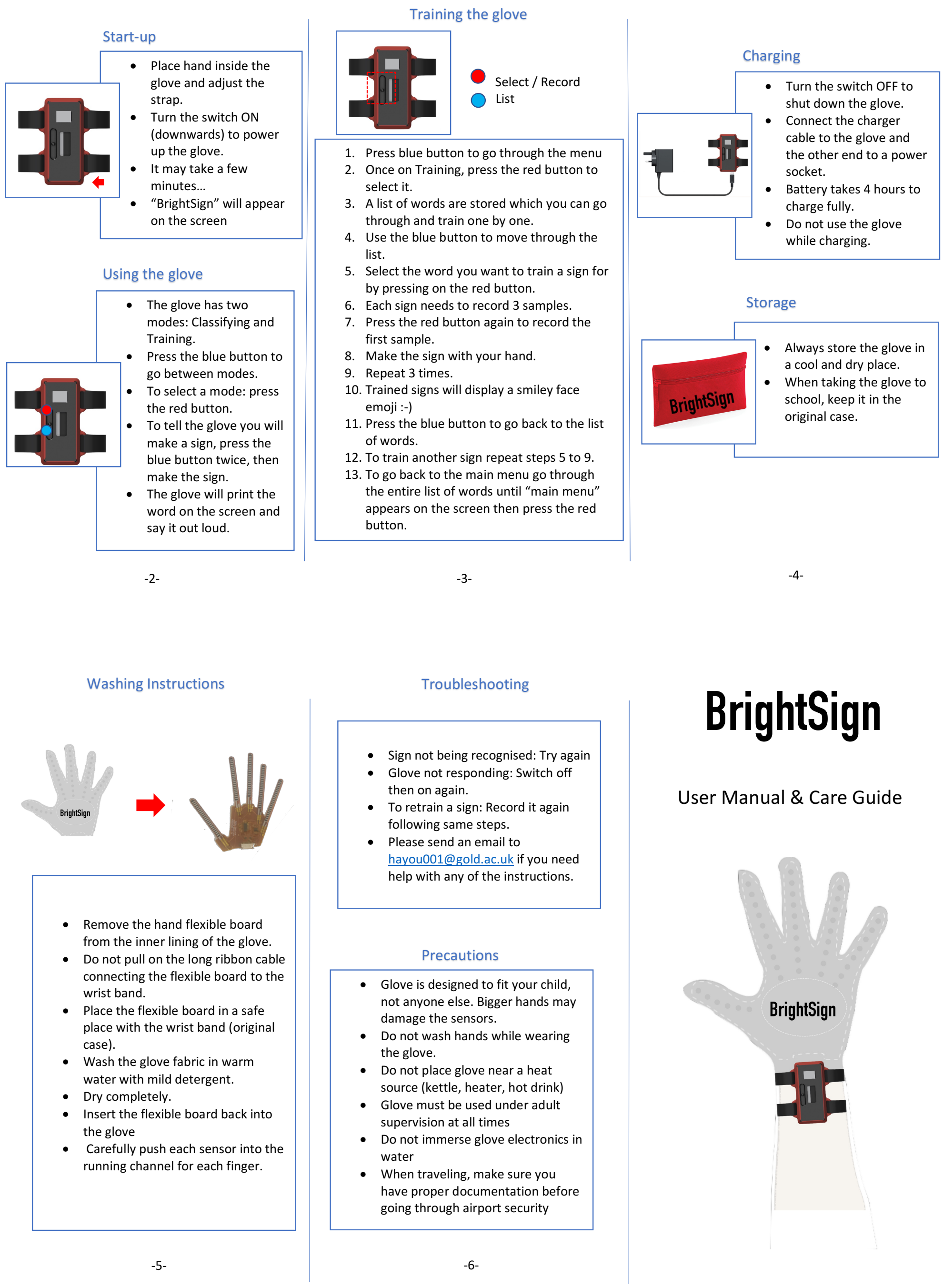
A user guide was distributed to aid with the operation of the glove prototype (see Figure 5.12) It included step-by-step instructions of how to train the glove then use it for translation. A simple care and troubleshooting section was also added to help with possible user challenges.

One-to-one sessions were scheduled with each student, their parent(s) and attending teacher to train them on how to use the glove, described in detail below. The gloves were then handed over to each participant to keep in their possession for use in school and at home. The researcher scheduled weekly visits to each of the six participating schools for observation and the provision of additional support using the technology (see Figure 5.13).

5.3.2 Study framework

Fifteen non-verbal participants were recruited, between the ages of 5 and 16 years old. Teachers identified the students who would be good candidates for the study. Selection criteria was based on familiarity with a form of sign language, consistency in signing and those who could benefit from using this technology to overcome communication challenges in school. A preliminary meeting was held at participating schools with children's parents and teachers to introduce the technology and describe all features. A usability guide was distributed to ensure adults who supervised children using the gloves, in school and at home, were aware of the safety regulations. Training sessions consisted of a two-hour long task (described below) and were broken into four, fifteen minute segments. Training sessions were done with the researcher and the participant's speech therapist in attendance. The first segment was reserved for getting the children familiar with the glove and asking them if they wanted to wear it. Once they gave consent, they were helped with putting the glove on and the researcher demonstrated how to use it. The participant was always the one who pressed the buttons while wearing the glove.

The glove has two modes: *Training* and *Classifying*. Participants were first shown how to use the glove to record signs (Figure 5.14 & 5.15). Each participant



Start-up

- Place hand inside the glove and adjust the strap.
- Turn the switch ON (downwards) to power up the glove.
- It may take a few minutes…
- "BrightSign" will appear on the screen

Using the glove

- The glove has two modes: Classifying and Training.
- Press the blue button to go between modes.
- To select a mode: press the red button.
- To tell the glove you will make a sign, press the blue button twice, then make the sign.
- The glove will print the word on the screen and say it out loud.

-2-

Training the glove

Select / Record
List

1. Press blue button to go through the menu
2. Once on Training, press the red button to select it.
3. A list of words are stored which you can go through and train one by one.
4. Use the blue button to move through the list.
5. Select the word you want to train a sign for by pressing on the red button.
6. Each sign needs to record 3 samples.
7. Press the red button again to record the first sample.
8. Make the sign with your hand.
9. Repeat 3 times.
10. Trained signs will display a smiley face emoji :-)
11. Press the blue button to go back to the list of words.
12. To train another sign repeat steps 5 to 9.
13. To go back to the main menu go through the entire list of words until "main menu" appears on the screen then press the red button.

-3-

Charging

- Turn the switch OFF to shut down the glove.
- Connect the charger cable to the glove and the other end to a power socket.
- Battery takes 4 hours to charge fully.
- Do not use the glove while charging.

Storage

BrightSign

- Always store the glove in a cool and dry place.
- When taking the glove to school, keep it in the original case.

-4-

Washing Instructions

BrightSign

- Remove the hand flexible board from the inner lining of the glove.
- Do not pull on the long ribbon cable connecting the flexible board to the wrist band.
- Place the flexible board in a safe place with the wrist band (original case).
- Wash the glove fabric in warm water with mild detergent.
- Dry completely.
- Insert the flexible board back into the glove
- Carefully push each sensor into the running channel for each finger.

-5-

Troubleshooting

- Sign not being recognised: Try again
- Glove not responding: Switch off then on again.
- To retrain a sign: Record it again following same steps.
- Please send an email to hayou001@gold.ac.uk if you need help with any of the instructions.

Precautions

- Glove is designed to fit your child, not anyone else. Bigger hands may damage the sensors.
- Do not wash hands while wearing the glove.
- Do not place glove near a heat source (kettle, heater, hot drink)
- Glove must be used under adult supervision at all times
- Do not immerse glove electronics in water
- When traveling, make sure you have proper documentation before going through airport security

-6-

BrightSign

User Manual & Care Guide

BrightSign

Figure 5.12: User manual and care guide for prototype used in this study

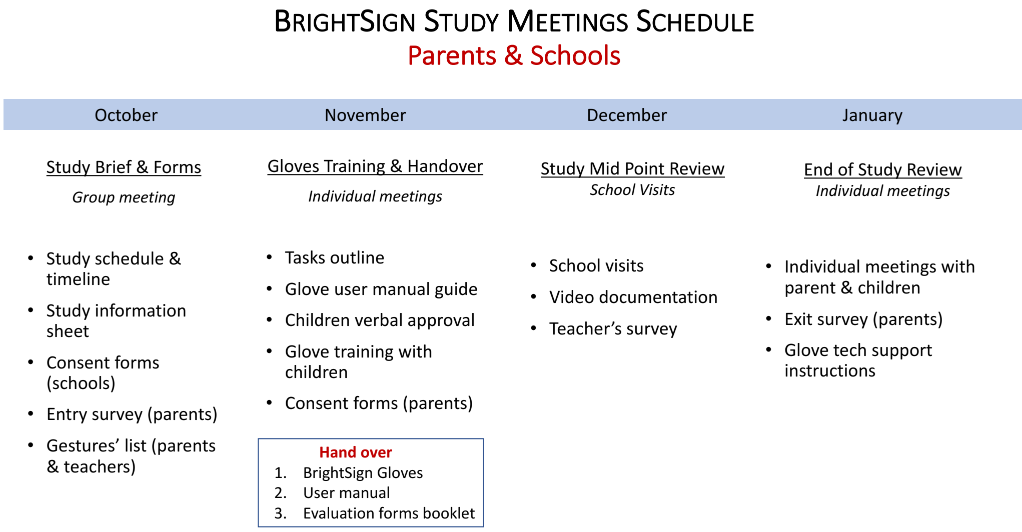


Figure 5.13: Study meeting schedule handed out to schools and parents

Figure 5.14: Participant training the hand sign for "Okay"

(a) Participant looking at the UI

(b) Participant training sample #5 for "Help"

Figure 5.15: Participants training the glove

recorded up to 10 sign samples for each word (as in Figure 5.16) by pressing the record button before and after making the hand gesture. This was necessary to train a personal classifier for each user. Gesture data was captured at 20 frames per second. To translate signs, the participant then switched to *Classifying* mode on the glove and made a sign. If the sign had a match it was displayed as text on the screen and spoken as speech though the speaker. Children had a selection of male or female voices to choose from. If no match for the sign was found, the screen displayed a "failed" message and returned to *Classifying* mode, waiting for new signs. If a sign continued to give a failed message it would be re-trained. The newly recorded samples would then replace the old ones for that sign.

The system was programmed to record dynamic gestures' sensor data received from a right or left-handed glove. In signs using both hands, only the participant's dominant hand was used for training. This was still effective because in the majority of signs using both hands, either both hands perform the same motion or one hand stays motionless in holding one position, while the other hand makes the sign (Tennant and Brown 1998).

The data glove screen showed a list of words with a user interface menu for the user to scroll through them. Each participant selected ten words from the list of 50 most used words in school, provided to us by attending teachers (see Table 5.1.

Figure 5.16: Ten samples have been recorded for the label "Game"

Each word (label) corresponded to a notional gesture which initially had no data recorded for it. Gesture data was recorded by the children during training sessions (described below). This method of a pre-defined dictionary of words was chosen although the software supports the definition of personalised labels. This was due to school regulations and the ethics clearance which did not allow the technology to connect to the internet, in order to protect children's data and to ensure none of the testing data was sent to the cloud or stored on any external servers.

Yes please	Wait	Can I play outside?	Water	Hello
No thank you	I don't understand	Can I have cake?	Friends	Can I help you?
I need help	I need the toilet	School	Can I use the computer?	Colour
Stop	Good morning	Cup of tea	Sorry	Puzzle
More	Can you sign?	What is your name?	I need my chair please	I want to sleep
Finished	Food	I don't want to	Class time	Home
Mom	Can you play with me?	I need a bath	I'm thirsty	I'm happy
Dad	I'm tired	Goodbye	Swimming	I'm sad
Please	I'm hungry	This is fun	I'm cold	I don't feel well
Thank you	I need a break	I love you	I'm hot	Where are we going?

Table 5.1: List of gesture labels

5.3.3 Study task outline

This is the process followed to use the glove and record new signs, which was explained to parents and teachers and follows the same structure in the distributed leaflet (see Figure 5.12).

Start-up

- Place hand inside the glove and adjust the strap.
- Turn the switch ON (downwards) to power up the glove.
- It may take a few minutes...
- "BrightSign" will appear on the screen

To use the glove

- The glove has two modes: *Classifying* and *Training*.
- Press the blue button to go between modes.
- To select a mode: press the red button.
- To tell the glove you will make a sign, press the blue button twice, then make the sign.
- The glove will print the word on the screen and say it out loud.

Training the glove

1. Press blue button to go through the menu
2. Once on "Training", press the red button to select it.
3. A list of words are stored which you can go through and train one by one.
4. Use the blue button to move through the list.
5. Select the word you want to train a sign for by pressing on the red button.
6. Each sign needs to record a minimum of 3 samples.
7. Press the red button again to record the first sample.
8. Make the sign with your hand.
9. Repeat 3 or more times.
10. Trained signs will display a smiley face symbol :-)
11. Press the blue button to go back to the list of words.

12. To train another sign repeat steps 5 to 9.
13. To go back to the main menu go through the entire list of words until "main menu" appears on the screen then press the red button.

Notes

1. To preserve battery power, the glove has been set to go into sleep mode if it remains still for more than 5 minutes.
2. To turn it back on, just press the on button (red button)
3. To reset the glove or recover from errors, press and hold the red button until the screen is turned off.

5.3.4 Study evaluation methods

Parents entry and exit surveys

An entry survey (Appendix E) for participating children's parents was designed to collect background information about each participant: their age, nature of disability(ies), and sign language library used[2]. This helped the researcher better understand the needs of each participant in order to provide them with the technology features most suitable to their condition. The survey also allowed the participant to make a choice with regards to the design, size and colour of the glove. A final feature was to collect the preferred voice and language for the speech to make sure all participant's preferred options were available in the software. This was particularly important as the glove needed to be able to operate offline, so only the languages and voices that were pre-loaded on the glove board would be available for the participants to use.

As in the previous study, in section 4.2, I was particularly keen to document what current technologies the participants used for communication in school and at home, and what the drawbacks were. This proved to be very useful and some changes were reflected to improve the proposed technology solution for this study.

The parents were asked to disclose the reasons they agreed to allow their child to participate in the study, and what they hoped to gain from it. These questions were

[2]For access to digital, anonymised copies of all survey responses and participants profiles, please visit https://resources.brightsignglove.com/study_surveys

included to act as an evaluation reference for the exit surveys where the parents reflect on the same points they have highlighted at the beginning of the study.

The exit survey acted more as an overall evaluation, documenting parents' experience throughout the study and whether the technology delivered the solution they were hoping for. Considering the fact that each family got to keep the prototype used by their child during the study, I was especially interested to know how they intended to use the gloves after the conclusion of the study and if there was any additional support that could be provided to help with that.

Parents' and teachers' periodic evaluation forms

A simple checklist evaluation form was provided to document the user experience of each participant at school, filled by the teacher and at home filled by the parent. The form was designed to take an average of five minutes to complete and to be submitted every two weeks (Figure 5.17).

Getting regular feedback throughout the duration of the study was essential to address challenges as they arise and resolve them when possible. Two evaluation criteria were defined, evaluating the technology and evaluating the participant's social and academic performance while using it. Even though this research is focused on the development and evaluation of the technology, it is of course essential to document the impact of using it for the purpose it was designed for.

Researcher's observation documentation

Regular visits to participating schools were scheduled for the researcher to observe the participants while using the gloves in the classroom. Evaluation criteria, explained in detail below, focused on the prototype's usability issues, as well as the participants' social and performance changes while using the technology. Teachers also used these visits to report on participants' experience and to address technical challenges.

Glove gesture and accuracy data on the attached board

Gesture data was stored on the glove micro-controller board. Recorded sensor data for each gesture training task was essential to explain performance issues with the classifier. Factors like number of samples, and consistency when signing greatly

Goldsmiths UNIVERSITY OF LONDON BrightSign Essex County Council

Usability Study Evaluation Form

Participant Name: ______________________________ Date: ______________

Evaluator Name: ______________________ [ ] PARENT [ ] TEACHER [ ] RESEARCHER

Evaluation Scale

Please evaluate the following criteria by ticking the metric that best reflects your observation: 1 being the lowest score where the criteria was not met/unsatisfactory and 5 being the highest score where the criteria exceeded expectations. If any of the points do not apply to the participant, please leave it blank. The baseline point of evaluation is the beginning of the study, NOT the last point of evaluation.

Evaluation Criteria: [1] BrightSign Technology

	1	2	3	4	5
Time to complete tasks is reasonable	☐	☐	☐	☐	☐
Tech output is accurate	☐	☐	☐	☐	☐
Tech gives adequate feedback	☐	☐	☐	☐	☐
Easy to recover from errors	☐	☐	☐	☐	☐
Overall tech is easy to use	☐	☐	☐	☐	☐

Evaluation Criteria: [2] Participant's Observed Improvement

Academic performance	☐	☐	☐	☐	☐
Communication skills	☐	☐	☐	☐	☐
Self confidence	☐	☐	☐	☐	☐
Relationships	☐	☐	☐	☐	☐
Overcoming challenges	☐	☐	☐	☐	☐
Overall social behaviour	☐	☐	☐	☐	☐

Additional Comments

Signature: ____

Figure 5.17: Periodic evaluation forms for parents and teachers

affected classification rates and was only possible to measure by analysing training gesture sensor data. This is visualised in multiple graphs in the results section and examined in detail in the discussion.

Gesture classification sensor data was extremely valuable in understanding how the software algorithm performed with each classification request. Matching training data with classification data, while considering participants' personal differences and observed factors like age, physical ability, and numbers of samples trained, was the backbone of this study's evaluation and results.

Further evaluation was made by comparing variations between individual trained samples' gesture data for each sign, and cross-examining that with the gesture data across participants for the same signs. An argument for personal classifiers and a general classifier arose and is explored in detail in the discussion.

Video documentation

Initially, video documentation was proposed and although some parents and schools opted out, it was still set-up to document the few participants who allowed it. However, many children felt uncomfortable being observed when trying to learn how to use a new technology device and it created a lot of tension during study sessions. As a result, the collection of video documentation was reconsidered as it caused distress to some of the participants and halted the progress of study sessions. The decision was therefore made to not include video documentation as an evaluation method for this study. With the exception of a few of the earliest sessions[3], the only video documentation retained on record for the study was of the participants verbal consent to participate in the study, which was the requirement of the ethical approval obtained for the study.

5.3.5 Study evaluation criteria to be measured

Technology usability and tasks issues

- **The time it takes to complete a task:** The time for recording gestures and translating signs was recorded locally on the glove. User experience was

[3] An example of this early documentation, of a participant that did not have a problem with the presence of a camera, is accessible at the following URL - https://resources.brightsignglove.com/essex_study

reflected on the periodic evaluation form and documented during observation by the researcher. Triangulation of data was effective in identifying delays and resolving them between study sessions.

- **Error margins and output accuracy:** The number of attempts it took to get correct classification was the primary reason to document error margins. It was particularly useful to compare those margins between participants for the purpose of identifying the cause of the inaccuracies and implementing a rapid solution for the following sessions.

- **Ease of use:** In this research, feedback is not gained directly from the participants but through their teachers and parents. By observing how the users interacted with the technology, it was possible to document the approximate level of confidence versus confusion while completing the different tasks of training and classifying. This was reflected in the evaluation forms and through the researcher's observation notes.

Participant's social and performance issues

Participant's social and performance issues are evaluated through the triangulation of data collected and reported by parents, teachers and the researcher. This is mostly done through periodic evaluation forms (Figure 5.17) and observation notes.

- **Performance in the classroom during the use of the glove:** As discussed above, although this criteria is not the purpose of the study, it would be valuable to document if there was an improvement observed in academic performance while using the glove. Classroom performance is evaluated by teachers and general performance by the parents, both reflected on the evaluation forms.

- **General social behaviour while using the glove:** This covers but is not limited to, does the technology make the participants calmer or more anxious while using it for communicating? Are the participants using it to initiate communication with people around them? Has using the glove given a boost to participants' self-confidence, now that they are able to communicate with non-signers? Some of the feedback in prior studies was related to the appearance and the design of the gloves and so by evaluating the behaviour of the participants, consideration was made to help them feel more relaxed when using them.

- **Sign language skills while using the glove:** Most of the study participants were proficient signers. However, many of them did not use sign language outside the school because no one at home understood it. Another factor was that the existing technology they were using to communicate did not require signing. So, it was valuable to observe and document how using the glove prototype altered their signing habits, as it was a direct reflection of whether the glove was solving their communication challenges outside of the study constraints.

Prototype wearability issues

- **Glove design restrictions or durability limitations:** This was only documented during the researcher's initial introductory one-to-one session with participants and during the regular schools visits. Questions that needed to be addressed were: Is the glove easy to wear and take off without tugging on parts or pulling sensors and causing damage to the hardware? Does wearing it restrict the participants hand movement when the enclosure is positioned on the wrist? Is the glove too tight or too loose? This can affect sensor placement and throw off recognition modules.

- **Glove and hardware enclosure size, design or comfort:** This was documented during researcher's observation school visits and verbally by the teachers. Hardware design is an integral part of the design iterative cycle of this research. Comfort was important because the participants were using the gloves for an average of six hours per day between school and home. Size and design are directly relevant and contribute a great deal to the user's comfort or lack thereof.

5.3.6 Study evaluation phases

The full duration of this study was six months. The first month was allocated to connecting with participating schools, finalising students' selection, and conducting introductory meetings with parents – described in detail above. This was followed by a month of individual meetings for the handover of the glove prototypes. One-to-one sessions were scheduled for each participant at their local school, with the attendance of their teacher, parent(s) and the researcher. During these sessions, gloves were fitted to each child's hand, wearable safety measures were explained and glove guide leaflets distributed.

The active phase of the study was then initiated. It was set to take place over a duration of three months. During which, the gloves were to be used by the participants in classrooms and at home for communication.

Three evaluation phases were defined, each having an evaluation period of three weeks followed by a reflection period of one week. During evaluation periods, a variety of problems were encountered. Those were addressed during the reflection period, which was primarily designed to implement feedback and upgrade prototypes for subsequent evaluation phases.

The final month of the study was dedicated to refining all glove prototypes considering feedback from the study, and preparing for the final handover to participants to keep, after the conclusion of the study.

As this is a longitudinal study, in-depth evaluations were conducted. Triangulation of records included parents' and teachers' evaluation forms, researcher's observation notes and sensor data from the glove board.

Evaluation phase 1: Weeks 1 to 4

This phase started immediately following the delivery of introductory meetings with schools, teachers and parents associated with the fifteen participants selected to enrol in the study. Background surveys were circulated and returned and relevant consent forms, for parents and schools, received. Glove allocation was complete and each participant had in their possession their own individual glove prototype which was designed specifically for them, according to the choices they had made on the registration forms.

Observation visits were arranged for two schools per week, in order to cover the six participating schools during the three-week period of this evaluation. Individual sessions were scheduled for the fifteen participants to record their hand gestures with the glove and build an individual library for each.

In this sense, this evaluation period was used to evaluate early usability issues rather than an early evaluation of using the full system. Wearability and durability of the glove design and enclosure was also assessed.

Evaluation methods used for this phase were the researcher's observation during training sessions and attending teacher's feedback through verbal communication. Parents and teacher's evaluation forms were not used in this phase as the system was being trained and not used for communication yet.

As this was the first evaluation phase, participants encountered a variety of issues, specifically with usability, and many changes were required before moving forward with the next phase of the study evaluation.

Glove prototypes were collected at the end of week 3 to implement feedback from this evaluation period during the reflection interval between evaluation phases.

Evaluation phase 2: Weeks 5 to 8

After implementing the changes to the prototypes during the reflection period of phase 1, the gloves were delivered to the schools, and in turn handed over to participants. Teachers requested that the gloves remain in school during the three-weeks of phase 2, for closer monitoring and until the children are more familiar with the system, and were able to operate the prototypes independently. It also made it easier for the researcher to have access to the gloves when/if modifications were needed.

In this phase, all gloves had individual gesture libraries stored on the local board. This period of evaluation was to report on using the gloves at school for communication. Observation visits were set for each participant to document their experience with the gloves in the classroom.

Evaluation methods used were teacher's evaluation forms, researcher observation visits and analysing gesture data stored locally on the glove. Most of the reporting during this phase was on the system performance.

To continue the iterative development loop, glove prototypes were again collected at the end of this evaluation period in order to implement gained feedback during the reflection interval before phase 3.

Evaluation phase 3: Weeks 9 to 12

Just like the previous phase, after upgrading the system during the reflection period, glove prototypes were returned to schools to be handed over to participants.

Prototypes for this phase were retained by the participants to be used in school and at home. Evaluation was collected from teachers, parents, the researcher and the system data. Emphasis was mostly on system performance in this phase. Triangulation of evaluation data was possible due to the participation of parents in this round.

Evaluation for this phase documented a fully executed system and concluded the study findings. It resulted in a new, final system that is described in detail under results.

5.4 Results

Fifteen participants' data was documented, but only ten of them were analysed due to gaps in data sets of the remaining five caused by incomplete sessions or failure to comply with the study's usability guidelines (see more under *Discussion*, Section 5.5).

Parent's surveys indicated that the ability to personalise the features of the technology to their children's individual needs was a primary concern. It is therefore addressed extensively in the iterative development cycles and results recorded below, and is considered to be one of the main contributions of this research.

Results are presented in the format of iteration cycles, described in Research Methods (Chapter 3), following the structure of the three evaluation phases that were defined in the previous section (Section 5.3.6).

5.4.1 Phase 1 Iteration and Evaluation Results

Many challenges were faced during the first evaluation period, some with usability, hardware, and a few with software. A considerable amount of time was therefore spent troubleshooting and debugging. Issues are listed below in chronological order, as written by the researcher at the time:

Technology usability and system architecture issues

Gesture training had a timer of three seconds to record a sample. It was observed that many participants would press the record button, start the timer, but do not immediately perform the gesture. This meant that the sensor data being recorded does not accurately reflect the gesture or correspond to the assigned label. Multiple solutions were considered to help resolve this issue. One solution, that was tested on site, was to only press the button after the participant starts performing the gesture. Another solution, that required a change in programming, was to make the recording samples longer, in order to guarantee that the recording window captured the gesture, even with a delay in performance. A different solution that was implemented and seemed to work better, was to replace the timer with a trigger to stop recording. That was set to a stationary gesture, which was detected when the hand was still and the feedback from the sensors was static. This update solved the issue for the majority of participants apart from one who was unable to keep their hand still. In this instance, the teacher's intervention was required to help the participant hold a static position so that the system can exit sample recording state. This prompted yet another change that finally did resolve this issue which was to set a before and after button for gesture sample recording. This proved to be effective and also improved previously detected inconsistencies in training samples.

Some teachers reported that "Classifying" and "Training" as terms used on the UI menu were confusing. They suggested simplifying them to "Teach" and "Sign" to make it easier for the children to understand as they seemed to be more relatable. Their request was easily resolved and implemented as part of the software upgrade during the reflection period.

Some participants, specifically younger ones, were not yet able to read. Teachers requested to change gesture labels displayed on the glove screen from text to images. They supplied a chart illustrating pictures used at school (Figure 5.18) which the children are familiar with and correspond to the signs they are training on the glove. This valuable feedback was added as a feature to choose for visual output of gestures, like choosing a voice and a language which is a fundamental experience we are trying to provide all users.

A few children wanted to play with the buttons and were constantly pressing them in no order. Although the system did not crash, it was difficult to focus on the task at hand and to press the buttons in the sequence required to perform a task. Parents and teachers suggested having a "lock" feature. While active, a "lock" feature would stop the UI from interacting with the user. A quick software solution was to activate such feature by pressing and holding on one of the buttons. Many of the children were fast to learn this feature and so it was no longer effective in

Figure 5.18: Sign language flashcards as used by the schools

resolving this issue. This lead to the conclusion that a hardware solution might be more suitable, like adding a hidden button on the back of the enclosure. As there was no room on the current board to add a third button, this suggestion would have to be taken in consideration for future board design revisions. To minimise unnecessary interaction with the board, and after the training phase is complete, a possible solution was updating the system to initiate *Classifying* mode at start-up. This way, participants can use the glove to sign immediately when turning it on and don't need to fiddle with any menus or buttons. This update greatly improved the experience of some children who were distracted with the button sequence. This way, the children would only have go through the UI menu in the event that they intend to train a new sign or retrain an existing one.

Connection issues

In some cases, the glove would turned on, LED on board would go green, but the screen would be black and the programme would not start. Charging the glove did not solve this. The glove was taken back to the lab for investigation. Upon switching the glove on, it appeared to be working. Looking at the code, a network issue was detected. The glove was attempting to connect to the lab's network, despite not needing it to operate, before initialisation of the programme. That line of code was amended and the issue was resolved.

Prototype design and wearability issues

The two touch buttons were placed within a plastic frame as part of the enclosure design. Some participants found it difficult to press them and couldn't align their fingers with the capacitive touch sensor. This was solved by clipping the acrylic divider for all prototypes which made it easier for users to interact with the system.

The text displayed on the screen was facing away from the participant, intended to be read by the receiver. Participants were distracted by this and kept trying to rotate the screen towards themselves. This issue was not resolved as there was no readily available font or text editing library for this piece of hardware (OLED screen model). It was also soldered onto the board with a ribbon cable and it proved to be very difficult to re-arrange other components on the board to accommodate this design revision within the time-frame of the study.

The glove screen displayed a "waiting" message when a request to record samples for training gestures was initiated. It was deduced that the board was not receiving any data from the sensors and therefore was not moving to the next line of the code which was to display a message with the sample number to be recorded. To eliminate hardware malfunction, the ribbon cable connection was replaced with a new one, and a fresh glove board was used. This did not solve the problem and the glove had to be taken back to the lab for examination. Upon connecting the glove to a debug screen, it was found that the flexible hand PCB was failing to send any sensor data as some of the connections were not intact. This was the result of tugging on the components by some of the participants who were curious to explore the insides of the glove, despite sealing the sensors inside the textiles, but that only made them pull harder, eventually breaking the connections. The only solution was to replace the faulty PCBs in order to continue with the sessions. However, a more sturdy design would have to be considered for the final product.

Summary of changes

To reflect the feedback from phase 1 evaluation period, much of which is mentioned above, some design revisions were required before the glove prototypes were ready to be used in phase 2. The gloves were therefore collected from the schools, and participants were informed that they will be returned to them after they are upgraded during the reflection period.

- Network connection was bypassed in the initialisation code to allow the system to start in schools without internet access.
- Enclosure design was modified by removing the acrylic frame to allow better access to the touch buttons.
- Faulty hand PCBs were replaced with new ones due to connections breaking during training sessions.
- UI menu was updated to display "Sign" and "Teach" to replace "Classifying" and "Training", in order to make it more user friendly.
- UI menu was updated to add "image" as an option for the displayed gesture label. This was to accommodate participants who were not yet able to read the text labels.

- Gesture training samples were recorded by pressing a button before and after performing the gesture. This replaced the initial 3 second timer for recording samples which did not always capture fully performed gestures.

- System was updated to initiate *Classifying* mode (which was updated to *Sign*) when it started, to minimise the steps required to use the glove for communication.

5.4.2 Phase 2 Iteration and Evaluation Results

This evaluation period revealed an enhanced independence experience for the participants while using the glove prototypes. Once the participants realised that the glove was saying what they were signing, they wanted to use it without assistance and outside of the classroom too.

Behaviour-wise, 6 out of 10 teachers reported a boost in self-confidence, while two teachers reported their students, three participants, initiated communication in the classroom for the first time. 70% of teachers reported an increase in interaction between participants and their peers, who are non-signers.

After using the glove for three weeks, it was found that a gesture library of fifty words was considered limited and that more words need to be added for the gloves to be fully functional communication devices. A unanimous request received from teachers, parents and students was to allow them to define and add new gesture labels on the system. This was communicated during group meetings the schools arranged for study participant's families and teachers. Although the system was designed to enable that feature, it would require connection to the internet to import the speech audio clips relevant to the label in the language requested. This was not possible during the study due to the regulations in place by the school, council and ethical clearance. This restriction will be removed after the conclusion of this research when the gloves ownership transitions to become the property of the participants, so they would be able to connect them to the internet at home to define and train new gestures. To increase the vocabulary provided by the system, a new list was collated from the schools with additional labels to be included.

Some classification errors were observed, specifically mismatching gestures. Training mistakes were eliminated based on the close observation of the participants, which reflects their signing consistency when recording gesture samples. To this effect, an investigation of the classifier performance was necessary to detect the cause.

Inspection of the gesture classification data showed that most of the signs trained were similar in finger positions, only minor differences detected in flex sensor margins, but varied mainly in orientation and/or position. The code was updated to prioritise the gyroscope and accelerometer data over the flex sensor values and reduce the error margins on the flex sensors. This adjustment improved accuracy when finding a gesture match.

Another issue was that when the system misclassified a gesture, it almost always output the first sign that was trained. Reflecting on the code, it appeared that the system was classifying based on first match rather than best match, and because it always started to search for a gesture match in order of training, any gesture that was within the classification boundaries of the first trained gesture was classified as that one, even if another gesture was a better match. The code was amended to change classification from first match to closest match and slightly relaxing classification boundaries. This resulted in the system taking longer to classify (on average twice as long), as it had to go through the entire library to establish the best match, but accuracy levels were greatly improved. However, it is worth looking at different classification solutions as the system can get significantly slow when the gesture library grows in size, especially when exceeding the current capacity of fifty gestures.

Some of the software issues observed during the evaluation period prompted revisions to the classification algorithm that was not always possible to be implemented on location, especially with the lack of internet connection. This meant that occasionally, the gloves had to be taken back to the lab for further investigation. Many issues were discovered while analysing the gesture data and various attempts were made for improvements.

Five participants who shared the same sign language library were selected for further analysis. Personal classifiers were retrained using greater processing power which was not possible to be performed in real time on the local glove boards. For comparison, general classifiers were also trained using the data of all users apart from the one whose signs were being tested in each case. This was to simulate the use of a pre-trained system, where the individual user would have no impact on the classifier.

Participants whose personal classifiers performed well (higher than 70%), achieved

Participant	Age	# of Trained Gestures	K=1				K=3			
			Personal Classifier		General Classifier		Personal Classifier		General Classifier	
			Accuracy	Correct/ Attempt	Accuracy	Correct/ Attempt	Accuracy	Correct/ Attempt	Accuracy	Correct/ Attempt
1	16	13	82.05%	32/39	58.97%	23/39	71.79%	28/39	51.28%	20/39
2	9	12	72.22%	26/36	63.88%	23/36	55.50%	20/36	55.56%	20/36
3	12	11	66.67%	22/33	90.91%	30/33	69.70%	23/33	72.72%	24/33
4	5	7	47.62%	10/21	80.09%	17/21	52.38%	11/21	57.14%	12/21
5	7	7	31.58%	6/19	73.36%	14/19	36.84%	7/19	42.1%	8/19

Table 5.2: Gesture data recordings for five participants using personal and general classifiers

lower results when their gesture data was tested with the general classifier. On the other hand, participants whose personal classifiers performed poorly (between 30-60%), mostly due to noisy or fewer training samples, greatly benefited from the greater number and quality of training samples used to produce the general classifiers, despite the fact that their own data did not feature.

As seen in Table 5.2, Participant 1, who was the oldest in this study group, achieved the highest classification accuracy of 82.05%, where 32 out of 39 their performed gesture attempts produced the correct label and resulted in the sign accurately being translated into speech. However, when their data was used to train a general classifier, the accuracy rate dropped to 58.97% with only 23 out of the 39 test signs being matched successfully. In contrast, participants 4 and 5, who were the youngest of the group, got an accurate match less than half of their attempts and gained improved accuracy results. It was observed during the training sessions that due to their younger age, participants 4 and 5 had substantially less experienced with sign language and were often not consistent when recording gesture samples.

This theory was further validated with the pattern reflected by participants 2 and 3. Participant 2 was also more experienced and was largely very consistent when signing, despite being slightly younger than some of the others, and as with participant 1, had better results using their own personal classifier than with a generalised one. Conversely, participant 3, who had only been signing for a shorter period of time, and who was far less confident, saw an improvement in accuracy when using the general classifier versus their own personalised one, replicating the results observed with other less proficient signers.

Another comparison made was between the K-nearest neighbours algorithm using one and three neighbours. Results established that with both the personal and general classifiers, one neighbour produced better results.

These results prompted the development of a new method for classification combining the two types of classifiers, still implementing personal classifiers but also using a general classifier to help guide the quality of recorded gestures. For the three unified libraries of sign language used across the six schools, a baseline for each gesture was generated by the general classifier trained by the group data. This baseline gesture was set to act as a benchmark for gesture samples recorded by participants. During training, the system will either accept or reject a gesture sample if it does not fall within the boundaries of the reference baseline gesture.

An initial calibration helped in defining the minimum and maximum boundaries of each sensor reflecting each user's motor ability and applying those to all baseline gestures in the library. To this effect, a smiley face was added to confirm to the participant if the gesture sample they just recorded was acceptable by the system or not. This improvement greatly enhanced the quality of gesture samples being recorded. It also allowed us to reduce the number of samples required to train a sign from ten to five or possibly three.

Summary of changes

Essential upgrades to the system for this phase were mostly executed to improve software classification. This was done by adding a gesture benchmarking system and giving users feedback when training samples of either accepting the sample and receiving a smiley face or to try again. The system was also upgraded to include an increased gesture library to provide participants with a larger vocabulary for communication.

5.4.3 Phase 3 Iteration and Evaluation Results

In this phase, the full system was evaluated by parents, teachers, and the researcher. This was in addition to the data stored on the glove boards. Gloves were being used in schools and at home for communication. Most of the participants, ages 7 and above, used the glove prototypes independently, both for training new gestures and classifying.

Parents feedback highlighted that wearing the glove for long hours made their children's hands sweaty and so they suggested making a glove textile design with open ended fingers. Another observation was that children were using the glove to wipe their face, mouth or nose and occasionally the textile may require washing. Both issues were resolved by providing the families with a second glove textile designed to house the sensors which was perforated to allow the skin to breathe, had open ended fingers and could be used while the other glove was being washed. All sensors were easily removable and instructions of how to do that were included in the care guide, distributed to parents at the beginning of the study.

When training new signs, the smiley face was received positively by the children and it motivated them to keep signing in order to achieve better gesture sample recordings. A new dialogue of "perfect" signs was witnessed between the participants and their teachers.

For the few children who were not committed to signing, and/or resisted to learn the school's standard library of sign language, this new method of training encouraged them to practice their signing skills to get more smiley faces. Teachers reported participants were voluntarily recording more gesture samples and staying for longer training sessions, even during break time. This eventually led to several participants becoming more consistent with their signing, and achieving better classification results, which was reflected on their evaluation forms. Teachers also reported an improvement in communication and a higher level of independence.

Classification accuracy reached 99% using the upgraded software and the new training method (Table 5.3). However, gesture data revealed that the classifier was now being trained using gesture samples that were too similar, and fewer samples were being recorded.

It was hypothesised that the small number of training samples each user provided did not sufficiently reflect the bounds of the actual distribution of signs performed in the real world. This was observed during classification when the glove mistranslated signs that were performed outside of the very small training distribution, but that might well have had a closer correct match, had a larger, more representative, set of training samples been recorded. This was particularly the case with the younger signers who were less consistent with their signing, and so would be less likely to attempt classification with more outlying samples.

A possible solution was to increase the amount of training data, with the hypoth-

Participant	Personalised Classifier	General Classifier
Participant 1	100.00%	87.88%
Participant 2	100.00%	95.24%
Participant 3	100.00%	89.74%
Participant 4	100.00%	82.05%
Participant 5	94.74%	52.60%
Participant 6	100.00%	96.97%
Participant 7	94.74%	89.47%
Participant 8	100.00%	97.22%
Participant 9	100.00%	77.78%
Participant 10	100.00%	85.71%

Table 5.3: Classification accuracy data for the personalised and general classifiers

esis that adding more data would make the training distribution more accurately reflect the ideal classification space. To test that theory, participants were encouraged to record additional gesture samples at home. This was easily achievable given most participants were familiar with the glove prototypes, at this stage of the study, and could operate it independently.

A new analysis was performed to evaluate the classifiers performance, accuracy rates recorded were between 95-99%. Participants younger in age, less consistent in signing and with fewer samples generally reported lower rates.

The results of the sessions with the participants, in terms of the translation accuracy that they experienced have been summarised in the plot in Figure 5.19.

For comparison, an identical classifier with the aggregate of all of the participants' data was also trained, excluding the user whose data was being classified in each instance. This acted as a general, non-personalised classifier, representing a pre-trained solution that would require and allow no individual customisation or training.

All participants achieved lower accuracy results using this generalised classifier, although some had more success than others. As expected, and based on the previous evaluation of phase 2, those who had relatively poor accuracy results using their own personally trained classifier, also tended to have worse results when using the

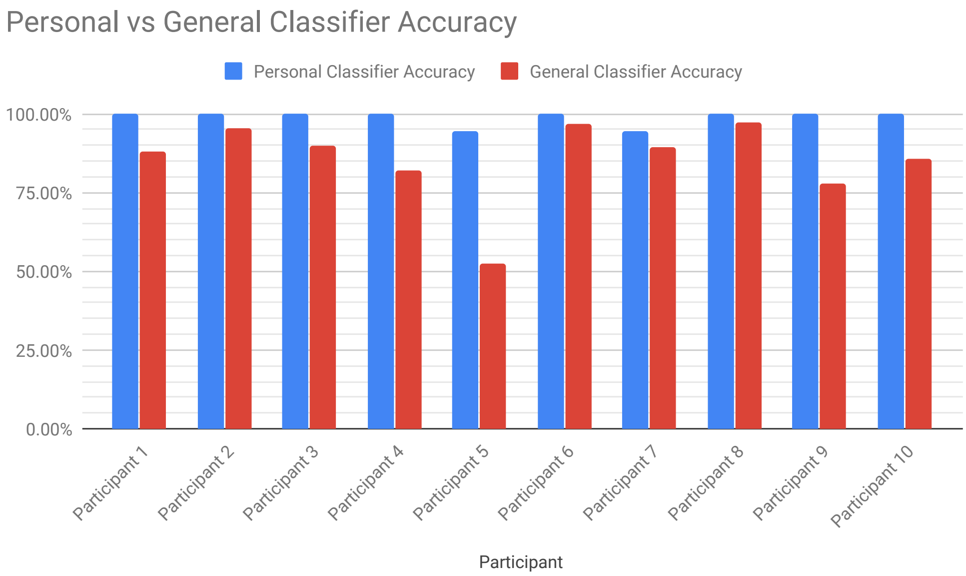


Figure 5.19: Comparison of personalized and general classifier accuracy between thirty and forty test signs were performed by each participant, with the number dependent on when the child wished to stop. 8 out of 10 participants had 100% accuracy of sign classification when their recorded sample data was trained with their own personally trained classifier. The remaining 2 participants had a 95% accuracy level.

generalised one.

5.4.4 The Final System Results

Software accuracy and classification

The system accuracy output was registered between 95% and 99% for a gesture library size of fifty words. 80% of participants trained three samples per gestures and 20% of them trained more. There are a number of factors that affected the results, the primary one being the number of training samples recorded for each sign. This was closely followed in impact by the participant's consistency of signing and unsurprisingly, the age of the child. The more consistent the child was with their signing, the higher the accuracy of the classification. Both of these two factors were significantly affected by the age of the child, as younger participants tended to be less willing to record larger numbers of training samples, and were also substantially less consistent due to their lesser experience using sign language. The children with the lowest accuracy levels tended to also be those of the youngest age. This was believed to be due to both a lower-than-average proficiency and consistency in sign language, as well as the fact that some were distracted by the technology during the training session.

Participant's social and performance

Parents and teachers documented an overall improvement in behaviour for the ten participants who used the glove to communicate over the course of this study. Highest rating was for increased independence and self-confidence. Academic performance was difficult to measure in the short period of evaluation that remained after training.

5.5 Discussion

In the initial study proposal, three phases were defined (section 5.3, study evaluation phases). The primary phase was for participant's selection, glove allocation, introductory meetings and glove's handover. This was set to be followed by the "active" phase where the participants would keep the gloves and use them, for a duration of three months, to communicate in classrooms and at home. Evaluation methods were arranged to report on the full system for that period (Section 5.3.4; Study Evaluation Methods). The final phase was for implementing feedback and refining the system followed by the delivery of the prototypes to participants.

There were multiple factors that did not allow the active phase of the study to go as planned. The main one being that most students were unable to operate the glove independently to train the gestures and therefore required the help of their teachers and parents.

During introductory meetings, a full demonstration of the system was performed to support the carers of the participants with the training task. As such, parents and teachers were expected to help the students with building gesture libraries in preparation for using them at school and at home during the active phase of the study. Arriving at the first school, it was discovered that the parents delegated gesture training to teachers, who in turn waited for the researcher's observation visits to complete this task. The same case was encountered with the remaining schools. Therefore, the first evaluation period of the study was no longer an observation/evaluation phase but rather became a timetable for gesture training sessions scheduled as one-to-one meetings with the participants, their teachers and the researcher. Given that there were fifteen students across six schools, the three-week period of evaluation for the active study phase was dedicated to setting up the gloves and building a gesture library for each participant.

An average of five signs were trained by most participants during their first session. The remainder of the gesture library was trained in school with the teachers over the following weeks. Some children got tired during training sessions or found it hard to stay focused on the training task for a long period. For those, the plan was to train one gesture per day, making the sessions shorter and more focused, slowly building their gesture libraries. While a group of them were happy to use the glove with a small library of about twenty gestures, others did not wish to perform the task of training the glove, and therefore were not able to continue with their participation in the study. In addition, children who missed the primary training session and the rescheduled session, were no longer considered for the study due to difficulties in accommodation between the teachers', parents' and researcher's schedules. This resulted in the withdrawal of five participants in total. The ten participants, who attended all sessions and were fully committed to the outlined tasks, remained in the study.

Given that the study structure had to be revisited, where the first evaluation phase was spent training rather than evaluating the system, evaluation forms were not applicable to be completed by parents or teachers as the gloves were not being used for daily communication yet. Instead, only the researcher's documentation of training sessions and the data collected from the glove boards were used to evaluate the performance of the glove prototypes for evaluation phase 1. Still, data collected was valuable in resolving early usability issues, discussed in detail in results Section 5.4, under *Phase 1 Iteration and Evaluation*.

Another issue that greatly affected the progress and timeline of the active phase of the study was internet connection. The decision to disable internet connection was made in compliance with school regulations, and the terms of the ethical approval in place for this study; both of which didn't allow the devices to connect to external networks, to prevent access to the participants' data stored on the devices.

At some point during the study, specifically during the second evaluation phase, when classification was being scrutinised, it was found that results produced thus far were not encouraging enough to move forward with the study. At that point, an average of 60% accuracy was reported by the initial 5 participants who completed the training tasks. The lowest being 31.58% and the highest achieved 81.05% (see Table 5.2). When compared with the prototype used in the previous chapter (see Section 4.2) where classification accuracy reached 99% (see Section 4.2.4), these results were disappointing and triggered a discussion about reconsidering using a cloud based system for classification. After three weeks of testing, a halt was called to using this version of the glove and the process was started to get permissions to use the software of the previous prototype which produced much better results but required internet connection to access the cloud server. Connecting to the cloud based system would massively improve classification, help in resolving system challenges remotely with minimal disruption to usage of the gloves, and also enable defining new gesture labels.

As a result, study sessions were stopped, the gloves were collected, and participants' families and teachers were informed that the study would be restarted after relevant permissions were granted and the system was updated. This caused further delays to the timeline of the study.

Although permission to connect to an external network was never received, the study moved forward using the software updates implemented in the interval between evaluation phases 2 and 3 (Section 5.4, under *Phase 2 Iteration and Evaluation*). During that time, extensive software analysis was executed to enhance classification. Gesture training samples were plotted to examine emerging patterns, identify individual differences and compare between participants using the same sign language library.

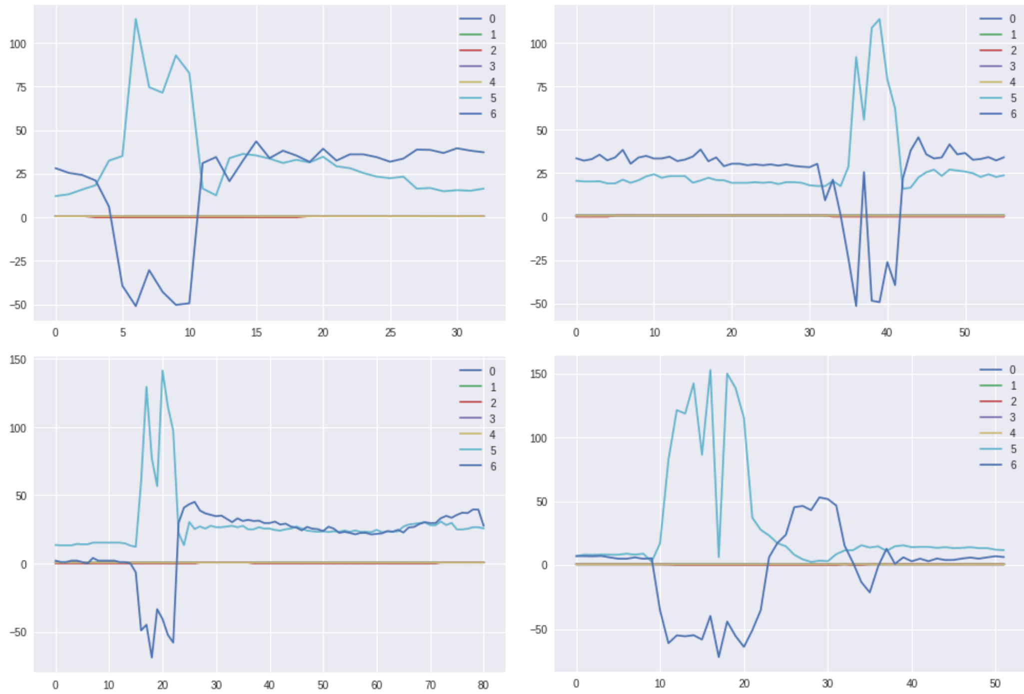


Figure 5.20: Line plots 0 to 4 correspond to flex sensors, with sensors 5 and 6 for the accelerometer. The plot for the same gesture performed by four different participants.

Figure 5.20 shows the plotting of the same gesture being performed by four different participants. Lines 0 to 4 reflect the five flex sensors, and lines 5 and 6 reflect accelerometer angles. The analysed gesture data shows individual differences across participants. A general classification curve can be perceived without being identical across samples. There is a clear variance in the timing of performing the gesture. However, a pattern is detected and classification was possible in this case.

In comparison, gesture data was analysed to show personal variance when recording four samples by the same participant. Figure 5.21 is a graph of hand gesture sensor data for “Good Morning” being signed by one participant. Overall the sign shape and orientation are similar but a closer look reveals variation in speed and duration between samples.

In general, personal variance observed in multiple gesture samples recorded by

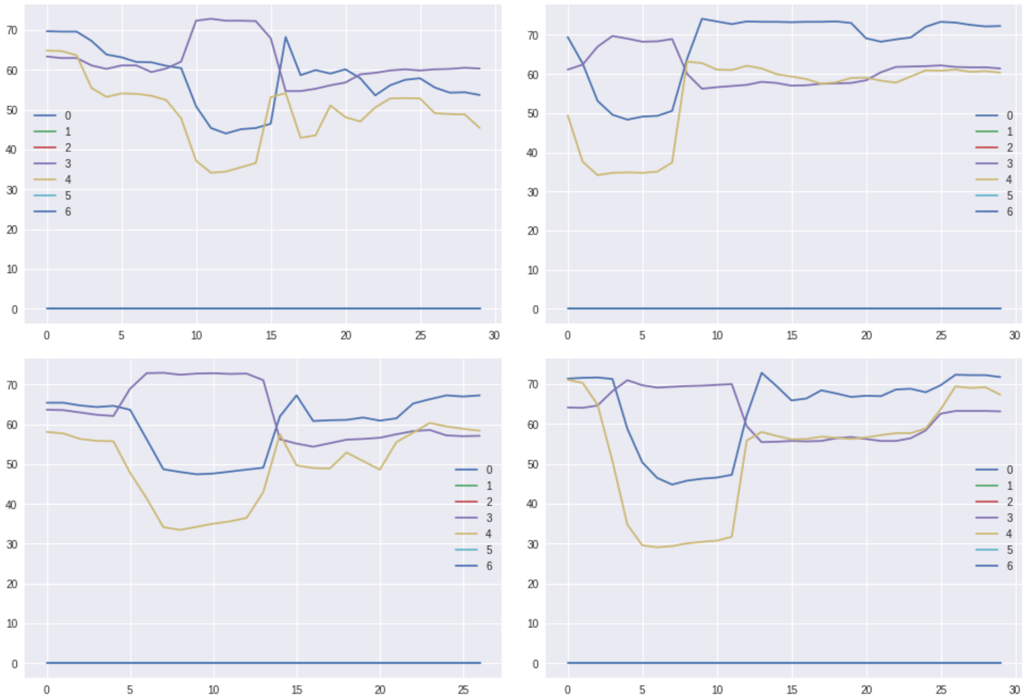


Figure 5.21: Sensor plotting for four gesture samples for "Good Morning" by the same user

one participant was minimal when compared to individual differences for the same signed when performed by different participants. This analysis further validates the final results of this study (Section 5.4, Final System Results) which documents that a personal classifier almost always achieved higher accuracy rates. This is especially the case with older participants who were experienced signers and were more consistent with gesture sample recordings (see Figure 5.22).

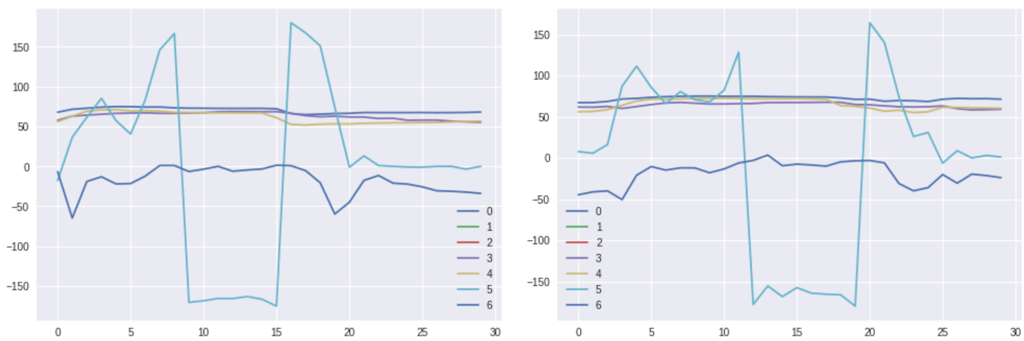


Figure 5.22: Sensor plotting for two examples of the gesture for "Thank You" by the same user who is the oldest in the testing group

Figure 5.22 shows multiple sign samples from the same user reflecting relatively minor differences, which in turn enables the classifier to produce a match with a high level of accuracy of 100% (see Table 5.3).

Further gesture data analysis was performed to evaluate how the classifier established matches between signs that were similar in position but differed only in in orientation or duration.

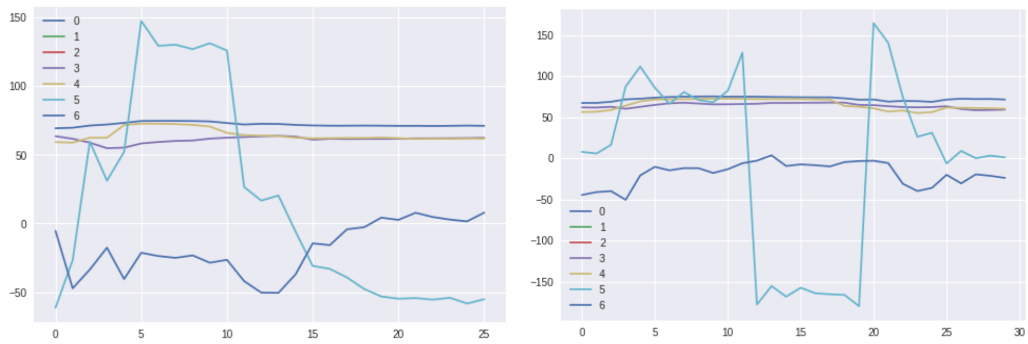


Figure 5.23: Sensor plotting for similar gestures, "Please" on the left and "Thank You" on the right, differing largely only in duration

The signs "Please" and "Thank you" utilize the same hand shape, and differ largely solely in duration (Figure 5.23). The classifier was successful in distinguishing the difference between the two signs in all cases, though the confidence provided by the classifier in such cases was lower than the average.

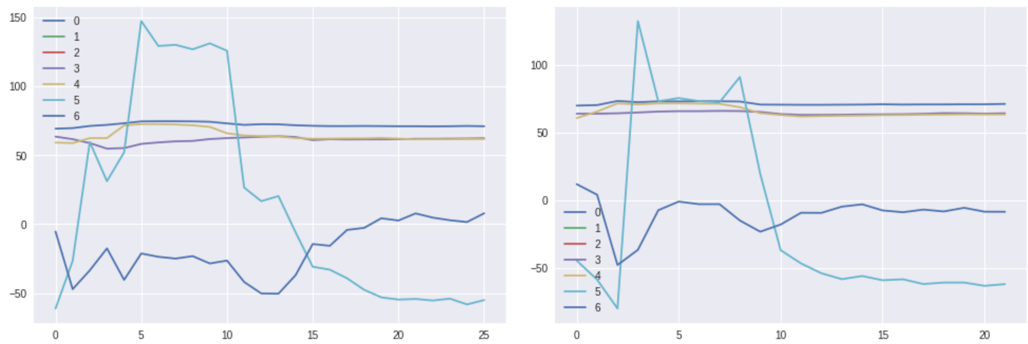


Figure 5.24: Sensor plotting for similar gestures, "Please" on the left and "Stop" on the right, differing only in orientation

The signs "Please" and "Stop" utilize the same hand shape and motion, with only a difference in rotation about a vertical axis (Figure 5.24). In this case, the classifier was not able to reliably distinguish the difference between those two signs.

There are sensors readily available in the market that can identify some of such differences (such as a magnetometer), however, no such sensors were used in the prototype designed for this study.

5.6 Conclusion

This study concludes the data collection, analysis and evaluation sections of this research (Chapters 4 and 5). Three iterative studies were conducted to develop and evaluate a wearable system which can recognise then translate hand gestures to text and speech. The aim was to produce a fully customisable system which can be controlled by the users to serve their individual needs. Over the course of this research, the software was continuously being upgraded to recognise custom hand gestures accurately based on testing with users who have different motor abilities. The final system presented (Section 5.4) allows each user to record their own gestures based on the sign language they master. A personal classifier is trained to build a sign library for each user. Users were able to define labels and display them as texts or images. Speech output was set to be in a voice and language selected by the user.

This study concludes that the proposed design of a stand-alone data glove can operate offline to train personal classifiers for the purpose of recognising custom dynamic hand gestures using DTW. A number of challenges were presented throughout the study, which occasionally altered the original structure, timeline or progression of the study. Nevertheless, sufficient data was collected and a full analysis was performed. The collected data shows that personal classifiers universally produced more accurate results than general classifiers due to individual differences in hand movements and motor abilities, with a confidence of 99.97% (a z-score of 3.42).

Recognising custom hand gestures widens the application of this technology to extend beyond the sign language community to include individuals who do not use a standard library of sign language due to their personal disabilities and physical limitations of hand movement, such as those seen in stroke victims and in those with other neural disorders.

The plan is to develop this prototype further in a number of ways, the principle one being the ability to sign continuously with the speech output occurring during, rather than after the sentence has been completed. This would allow users to chain signs together in quick succession to combine individual phrases into full sentences. We also intend to adapt the glove for connection to a smart device in order to provide further customisation.

5.6.1 Hardware and Design

Based on the hours of training carried out with the children, it was very clear that a less bulky, but still wearable solution would make usage substantially easier. The plan therefore is to look for ways to minimise the on-body embedded device. Adding a Bluetooth Low Energy (BLE) chip to the flexible glove hand PCB is proposed in order to send gesture data to smart devices for wider applications, and provide further personalisation options as detailed below.

5.6.2 Software

In order to give users more control, an app would need to be developed for use on such smart devices. The app would enable users to save their gesture data under a label of their choice, allowing them to build and edit a personal library of signs and could support the ability for the user to modify the language and age of the voice produced by the speech synthesizer.

As described above, the classifier currently waits until the end of the sign before being applied to the entire duration of it. Instead, there is a plan to carry out classification continuously on a sliding window over the incoming data. Previous researchers results (Luzhnica et al. 2016) show great promise and could be applied to the current glove users' custom libraries of hand gestures, while still allowing them to train personalized classifiers. To improve accuracy, this could be combined with a Bayesian model to predict future words based on those already signed. Signs could also be separated into sub-libraries to reduce the number of possible matches.

Chapter 6

Discussion

6.1 Introduction

The system proposed by this research was developed with the intended users' needs in mind at all times, as the aim was for the final technology and the system encompassing it, to be effective in solving the problem of the lack of ability to communicate independently faced by users with different abilities, and eventually to be commercialised.

Throughout this research, interaction design methodologies were applied to collect data through a series of usability studies. Initially, a pilot study was conducted (Section 4.1) to establish the nature of those needs, and to outline the system design and software architecture of future prototypes for this research. A set of three iterative case studies were then carried out to further develop the initial prototype and to implement the conclusions drawn from the feedback of the user's therapists and the researcher's observation (thus forming the build-measure-learn cycle, as described in Section 3.1.2). After the prototypes had undergone these rounds of incremental refinement, a descriptive, more in-depth, user focused longitudinal case study was then carried out to evaluate the performance and design of the system over an extended period of time through usability testing.

6.2 Case Studies

In the pilot study, a vocabulary of ten Makaton signs was selected by the researcher and pre-programmed manually into a wireless, standalone data glove prototype.

This prototype had no external connectivity, and all processing was done on the device. Recognition of the signs was performed only on a static basis (measuring the configuration, position and orientation of the hand in a fixed position), rather than on a dynamic basis (measuring both the absolute values of these factors as well as their change over time, constituting the movement of the hand as it performs the sign). This data was hard coded in the form of ranges of acceptable sensor values calculated by the researcher for each sign, against which incoming sensor data could be matched.

This study served to validate the initial concept and demonstrated the potential of the system, albeit with refinement.

It was recognised that the primary cause of misclassifications of the trained signs, were due to the difference in the performance of the sign between the researcher, that had pre-programmed sensor values for each sign into the glove, and the participants when they were testing the glove.

The standardisation of software and hardware features and the provision of pre-programmed gesture libraries, which was the system used for the pilot study (due the relative ease of implementing such a system), decreased gesture recognition accuracy and prevented the testing of the technology at a larger scale, and also limited user cases to users of the Makaton sign language only. This demonstrated that in order for the research to progress further, the system required further development to provide sufficient, more advanced customisation features to accommodate user's individual needs.

It was therefore concluded that the primary goal for the iterative case studies should be to design and evaluate the performance of a mechanism for training a personalised gesture classifier, in a more realistic environment, with the classifier trained by each user for their own individual hand signs, and when restricted as a result of their own personal abilities and limitations.

The first prototype of such a system developed was tested by 18 study participants, where it was primarily the participants' first time using any form of assistive technology, and where many were not familiar with any standardised sign language. While still wireless, this prototype connected to servers hosted in IBM's cloud to perform the gesture classification, with output provided through a laptop screen. In these testing sessions, all correctly performed signs were recognised accurately, given a library of five signs trained by each user individually.

In the second round of testing, with the prototype updated to fix usability issues, and to provide feedback to the user showing the recognised sign on a small screen on the glove, seven participants, who were all proficient users of sign language, again showed accuracy levels of 100%, with each training a minimum of five signs (and in some cases more), but with tests including full sentences, rather than just individual words, and "shortcut" signs for otherwise time-consuming phrases.

In the third and final round of cyclic prototyping, the same sign classifier was used, however, the glove design was improved to be smaller, lighter and more wearable, as well as to provide better user interaction with improvements to the interface on the attached screen. Each participant trained a larger number of samples for each gesture, which helped to disregard noise in the sensor data and made it easier for the classifier to identify patterns in the signs. However, as many users had disabilities that affected their motor abilities or range of hand or finger movement, accuracy rates were substantially affected.

For the final, longitudinal study, a new prototype was created, which was upgraded to perform classification entirely offline. This new version also featured multiple different size options for adult and child users, as well as improved battery life, more refined and resilient hardware, and with a flexible PCB connected to the sensors that could be removed to allow the glove textile to be washed. This glove could be trained and used with the on-device screen and buttons, requiring no connection to the internet or to a laptop. The classifier was also updated in response to recommendations from the previous study, and was enhanced to better recognised variations in signing and consistency, and to add structure and feedback when training addition gesture samples.

This final study took part in collaboration with Essex County Council, and engaged six Special Education Needs schools, over a period of six months, during which three evaluation periods were performed. The data from this study validated the proposed design of an offline, stand alone data glove, and demonstrated a material improvement in sign recognition accuracy using personalised classifiers, rather than generalised classifiers, with a confidence interval of 99.97%.

Personalised gesture recognition, together with testing with real users, ultimately proved to be highly challenging, especially for the studies involving younger participants. The required ethical approvals were far more comprehensive, access to external networks and the internet was limited and evaluation sessions took far longer to carry out.

However, the insight gained from testing this form of technology with sign language users in public environments, as opposed to with research assistants in the sterility of a lab, far outweighed the burdens of undertaking the studies in a less artificial way.

Furthermore, restricting internet access, although was considered a major obstruction at the time, necessitated extensive revisions to the system to enable it to operate offline. This resulted in a novel approach to gesture recognition and classification, which was never achieved before, and constituted a substantial contribution to the research findings.

6.3 Customisation

After multiple rounds of development and testing, it was identified that the high level of gesture customisation was the most vital feature that had been developed for the data glove, to serve its intended purpose of communication in the real world. The system was enhanced and the software was upgraded to recognise individual signs, allowing users to be able to build their own gesture libraries; a restriction that was universal amongst previous similar technologies.

It comes as no surprise then, that the key factor which significantly impacted the results of this research, was the extent of this technology's ability to adhere to individual users' personal needs. This was only achieved to a great degree in the final iteration of the development of the technology and only properly observed during the last cycle of evaluation. Evidence of improvement in social behaviour and a more confident approach to communication was documented when participants used the enhanced technology for the last phase of the study.

In schools, students with learning disabilities and those on the Autism spectrum used the improved glove for three months, during which, an increase in independence and reduced incidents of challenging behaviour were reported by their teachers and parents (Section 5.4).

These results achieved did not come without challenges, however, and while some were easily solvable, others greatly restricted the progress of the research.

6.4 Limitations

The case studies for this research were set in public environments and engaged participants from highly vulnerable groups. As such, many restrictions were encountered that limited the scope, duration and data collection that was originally planned. In this section, limitations are discussed in detail, highlighting the nature and extent of the impact that each one had on the progress and results of this research.

6.4.1 Case study user groups

Testing with vulnerable groups, such as people with disabilities and young children, proved to be highly challenging. This was largely due to the higher levels of protection set in place when working with such groups, as well as the difficulty in communicating directly with the participants.

Feedback was primarily gained through the participants' caregivers rather than from the participants themselves. This resulted in longer sessions, as more people were involved in each feedback cycle, and fewer participants completing the study, due to their teachers' or parents' busy schedules. This issue was more noticeable with younger participants as they tended to get tired mid-session and sometimes grew impatient and could not commit to the study tasks in the allotted time. In addition, participants with severe physical disabilities had limited movement, so they were not able to test the full limits of the glove prototypes. Some required extended sessions while others were eliminated because of the lack of consistency in training samples. Ultimately, these issues affected the amount of reliable data being collected, with the volume of recorded data being ultimately reduced by a third, in some cases, as seen in the longitudinal study (Section 5.5).

6.4.2 Case study locations and regulations

Conducting the case studies in public environments, like exhibitions and schools, required compliance with multiple governing bodies' regulations. Initial approvals required extensive documentation and took substantial time to be granted. This included the University of London ethical clearance and Essex County Council's Information Governance (IG) approval. This is in addition to adherence to the UK's

General Data Protection Regulation (GDPR)[1], that became compulsory by law in May 2018, a few months prior to the start of the final case study with the schools in the UK. Some of the regulations enforced insurance policies for the participants (public liability insurance), certification for hardware safety (battery testing and risk assessments), and dictated restrictions in the handling of participants' data. Clearly specifying what data was being communicated to the cloud, how it was processed and where it was stored (inside or outside the UK) was essential in securing study approvals.

Complying with multiple regulatory bodies became evidently restrictive when updates to the system being tested were required during iteration cycles for features that were not included in the original proposal, or any of the consent forms. By way of example, during the longitudinal study (Section 5.4 - Phase 2), it was found that connecting to a cloud based system would help substantially in improving classification and allow access to the system remotely for diagnostics without interrupting the progress of the study. As the initial ethical clearance did not grant permission to connecting to any external network, an appeal was submitted to all relevant governing parties justifying the need to connect the gloves to the internet, stating that in compliance with the initial approval terms, it was difficult to achieve the desired results. As each of the governing bodies had a different protocol to granting such permissions, it was difficult to accommodate the process within the limited time frame of the study. This resulted in further extensive delays, partially waiting for the permissions, but primarily because the majority of the development time was spent upgrading the system to perform better offline even though the final deployed system would have access to cloud based servers and processing.

6.4.3 Case study prototype's access to the internet

Connecting the glove prototypes to the internet, or in some cases managing without a connection, was an issue throughout the different case studies of this research. Earlier prototype versions, which were a proof of concept, had a very limited vocabulary to be able to work offline. To improve that, the prototypes that followed relied on a cloud based system but struggled to access a stable and/or secure internet connection using the public networks provided at exhibitions, where the study

[1]Information Comissioners Office - https://ico.org.uk/

took place. Finally, the last glove prototype was not granted permission to connect to an external network, to restrict any access to participant's data, so it was not possible to make any system updates remotely and the study was constantly being interrupted to collect the prototypes for development during iteration cycles. This was in addition to limiting the features the system could offer to participants during the study, such as defining new gestures and enhancing classification output. These connection issues resulted in the slowing of the research progress and in reduced data collection periods, which ultimately had an impact on the final results.

6.5 Commercial Alignment of Research and Development

The longitudinal case study (Chapter 5), which was conducted in collaboration with Essex County Council, served as a validation for the technology of the proposed data glove to translate user-specific custom hand gestures to text and speech. The results were sufficiently encouraging to warrant progression into the development of a minimal viable product that subsequently underwent more rigorous market testing.

Due to the wide network of schools that we worked with during this research, and the shortage of assistive technology in the market, additional schools and families signed up to test the new glove.

Keeping the research academically relevant within the field of knowledge, while still aligning the technological development with the differing priorities of a commercial product, all while complying with industry regulations, was an additional, but necessary challenge, to ensure that the technology could ultimately be commercialised and made available to the people that can benefit from using it.

Chapter 7

Conclusion

7.1 Introduction

As discussed in the literature review (Section 2.6), no prior research in developing data gloves to translate sign language had ever engaged real users or was conducted outside of a controlled lab environment.

Additionally, and due to the nature of some disabilities, there was no single technology system that was available to be used for communication, which was deemed suitable for the vast range of user conditions.

To quote one of the parents of a participating student in one of this research case studies:

> "[My child] has severe hearing loss, but due to [their] learning disabilities, [they have] been unable to completely grasp sign language and fit in with other children that are deaf, but do not have other learning disabilities. This has kept [them] in a situation where it is very difficult, if not impossible, to make new friends and interact socially. [They do], however, have an aptitude for technology, and would take the technology very seriously. We hope that [they] will be able to communicate with others. We are especially keen for [them] to embrace technology to achieve this."
>
> - *A participating student's parent*

The user of the technology developed in this research was placed at the centre of the design iteration cycle. Therefore, testing was conducted with users who use sign language for daily communication, and in their natural environments. This was a necessary approach for a credible evaluation of the proposed system's performance.

This research was a fundamental part of a programme to develop and produce an affordable hardware technology solution to provide machine translation services from custom hand gestures to written languages, and then by extension to spoken languages in the form of audio output.

To achieved that, a series of action research cycles were conducted to develop a fully customisable on-body translation system to recognise hand gestures and outputs speech (Chapters 4 and 5).

The primary purpose is to facilitate daily communications between individuals with speech disabilities and the general public.

The results of this research demonstrate that using technology for communication can be achieved using a stand-alone data glove, which is fully customisable, operates offline and with high accuracy. Furthermore, using this technology effectively can have a positive impact on behaviour, by substantially increasing self-confidence and independence (Section 5.4).

7.2 Research Contribution

The main contribution of this research is the development of a fully customisable and stand-alone wearable device, that employs machine learning techniques to recognise individual hand gestures and translate them into text, images and speech.

The purpose of this system is to be used as an assistive technology tool to enable independent communication for individuals who are unable to communicate via vocal speech.

The data glove could also be used to teach sign language. In one of the user cases (Section 5.4 - Evaluation Phase 3) it was found that the glove was used as an educational tool to teach some children sign language. It was reported that younger children who were not yet proficient in signing found that training the glove prototypes to build a gesture library for the study helped them become more consistent, as well as to learn new signs.

Furthermore, this technology can have a positive impact on behaviour by promoting independent living. As the results show, (Section 5.4) students who used the data glove in school over a period of three months showed greater independence and improved self-confidence when communicating.

The specifications of the system created through this research are as follows:

- An on-body gesture recognition system that works offline with a classification accuracy rate of 99%.
- The system is embedded in a wearable device with a simple user interface, designed for users to operate it.
- The system can recognise and translate custom hand gestures by training a personal classifier for each user, relying on a small training sample size of one to three recordings. This was accomplished by utilising a KNN classifier, using Dynamic Time Warping for temporal invariance.
- The system's visual output can be set to text phrases or images, appearing on a small screen embedded in the wearable device.
- The system's audio output can be spoken in a male, female or child voice, in a language chosen by the user, through a small speaker embedded in the wearable device.
- The system has a clear route to commercialisation and would be relatively simple to manufacture in a cost-effective manner (Section 9.3).
- The wearable system costs are within the bounds recommended by public sector and private non-profit organisations to provide it through grant schemes, to people who need it for daily communication in school, at work and for independent living.

7.3 Summary

This research aims to contribute meaningfully to improve the daily communication experience for people who are non-verbal, by developing a technology innovation that promotes independent living, and making it accessible to the user groups that could benefit from using it.

Multiple prototypes of a data glove were developed and tested during this research. A final system was designed implementing the results of three iterative design cycles. A fully customisable wearable device was produced which addresses different user needs and offers a mean of direct communication with non-verbal individuals.

A path to commercialisation was identified (Section 9.3) to make this technology available to the people who need it. Integration with current providers of technology for disability schemes were considered (Section:9.4), to extend the same experience witnessed during the case studies to more children and adults.

This technology can help users with speech disabilities to perform better in their respective roles, promoting their inclusion in their communities, in education, at work or simply when they are out socialising.

I discuss collaborations, government schemes and regulations, and commercialisation in detail under Research Impact (Chapter 9).

As of now, 100 units of the data gloves were manufactured. 30 of them assigned to students across the six schools for Special Educational Needs (SEN) who collaborated with us to conduct the research studies. Some were sent to the United States, South Africa and Saudi Arabia. The technology has been reported to being used by students, business professionals, performers, and speech therapists[1].

[1] A video demonstration of the BrightSign glove is accessible at the following URL - https://resources.brightsignglove.com/brightsign_demo

Chapter 8

Future Work

8.1 Further Research

In the conclusion of the final case study chapter (Section 5.6), the plan to take this research further was focused on upgrading the system to classify continuously, reducing the hardware and pairing with a smartphone application.

There are multiple features that could be combined with continuous classification in order to further enhance usability and accuracy.

Creating sub-libraries for recorded gestures, for example, can speed up recognition as it reduces the match-finding process to be limited within the specific library the user is signing from. Sub-libraries could also increase the accuracy of prediction models if employed, as predictions could only be selected from the smaller, setting-specific vocabulary of the library.

As it takes longer to form sentences with signs as opposed to spoken words (Bellugi and Fischer 1972), an objective is to try to match the signing speed to the speech output speed, and to achieve that concurrently, in order to create a smooth interactive conversation experience for signers using data gloves to communicate.

To create this seamless social interaction, the data glove system could be integrated with existing technology, generally used by the majority of people in order to add more features.

For example, the microphone of a smart device compatible with the data glove could serve to provide two-way communication by connecting to transcription services which can transcribe the verbal side of the conversation. The speech could be converted to text for the hearing-impaired person to read on the wearable device.

This is an area of research that has already been implemented successfully in the commercial world[1].

Furthermore, if the compatible device has a camera, it could be used to recognise facial expressions and detect body language used in conjunction with signing for comprehensive translation of sign language. This is an active research topic with several advances in recent years (Pławiak Paweland Sośnicki et al. 2016).

Finally, as sign language has a different structure to spoken language, connecting to a cloud service could allow the implementation of software that could help in structuring grammatically accurate sentences derived from the signed words. This would help the person receiving the speech since they are costumed to communicating in full sentences.

With regard to redesigning the hardware and developing an accompanying application, both upgrades were implemented in the commercial version of the data glove, mentioned in more detail under commercialisation (Section 9.3).

8.2 Further Technology Applications

Based on engagement in the field and taking part in various assistive technology events, it has become evident that there are many different applications for the data glove which was developed during the iterative studies of this research. Some of these applications are directly relevant to the communities it was designed for, to translate sign language to text and speech. Other applications include fields that could benefit from advancements in sensor based gesture recognition, such as in the gaming, live performance and defence sectors.

8.2.1 Data glove applications for sign language translation

Of the various groups that will benefit from the data glove and related technology developed during this research, the foremost will be the hearing impaired and non-verbal communities, who currently use some form of sign language as their primary form of communication. This new technology can help them with their daily communication at work, at school and at home, without the intrusion of an interpreter. Having the ability to build a personal gesture library means that the glove

[1] Hepian Vox - https://www.hepian.co.uk/

can be used to translate from any form of sign language, including bespoke libraries created by those with different motor abilities. With over 30 speech languages to choose from, the glove can be used to communicate within multi-lingual families and in any country.

The user scenario that was employed as the test case for the iterative development cycles of this research was in integrated classrooms, enabling children with various non-verbal disabilities to interact with their peers directly.

Professionals with speech disabilities and hearing impairments could conduct meetings, give talks and speeches, or go on business trips without the necessity and burden of having to hire a personal translator or interpreter and align their schedules, as well as paying for that interpreter's time, expenses and travel.

Further, those with many physical or motor disabilities, such as stroke survivors, who lost the ability to talk at a later stage in life, and who are not already familiar with a formal sign language can teach the glove their own customised hand gestures, and build personal libraries of sign language according to the limitations of their specific, individual motor abilities and physical range of movement.

Accessibility units at airports, hospitals, police stations and shopping centres, can utilise the glove to communicate with visitors who are only able to communicate using sign language and don't have a companion, rather than wait for hours for an interpreter. It can also be used in situations when privacy is required, such as when a non-verbal individual is with a doctor in a clinic, or when participating in an investigation, or reporting a crime at a police station.

The glove can help companies to become fully inclusive, by providing it to their deaf employees or those who have speech disabilities, to enable them to assume more interaction-driven roles, including communicating directly with customers, as opposed to being constrained to desk jobs, as they often are, due to their limited speech abilities. There are multiple schemes in place to provide assistive technology to employees who need it, discussed in detail under research impact (Section 9).

The elderly community who use assisted living technology for smarter homes can benefit from the data glove as well, as hearing loss often becomes increasingly profound when people get older. Combining the data glove with their existing technology can be useful for greater communication both in and out of the users' homes. For example, the glove could be used to trigger speech interactive technology, such as the Amazon Alexa[2], to make calls, operate personal digital devices, and smart home controllers including door security cameras and thermostats.

8.2.2 Data glove applications in other fields

Data gloves are no longer limited for use in human computer interaction or exclusively for sign language applications. While some gloves are designed for interacting with a computer for gaming, animation, motion capture and movie production (Premaratne et al. 2010), other applications may include defence, entertainment and healthcare industries. The defence industry is currently considering advancements in sensor based gesture recognition for military applications. The technology developed in this research can be embedded in the wearable devices they use in the field or for simulation and training.

Similarly, the entertainment industry has recently moved toward providing a fully immersive experience by employing virtual reality (VR) and augmented reality (AR) monitors. That experience can be enhanced by pairing the units with a data glove for greater interaction with hands and gestures. Possible applications include interacting with gaming consoles, immersive theatre, drama and music performances.

The developed data glove may also have healthcare applications to communicate feedback on the range of hand movement, possibly for physiotherapy.

8.3 Route to Commercialisation

Initially, and despite the primary goal of this research being the solution of a real problem, it was never originally intended for the technology that was developed to be commercialised or to evolve into a marketable product. However, every user that the technology was tested with inquired about the possibility of them acquiring a glove of their own; despite the fact that it was, at that point, not a saleable product. Many study participants expressed an interest to be involved in further development rounds of the technology, and all registered for pre-order units once able to. As a result, at some point during the latter stages of user testing, the technological development began to pivot from a prototyping focus, to one of mass

[2] https://www.amazon.co.uk/alexa/dp/B06Y5ZW72J

manufacturability.

Simultaneously, my role transitioned from one primarily of academic research, into one of entrepreneurship - driven by the fact that I was addressing a genuine, real-world need, and had always maintained the focus on the role of the user at the centre of all research and development.

As the glove developed from a prototype into a marketable product, I participated in many programmes through which I received extensive business support and mentorship. After applying for a number of small grants and competitions (many of which were successful), I founded a start-up to develop and manufacture assistive technology devices, with the goal of making such technologies accessible to all those who need them to experience a more independent lifestyle. A full list of public participation and support for this research is disclosed under research industry placement and public engagement (Chapter 10).

Chapter 9

Research Impact

Over the course of this research, I have worked closely with a network of schools across the UK to adopt a scheme similar to the successful pilot implemented with Essex County Council (Chapter 5), where data gloves are issued to the students who need communication technology to help them integrate in mainstream classrooms with students of different abilities.

To take that further, I am currently working with assistive technology platforms and medical insurance companies in the UK to regulate the data glove developed in this research and provide it to the people who need it as an employment and/or disability benefit.

There are official government schemes existing today, mentioned in detail below, that provide communication technology free of charge to registered users on their database. By complying with their regulations, the plan is for the data glove to become included to be supplied as a part of these programmes.

This research was placed in a unique position to have a community impact. In this section, I discuss this impact from a social and economic perspective. I also present the commercial route the technology progressed into, means of integration into current regulation schemes, and ways of documenting this contribution to the field of knowledge.

9.1 Social impact

Assistive technology in general, and the data glove developed for this research in particular, can significantly alter social norms and improve quality of life by enabling people with sensory disabilities, who are either isolated or usually reliant on others to communicate, to live more independent and socially active lives by enabling them to have two-way conversations and supporting them in their education and employment.

This data glove can promote new methods of communication for people who are non-verbal. Most parents participating in our studies cited "[promoting] communication independence" and "[enhancing] social interaction" as their primary reason for adoption communication technology for their children. They also highlighted the customisation feature provided by this glove as the main reason they would choose the data glove developed during this research over other available technologies.

The longitudinal case study (Chapter 5) to test the data glove was sponsored by the local council as a first step towards a programme offering students with disability an opportunity to join their peers of different abilities in mainstream classrooms.

Furthermore, when used in the workplace, the data glove can provide speech impaired employees with job placements they would otherwise not be able to hold due to communication requirements.

In the settings mentioned above, the data glove can be used to prevent discrimination in schools and the workplace, where usually children and adults face different challenges due to their conditions.

9.2 Economic Impact

Technological communication aids for people with speech impairments often come with high price tags, and can be very difficult for individual users to evaluate without assistance from experts.

As such, the cost of the end product was a substantial consideration when undertaking the iterative design cycles for this research to ensure that users would be able to access it affordably, and that it would be included in existing schemes and grants which can provide the technology to them at either a reduced or no cost. In the UK, a number of these schemes exist (Section 9.4), including, for example, grants paid for by local government, to provide assistive technologies to those in education for free. However, those schemes have limits on the per-user price of the technologies that they can provide. Many employers also have schemes to allow their employees to choose their own technology, though again, with some restrictions.

The alternative way for those with sensory disabilities to access education and employment through such schemes is by matching them with a sign language interpreter for the duration of the course or for specific tasks on the job.

Presently, there is a huge shortage in the number of interpreters available, with only one interpreter for every hundred and fifty sign language users, meaning that many of those that need them, are unable to access them when necessary (*British Deaf Association* 2020). Even when they are available, due to the high demand but severely restricted supply, the cost of an interpreter can be very high, and must be paid on an hourly or daily basis, meaning that the use of an interpreter is a constant financial burden. In the workplace, this burden falls upon the employer, as per the Equality Act 2010[1], meaning that hiring employees that require such services regularly to carry out their work can swiftly become very expensive. The adoption of a piece of technology such as that developed in this research, would help to cater for the excess demand for interpreters, as the technology could be used for communication in many day to day situations, when an interpreter would not otherwise be available.

Furthermore, due to the fact that the only major cost is a single up front purchase, it can also act to reduce the financial outlay incurred by the employer. The additional independence that employees can then gain will also be reflected in their productivity, in turn, directly impacting the employer's bottom line. This increased efficiency, spread across many companies would provide a boost to the economy, and would reduce the currently high levels of unemployment that many of society's most isolated and disadvantaged individuals presently suffer from.

For self-employed individuals, the continual necessity to pay for such an interpreter could easily make their business unsustainable or would force their prices to increase, thus making them less competitive. Being able to utilise a technology such as this would remove that burden, allowing them to operate without the additional overhead.

As for individuals who do not fit into a specific scheme, there are non-profit platforms created to evaluate assistive technologies and then advise individuals based on their specific requirements. These platforms reduce the cost of accessing such products, by buying them in bulk at a reduced price and offering them through instalments, with only a fraction of the cost required upfront to obtain and start using the technology.

[1] http://www.legislation.gov.uk/ukpga/2010/15/contents

9.3 Commercialisation

I joined a network which supports academics and students whose research has industry implementations and potential to have a viable business model (Section: 10.1) and founded a technology start-up in 2017, now trading as BrightSign[2], to develop custom assistive technology innovations.

I closed the first round of funding soon after and started manufacturing the BrightSign Glove, based on the technology developed during this research. Pre-orders were launched in 2019 and were fulfilled early 2020. Today, there are over 100 gloves being used in the UK, US and the Middle East by adults and children to help them communicate independently.

Based on the feedback gained from the users and to make the glove hardware lighter, an accompanying smartphone application was developed to further customise the features offered by the system. The application enables each user to have full control over how to use the glove and choose the language and voice of the speech from a range of 30 languages in 180 voices. Individual libraries of gestures are generated by each user with the option to create sub-libraries for easier access in different settings, in school, work or for socialising.

BrightSign was invited to participate in a number of assistive technology exhibitions and trade shows, listed under Chapter 10. Positioned amongst other technologies for communication, the BrightSign Glove attracted considerable attention, since it can be customised to individual needs, an important feature to have in technology designed for people with different abilities.

Collaborations with different platforms to include BrightSign were initiated, starting with CENMAC[3] and London Grid for Learning[4], official providers of assistive technology in education in London, who placed a group order of gloves to make available to their network of schools.

A series of meetings are scheduled with schools across the UK to implement a scheme where BrightSign Gloves are introduced in integrated classrooms for students of different abilities, following on the successful pilot conducted with the 6 initial schools in Essex (Chapter 5).

Other programmes to provide BrightSign Glove to people who need it are avail-

[2]https://www.brightsignglove.com/

[3]CENMAC - http://cenmac.com

[4]London Grid for Learning - https://www.lgfl.net/

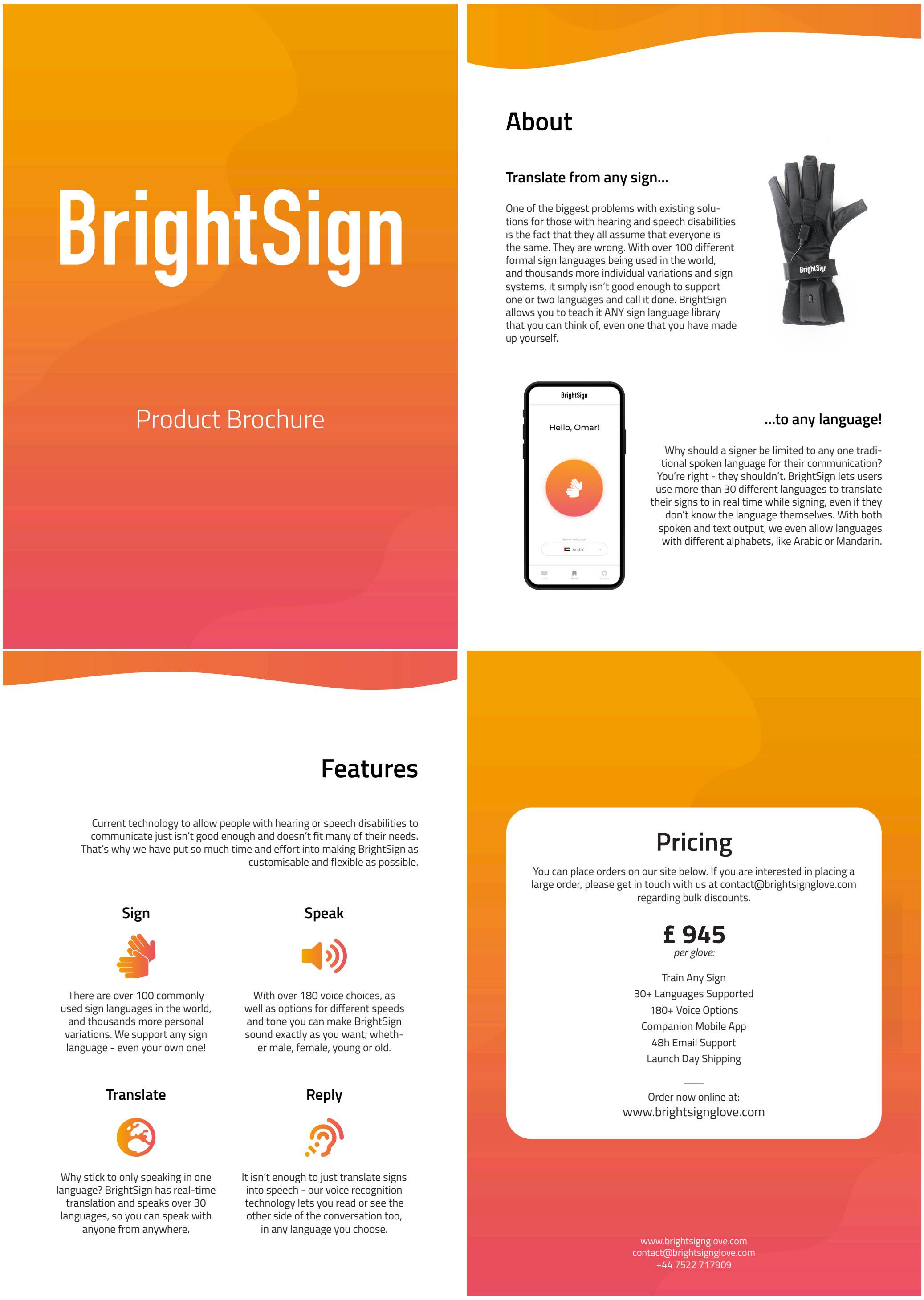


Figure 9.1: Product brochure for the BrightSign Glove

able and discussed in detail under Regulation (Section 9.4).

9.4 Regulation

The data glove developed during this research is commercially classified under "Assistive Technology for Communication". Assistive technologies are "products that empower disabled people to become more independent" (*Together for Short Lives* 2020). Individuals with speech impairment in the UK who register for "reasonable adjustment" are entitled to have assistive technology provided to them by law under the Equality Act 2010.

Due to the high cost of communication aids and to comply with the Equality Act and prevent discrimination, there are multiple schemes in the UK that provide assistive technology through different routes. That includes government schemes, charities and assistive technology platforms. Official claims are usually submitted under education, employment or independent living benefits.

Notable government schemes include The Access to Work Programme[5], financing equipment for employees with disability, The Disabled Students' Allowance (DSA)[6], sponsoring technology to support students with disabilities in higher education, and The National Health Service (NHS)[7], authorising and issuing assistive technologies to disabled people throughout the UK, usually via referrals by a health professional.

There are also multiple charities that offer individuals with disability free access to assistive technology to use at home, in education and at work. AbilityNet[8] extends that service to include the families, carers and employers' of such groups. The Aidis Trust[9] and Disabled Living[10] offer additional support by providing advice and training for the type of assistive technology that best matches the needs of each user case. That includes impartial information for disabled adults, children and older people as well as the professionals who support them. The Disabled Living Foundation[11] focuses on using assistive technology for independent living by acting as a useful reference for a wide range of assistive technology suppliers and sources

[5]Access to Work - https://www.gov.uk/access-to-work/overview
[6]Disabled Student's Allowance - www.yourdsa.com
[7]National Health Service - www.nhs.uk
[8]AbilityNet - www.abilitynet.org.uk
[9]The Aidis Trust - www.aidis.org
[10]Disabled Living - www.disabledliving.co.uk
[11]Disabled Living Foundation - www.dlf.org.uk

of funding.

As for commercial providers of assistive technology, there are platforms that supply digital catalogues and offer industry specific communication technology through a subscription model.

In education, CENMAC is one of the main providers of assistive technology to help students with disabilities access the curriculum. They work in the Greater London area and have eight local authorities subscribed to their service. As for online learning resources, London Grid for Learning (LGFL) is a technology community of schools and local authorities in London. They have a digital inclusive resource library for students with learning disabilities.

For companies and employers, the British Healthcare Trade Association (BHTA)[12] is a network of suppliers of assistive technologies, with memberships of over 500 companies making or selling assistive technology products that help people live more independently. The equivalent online service of accessible resources, is Inclusive Technology[13], a leading supplier providing accessible communication technology, specifically for people with sensory and learning impairments.

Finally, there are assistive technology websites that provide advice and information about hardware and software inclusive equipment, disability support schemes, and funding sources.

Of those I mention, Independent Living[14] and Living Made Easy[15], both of which host online catalogues with a full range of communication aids to support the daily living and independence of people with sensory impairments.

9.5 Field of Knowledge

This research is submitted in fulfilment of the degree of Doctor of Philosophy in Arts & Computational Technology at Goldsmiths, University of London. The thesis will be published in 2024. Main contributions to the field of knowledge are summarised in Section 7.2.

Some of the work demonstrated in this research generated a patent titled: "Method and system for gesture recognition", granted by the United Kingdom Intellectual

[12] British Healthcare Trade Association - http://bhta.com
[13] Inclusive Technology - www.inclusive.co.uk
[14] Independent Living - www.independentliving.co.uk
[15] Living Made Easy - www.livingmadeeasy.org.uk

Property Office (UKPTO) on the 16th November 2021, with patent No. GB2590502 (Appendix F.1).

Chapter 10

Research Industry Placement and Public Engagement

This is a practice-based research degree, therefore, it took place within the industry. The data glove developed during this research was showcased in multiple local and international exhibitions, where much of the data collection occurred. In this section, I list the support received to complete this research, the grants awarded to recognise it and the technology conferences and events it was presented at.

10.1 Funding and support received

I received support from the deK Growth Programme[1], which is a collaboration between Lewisham Council, Goldsmiths University of London and London Southbank University, and is co-funded by the European Regional Development Fund (ERDF)[2]. The programme provided me with 12 mentorship sessions delivered by industry experts to build my knowledge in key areas relevant to my research and matched me with academic leaders who guided me in ways to take my project further.

Simulation for Digital Health[3], hosted by London Southbank University and funded by ERDF, offered multiple workshops to help me innovate, develop and deliver the final wearable designed solution of the data glove, which was used for the first preliminary case study.

[1] deK London - https://www.deklondon.com

[2] European Regional Development Fund - https://ec.europa.eu/regional_policy/en/funding/erdf/

[3] Simulation for Digital Health - https://www.simdh.com

I joined Central Research Laboratory hardware accelerator [4] for six months, also funded by ERDF. With them, I further developed the data glove from a simple prototype to a minimal viable product, which was used for the longitudinal case study in Chapter 5.

I applied for and was awarded Goldsmith's Innovation Award to help finance the development of the second glove prototype, which was used for the case studies in Chapter 4.

Essex County Council funded the longitudinal case study in Chapter 5; with the grant including the manufacturing of 15 data gloves.

Imperial College London provided me with work space in their Innovation Hub for one year, as part of the Scalable Business Awards[5], with access to a prototyping lab and individual coaching sessions. It was there that I formed strong networking links with fellow academics turned entrepreneurs, and eventually based my start-up office after securing funding.

10.2 Conferences

I was invited to participate in conferences, relevant to this research area, to present the ongoing research of the system developed during the PhD degree and share primary results.

In 2016, I presented early findings of the gesture recognition system at the Wearable Technology conference in London and Facets, an interdisciplinary interactive art un-conference in New York.

In 2017, I presented an improved system with machine learning applications to recognise custom hand gestures at CENMAC Assistive Technology for Communication conference in London and No Barriers Summit in Lake Tahoe.

In 2018, I presented the final on-body gesture recognition system at Cambridge Rare Disease Network RAREfest in Cambridge, International Technology Enabled Care conference in Birmingham, North West ADASS Assistive Technology conference in Manchester and Forbes 30 Under 30 Summit for young entrepreneurs in Amsterdam.

[4] Central Research Laboratory - https://www.centralresearchlaboratory.com/

[5] Scalable Business Awards - https://www.imperial.ac.uk/news/186606/inspired-start-ups-support-worth-combined-250000/

In 2019, I presented the commercial product, the BrightSign Glove, which is the data glove progression of this research, at the International Accessibility conference in Dubai, and MIT Minds and Tech conference in Toulouse, France.

10.3 Exhibitions

I participated in the following exhibitions, to showcase the technology developed during this research as well as to collect data from different user groups in attendance.

I conducted the controlled iterative case study presented in chapter 4 by participating in CENMAC Assistive Technology for Communication Exhibition in London in 2017/18, and No Barriers Summit's Innovation Village, Lake Tahoe in 2017.

I also collected a wider range of usability data from public attendances during my participation at TechCrunch Disrupt in Berlin, GITEX in Dubai, Festival of Digital Disruption (FoDD) in Reading, TechDay in London, TechXLR8 in London, Viva Technology in Paris, Accessibility Expo in Dubai, Braun Tech for Good in Frankfurt and AXA Health Tech in London.

10.4 Awards

The research received multiple awards specifically in the areas of artificial intelligence, wearable technology, healthcare innovation and technology with social impact. Some awards offered monetary grants which helped in funding the research and developing the hardware for the prototypes, while others provided valuable partnerships and access to research and market networks.

Innovation and Entrepreneurship Award for Saudi Students in the UK, London 2015.

IBM Global Hackathon in Artificial Intelligence for Social Care Grand Prize, Seoul 2016, providing a cash award.

The Wearable Technology Show Innovation Award, London 2016, providing exhibition space and a presentation opportunity at the parallel conference. Wareable Technology Save the Day Award, recognising technology that is life-changing, London 2017.

Arab Deaf Women Conference for Assistive Technology, Kuwait 2017.

Santander Universities Innovation Award, London 2018, providing a cash award and a paid internship placement for 10 weeks at BrightSign.

AXA Health Tech Award, recognising innovations which improves health and wellbeing by helping people live happier lives, London 2018, providing regulation support and access to network.

Booking.com Tech Playmaker of the year Award & Social Impact Award, London 2018, providing cash award, media coverage and access to network.

Viva Technology Innovation Award, Paris 2018.

Saudi Youth Award in Technology Community Impact, Dammam 2018, providing a cash award.

Mayor of London Entrepreneurship Award, London 2019, providing one year membership at The Office Group, a dedicated mentor from the industry and coaching sessions.

Saudi Ministry of Communications Award for Assistive Technology, Riyadh, 2019, providing a cash award.

MIT Centre for Collective Intelligence, Minds & Tech Award, recognising innovation using artificial intelligence to solve problems or bring value to society, Toulouse, France 2019.

The Not Impossible Award, recognising technology for the sake of humanity, USA 2020.

Entrepreneurship World Cup, global competition recognising leaders who are pursuing groundbreaking research that could change the world, 2020.

10.5 Media

The research was recognised in a number of reputable and in many cases high profile media outlets, including the BBC, Forbes, The Guardian and the Financial Times, as well as some international news organisations. The glove prototype was featured on the BBC One Show and The Discovery Channel.

10.6 Networks and memberships

Valuable networks and partnerships resulted from working with the industry to conduct this research. I have established collaborations with CENMAC, providers of assistive technology for education, London Grid for Learning, providers of accessible resources for students with learning difficulties, AXA, providers of health insurance with coverage for assistive technology and IBM, who granted me lifetime access to their text to speech and translation engines.

I am a member of Women of Wearables[6], a network of women in tech who develop wearables that serve the community and create a difference.

I was also invited by the iDiscover Programme[7] to take the role of a STEM (Science, Technology, Engineering and Math) ambassador, where I get to share the data glove technology and the innovation behind it with elementary school students all over London, to widen the access of these fields of knowledge.

[6] Women of Wearables https://www.womenofwearables.com

[7] iDiscover https://www.inspire-ebp.org.uk/wp-content/uploads/2018/10/iDiscover-flyer-2018.pdf

Chapter 11

Summary

In this research, I document the process of designing a sensor-based wearable computing system for custom hand gesture recognition using machine learning.

I have presented examples of how this task was achieved in prior research and demonstrate how a single user or a small group of users with specific needs are able to test a proposed system with the results in turn applied to inform the development for a larger user group (Section: 3.3).

I began by developing an initial data glove system wired with flex sensors and a gyroscope to record gesture data collected from hand positions and movements.

I implemented interaction design research methods to conduct a series of design iterations (using the build-measure-learn system, as in Section 3.1.2) to develop a number of incrementally improving prototypes of this system. Starting with preliminary case studies (Chapter 4), rapidly prototyping various isolated system features, I then conducted a longitudinal case study that evaluated the system features and performance in-depth when used over a period of six months (Chapter 5).

During these studies, I tested the data glove with adults and children who use hand gestures for their everyday communications. I used the testing sessions to evaluate the performance of the data glove prototypes when used in public spaces, in school and at home and collected detailed feedback from the care givers of the users, the teachers and therapists in attendance, and through observation. Throughout, the system was always evaluated against the fundamental requirements that it must be Assistive, Accessible, Adaptive and Affordable (as detailed in Section 3.1).

I combined the findings of each study with recorded gesture data, and implemented further system analyses including failure analysis, individual difference analysis and time profiling. This allowed me to use the results to update the system for each of the subsequent testing cycles.

In total, the system was tested by 40 participants, with the youngest being 5 years old. In aggregate, the participants used five different sign language libraries as well as several non standard ones. The conditions that affected them included full or partial hearing impairment, multiple different learning disabilities, cerebral palsy, visual impairment, neurological and physical disabilities, and sometimes a combination of multiple of the above.

The final system achieved 99.97% in recognising and accurately classifying custom hand gestures within a gesture library of 100 words using a K-Nearest Neighbours classifier, with Dynamic Time Warping used as a distance measure.

A text to speech API was integrated to translate the recognised hand gestures to speech. For further personalisation, the system also offered different voices and languages for the speech output.

The final data glove prototype developed through this research is able to operate as a wireless and stand alone wearable device, which can translate hand gestures to speech offline. The hardware circuitry is entirely embedded within the design of the glove which also features a small screen to allow the user to interact with it, and a speaker to output the words corresponding to the recognised gestures.

This data glove has been designed to be used as a communication tool to enable non-verbal users to interact independently with their peers and be more included within their communities.

The results of this research were ultimately used to inform the production of a commercial version of the data glove, trading as BrightSign, which is currently used in special educational needs schools, by students and teachers, as well as by speech disabled professionals in multiple countries (Chapter 10).

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Appendices

Appendix A

Ethics Approval Forms

A.1 Research Ethics and Integrity Sub-Committee (REISC)

Goldsmiths
UNIVERSITY OF LONDON

Research Ethics & Integrity Sub-Committee [REISC]

Approval Status: Approved

To:	**Ms Hadeel Ayoub, Department of Computing**
From:	Professor Simon McVeigh, Chair (cc: REISC Secretary)
Date:	9 November, 2018
Reference:	**1419**

We are pleased to inform you that the Research Ethics & Integrity Sub-Committee has approved your project: *BrightSign Usability Study*.

Approved ethical applications are available in the Research Office for other researchers in the college who are applying for grants; they may also be sent out as email attachments if requested. This is to help applicants. Please let Karen Rumsey know within two weeks of this letter if you would rather not have your ethical application form available in this way.

Best wishes for your project,

[redacted]

Professor Simon McVeigh
Chair, Research Ethics & Integrity Sub-Committee

A.2 Goldsmiths Ethical Approval Form (EAF1)

Ethical Approval Form (EAF1)

CONFIDENTIAL

GOLDSMITHS COLLEGE University of London

Research Ethics Committee

NAME OF APPLICANT Hadeel Ayoub

DEPARTMENT Computing

This form should be completed in typescript and returned to the Secretary of the Research Ethics Committee, for any research project, teaching procedure or routine investigation involving human participants or animals to be undertaken in the College or by or upon Goldsmiths College staff outside the College.

1. **Title of proposed project:**
   BrightSign Usability Study

2. **Brief outline of the project, including its purpose:**
   Bright Sign Glove (BSG) is a data glove, which aims to translate sign language hand gestures to text and speech. The main purpose of BSG is to facilitate communication between speech-disabled students in the classroom with their peers and teachers in mainstream schools. This study will recruit 10 students to evaluate the performance of the glove prototypes and the impact BSG has on the social behaviour of the children in overcoming their daily communication challenges.

3. **Proposed starting date:**
   15 October 2018

4. **If external grant funding is being secured, does the research need ethical approval prior to the initiation of that funding?**
   No

5. **Has the project been approved by an Ethics Committee external to the College? If so please specify.**
   (NB for projects so approved, applicants may if they wish submit a copy of that application, but should sign the back of the form and return it as specified above)
   N/A

6. **Please provide an ethical self-evaluation of the proposed research. Reference should be made to the ESRC Research Ethics Framework , to professional guidelines (such as provided by the BPS, the BSA or the SRA) or to guidelines by government (e.g. GSR) on ethical practice and research. You may wish to provide your response on a separate sheet.**
   Attached:
   - Research ethics initial checklist (Template from https://esrc.ukri.org)
   - Usability study information sheet
   - Study consent form
   - (Disclosure & Barring Service) DBS Check

7. **State the variables to be studied, topics to be investigated, procedures to be used and/or the measurements to be made. (Please attach a separate sheet if necessary)**

The study aims to test the accuracy of the technology prototype's output and performance and how that affects the daily communication of non-verbal children. Participants will be directed on how to put the glove on and how to use it. They will be trained on how to use the technology in the presence of a parent/legal guardian and a teacher/therapist.

The main objectives of the study is to evaluate the following:

1. Accuracy and results consistency
2. Time to complete each assigned task
3. Ease of use
4. Durability as a wearable technology
5. Impact on social behaviour

Primary study documentation will be video documentation and observation. Attending speech therapists and teachers will be recruited for help with evaluation. Parents will be asked to fill surveys before and after the study is conducted.

8. **Specify the number of and type of participant(s) likely to be involved.**
The participants will be recruited through local schools for children with special needs. The plan is to recruit 10 participants.

9. **State the likely duration of the project and where it will be undertaken.**
The duration of the study is 6 months. Active testing will be during three months 15 October to 15 December 2018.

10. **State the potential adverse consequences to the participant(s), or particular groups of people, if any, and what precautions are to be taken.**
The glove is wired with sensors and an electronic circuit. All hardware is placed in the inner lining of the glove material. No contact with the skin will occur at any point of the study. The material used for the glove is fire resistant as well as water resistant to protect the participants' skin and insure the hardware is insulated. The electronic board is encapsulated in a 3D printed enclosure to be worn as wrist band.

11. **State any procedures which may cause discomfort, distress or harm to the participant(s), or particular groups of people, and the degree of discomfort or distress likely to be entailed.**
Some participants might feel frustrated if they don't understand how to use the glove. There will be training session prior to handing over the gloves. Parents and therapists will be present at all times to insure effective communication.

12. **State how the participant(s) will be recruited. (Please attach copies of any recruiting materials if used).**

Teachers in the school will identify the students who are able to take part in the study. Only students who have parents' consent will be considered for the study.

13. **State if the participant(s) will be paid, and if so, provide details and state reasons for payment.**
No payment will be offered to take part in the study. However, the council funding the study has agreed to leave the gloves with the participants after the study is concluded.

14. **State the manner in which the participant(s) consent will be obtained (if written, please include a copy of the intended consent form).**
Written consent form will be signed by each participant's parent/legal guardian.

14a. Will the participant(s) be fully informed about the nature of the project and of what they will be required to do?
Yes

14b. Is there any deception involved?
No

14c. Will the participant(s) be told they can withdraw from participation at any time, if they wish?
Yes

14d. Will data be treated confidentially regarding personal information, and what will the participant(s) be told about this?
Yes

14e. If the participant(s) are young persons under the age of 18 years or 'vulnerable persons' (e.g. with learning difficulties or with severe cognitive disability), how will consent be given (i.e. from the participant themselves or from a third party such as a parent or guardian) and how will assent to the research be asked for?
Parent or legal guardian.

15. **Will the data be confidential?**
Yes

15a. Will the data be anonymous?
No

15b. How will the data remain confidential?

Participants personal information will not be made public. Data collection will be in compliance with GDPR regulations.

15c. How long will the data be stored? And how will it be eventually destroyed?
Data will be stored locally on the prototype units during the duration of the study. All data will be destroyed after the conclusion of the study.

16. **Will the research involve the investigation of illegal conduct? If yes, give details and say how you will be protected from harm or suspicion of illegal conduct?**
No

17. **Is it possible that the research might disclose information regarding child sexual abuse or neglect? If yes, indicate how such information will be passed to the relevant authorities (e.g. social workers, police), but also indicate how participants will be informed about the handling of such information were disclosure of this kind to occur. A warning to this effect must be included in the consent form if such disclosure is likely to occur.**
No

18. **State what kind of feedback, if any, will be offered to participants.**
The performance of the glove prototype is the feedback the participants will get from their sign language hand gestures. Speech will be spoken from the glove speaker and text will be shown on the glove screen.

19. **State the expertise of the applicant for conducting the research proposed.**
This study is part of the PhD research in Arts & Computational Technology the applicant is registered in at the University.

20. **In cases of research with young persons under the age of 18 years or 'vulnerable persons' (e.g. with learning difficulties or with severe cognitive disability), or with those in legal custody, will face-to-face interviews or observations or experiments be overseen by a third party (such as a teacher, care worker or prison officer)?**
Yes, every participant's teacher will be present during the testing documentation and observation of the study.

21. **If data is collected from an institutional location (such as a school, prison, hospital), has agreement been obtained by the relevant authority (e.g. Head Teacher, Local Education Authority, Home Office)?**
Yes

22. **For those conducting research with young persons under the age of 18 years or 'vulnerable persons' (e.g. with learning difficulties or with severe cognitive disability), do the investigators have Criminal Records Bureau**

clearance? (Ordinarily unsupervised research with minors would require such clearance. Please see College *Code of Practice on Research Ethics*, 2005).
Yes

23. **Will research place the investigators in situations of harm, injury or criminality?**
No

24. **Will the research cause harm or damage to bystanders or the immediate environment?**
No

25. **Are there any conflicts of interest regarding the investigation and dissemination of the research (e.g. with regard to compromising independence or objectivity due to financial gain)?**
No

26. **Is the research likely to have any negative impact on the academic status or reputation of the College?**
No

ALL APPLICANTS

Please note that the Committee should be notified of any adverse or unforeseen circumstances arising out of this study.

Signature of Applicant	**Date**
HADEEL AYOUB	**25.09.2018**

TO BE COMPLETED BY HEAD OF DEPARTMENT

Please note that the College Research Ethics Committee should be notified of any adverse or unforeseen circumstances arising out of this study or of any emerging ethical concerns that the Head of Department may have about the research once it has commenced.

Has there been appropriate peer review and discussion of the ethical implications of the research in the department (i.e. with yourself as Head of Department or the Departmental Research Ethics Committee or Research Committee)?

Yes/No (Please circle)

Are the ethical implications of the proposed research adequately described in this application?

Yes/No (Please circle)

Signature of Head of Department **Date**

[redacted] 2nd October 2018

A.3 Computing Ethics Initial Checklist

Research ethics initial checklist

An appropriate checklist must be completed before potential participants are approached to take part in any research.

Project details	
Project title	BrightSign Usability Study
Applicant details	
Name of researcher (applicant)	Hadeel Ayoub
Role	PhD student, research investigator
Contact address	[redacted]
Email	[redacted]
Telephone	[redacted]
For students only	
Module name and number or MA/MPhil course and department	PhD Arts and Computational Technology Department of Computing
Supervisor's or module leader's name	Mick Grierson

Research ethics initial checklist		
Please answer each question by ticking the appropriate box:		
	Yes	No
Research that may need to be reviewed by NHS Research Ethics Committee or another external Ethics Committee (if yes, please give brief details as an annex)		
Will the study involve recruitment of patients or staff through the NHS or the use of NHS data or premises and/or equipment?		√
Does the study involve participants age 16 or over who are unable to give informed consent? (eg people with learning disabilities: see Mental Capacity Act 2005 / Adults with Incapacity (Scotland) Act 2000. All research that falls under the auspices MCA/AWI must be reviewed by NHS REC)		√
Research that may need a full review		
Does the research involve potentially vulnerable groups: children, those with cognitive impairment, or those in unequal relationships? (eg your own students)	√	
Will the study require the co-operation of a gatekeeper for initial access to the groups or individuals to be recruited? (eg students at school, members of self- help group, residents of nursing home?)	√	
Will it be necessary for participants to take part in the study without their knowledge and consent at the time? (eg covert observation of people in non-public places)		√
Will the study involve discussion of sensitive topics? (eg sexual activity, drug use, politics)		√
Are drugs, placebos or other substances (eg food substances, vitamins) to be		√

administered to the study participants, or will the study involve invasive, intrusive or potentially harmful procedures of any kind?		
Will tissue samples (including blood) be obtained from participants?		√
Is pain or more than mild discomfort likely to result from the study?		√
Could the study induce psychological stress, discomfort, anxiety or cause harm or negative consequences beyond the risks encountered in normal life?		√
Will the study involve prolonged or repetitive testing?	√	
Will the research involve administrative or secure data that requires permission from the appropriate authorities before use?		√
Is there a possibility that the safety of the researcher may be in question? (eg in international research: locally employed research assistants)		√
Does the research involve members of the public in a research capacity (participant research)?		√
Will the research take place outside the UK?		√
Will the research involve respondents to the internet or other visual/vocal methods where respondents may be identified?	√	
Will research involve the sharing of data or confidential information beyond the initial consent given?		√
Will financial recompense be offered to participants?		√

Principal Investigator			
Signed: [redacted]		Date:	25.09.2018
Supervisor or module leader (where appropriate)			
Signed: [redacted]		Date:	01/10/18

It is a researcher's responsibility to follow the research organisation's code of practice on ethical standards, and any relevant academic or professional guidelines in the conduct of their study. This includes providing appropriate information sheets and consent forms, and ensuring confidentiality in the storage and use of data.

Any significant change in the question, design or conduct over the course of the research should be notified to the faculty or school research ethics officer and may require a new application for ethics approval.

A.4 DBS Check

Enhanced Certificate

Page 1 of 2

Disclosure & Barring Service

DBS Fee Charged

Certificate Number [redacted]

Date of Issue: 08 MAY 2018

Applicant Personal Details

Surname: AYOUB

Forename(s): HADEEL DIAAELDIN

Other Names: AYOUB, HADEEL DIAAELDIN

Date of Birth: [redacted]

Place of Birth: [redacted]

Gender: FEMALE

Employment Details

Position applied for:
CHILD WORKFORCE STUDENT PLACEMENT - CHILD

Name of Employer:
GOLDSMITHS - STUDENT PLACEMENT (CHILDREN)

Countersignatory Details

Registered Person/Body:
GB GROUP PLC

Countersignatory:
ALLISON HALLAM

Police Records of Convictions, Cautions, Reprimands and Warnings

NONE RECORDED

Information from the list held under Section 142 of the Education Act 2002

NONE RECORDED

DBS Children's Barred List information

NONE RECORDED

DBS Adults' Barred List information

NOT REQUESTED

Other relevant information disclosed at the Chief Police Officer(s) discretion

NONE RECORDED

Enhanced Certificate

This document is an Enhanced Criminal Record Certificate within the meaning of sections 113B and 116 of the Police Act 1997.

THIS CERTIFICATE IS NOT EVIDENCE OF IDENTITY

Continued on page 2

Disclosure and Barring Service, PO Box 165, Liverpool, L69 3JD, Helpline: 03000 200 190

Page 2 of 2 **Certificate Number** [redacted]

Use of certificate information

The information contained in this certificate is confidential and all recipients must keep it secure and protect it from loss or unauthorised access. This Certificate must only be used in accordance with the Disclosure and Barring Service's (DBS) Code of Practice and any other guidance issued by the DBS. Particular attention must be given to the guidance in the fair use of the information in respect of those whose Certificate reveals a conviction or similar information. The DBS will monitor the compliance of Registered Bodies with this Code of Practice and other guidance.
This Certificate is issued in accordance with Part V of the Police Act 1997, which creates a number of offences. These offences include forgery or alteration of Certificates, obtaining Certificates under false pretences, and using a Certificate issued to another person as if it was one's own.
This Certificate is not evidence of the identity of the bearer, nor does it establish a person's entitlement to work in the UK.

Certificate content

The personal details contained in this Certificate are those supplied by or on behalf of the person to whom the Certificate relates at the time the application was made and that appear to match any conviction or other details linked to that identity.
The information contained in this Certificate is derived from police records, and from records held of those who are unsuitable to work with children and/or adults, where indicated. The police records are those held on the Police National Computer (PNC) that contains details of Convictions, Cautions, Reprimands and Warnings in England and Wales, and most of the relevant convictions in Scotland and Northern Ireland may also be included. The DBS reserves the right to add new data sources. For the most up to date list of data sources which are searched by the DBS please visit the DBS website.
The Other Relevant Information is disclosed at the discretion of the Chief Police Officers or those of an equivalent level in other policing agencies, who have been approached by the DBS, with due regard to the position sought by the person to whom the Certificate relates.

Certificate accuracy

The DBS is not responsible for the accuracy of police records.
If the person to whom this Certificate relates is aware of any inaccuracy in the information contained in the Certificate, he or she should contact the Countersignatory immediately, in order to prevent an inappropriate decision being made on their suitability. This Countersignatory will advise how to dispute that information, and if requested arrange for it to be referred to the DBS on their behalf. The information should be disputed within 3 months of the date of issue of the Certificate.
The DBS will seek to resolve the matter with the source of the record and the person to whom the Certificate relates. In some circumstances it may only be possible to resolve a dispute using fingerprints, for which consent of the person to whom the Certificate relates will be required.
If the DBS upholds the dispute a new Certificate will be issued free-of-charge. Details of the DBS's disputes and complaints procedure can be found on the DBS's website.

Contact us

Post:	Disclosure and Barring Service PO Box 165 Liverpool L69 3JD	Telephone:	Customer Services: Welsh line: Minicom: General Information	03000 200 190 03000 200 191 03000 200 192 03000 200 190
Web:	www.gov.uk/dbs			
Email:	customerservices@dbs.gsi.gov.uk			

If you find this certificate and are not able to return it to the person to whom it relates, please return it to the DBS at the address above or hand it in at the nearest police station.

End of Details

A.5 Goldsmiths Public Liability Insurance

ZURICH
MUNICIPAL

To Whom It May Concern

Our ref: TK/IND 5 July, 2018

Zurich Municipal Customer: Goldsmiths College

This is to confirm that Goldsmiths College has in force with this Company until the policy expiry on 31 July 2019 Insurance incorporating the following essential features:

Policy Number:	**NHE-01CA11-0013**	
Limit of Indemnity:		
Public Liability:	£ 30,000,000	any one event
Products Liability:	£ 30,000,000	for all claims in the aggregate during any one period of insurance
Pollution:		
Employers' Liability:	£ 30,000,000	any one event inclusive of costs

Excess:

Public Liability/Products Liability/Pollution:	£ 250 any one event
Employers' Liability:	Nil any one claim

Indemnity to Principals:
Covers include a standard Indemnity to Principals Clause in respect of contractual obligations.

Full Policy:
The policy documents should be referred to for details of full cover.

Yours faithfully

[redacted]

Underwriting Services
Zurich Municipal

Zurich Municipal
Zurich House
1 Gladiator Way
Farnborough
Hampshire
GU14 6GB

Telephone: 0800 335500
E-mail:
martin.waight@uk.zurich.com

Zurich Municipal
Zurich Municipal is a trading name Zurich Insurance plc
A public limited company incorporated in Ireland
Registration No. 13460

Registered Office: Zurich House, Ballsbridge Park, Dublin 4, Ireland.
UK Branch registered in England and Wales Registration No. BR7985.
UK Branch Head Office: The Zurich Centre, 3000 Parkway, Whiteley, Fareham, Hampshire PO15 7JZ.

Zurich Insurance plc is authorised by the Central Bank of Ireland and authorised and subject to limited regulation by the Financial Conduct Authority. Details about the extent of our authorisation by the Financial Conduct Authority are available from us on request. Our FCA Firm Reference Number is 203093.

MSTDNA01

Appendix B

Research Grant Agreement

B.1 Essex County Council Research Grant Agreement (Abridged)

DATED **13 JUNE 2018**

GRANT AGREEMENT

between

ESSEX COUNTY COUNCIL

and

BRIGHTSIGN TECHNOLOGY LIMITED
Company Number 11017734

Schedule 1 The Project

The purpose of the pilot is to determine if students with Learning Disabilities and/or Autism Spectrum Disorder use BrightSign will increase their independence and / or reduce incidents of challenging behaviour.

The project is to fund a pilot of 14 BrightSign gloves for use in Essex schools by students with Learning Disabilities and/or Autism Spectrum Disorder for a period of 6 weeks.

The Recipient will:

- Work with each pilot user to implement the glove
- Act on feedback from pilot users to make improvements to the functionality of the hardware and/or software/code of BrightSign in order to better suit the pilot user during the pilot
- Provide technical support to the individuals and the schools involved in the pilot for the duration of the pilot
- Provide a copy of the findings of the pilot to the Funder
- Publish the conclusion of the pilot study in Academic Journals
- Include the pilot study outline and results in PhD thesis.

Appendix C

Essex Schools Usability Study Information Sheet

C.1 Assistive Technology for Education Usability Study

Assistive Technology for Education Usability Study
BrightSign Technology & Essex County Council

Background:

BrightSign is a data glove wired with multiple sensors and equipped with machine learning software. BrightSign translates custom sign language hand gestures to text and speech in real-time. It is designed to enable sign language users to interact directly with the public who do not speak sign language.

Over the past three years, I have developed multiple prototypes of BrightSign glove. Two pilot studies have been conducted on early prototypes using interactive design research methodology. The outcome of each study fed back into the design loop to improve software, hardware and the design of the glove. The study outlined here is the final study of the research. The results will set the framework for the mass producible version of the glove in preparation for commercialisation.

This usability study will be conducted in collaboration with Essex Council and four local special schools appointed by the council.

Usability Study Outline:

The study is a longitudinal study during which the participants will keep the prototypes for 3 months and use them for daily communication. It is designed to document whether the glove enables children who use sign language as their primary language to communicate with the public without the presence of an interpreter.

Participants:
Children ages 4 to 18 who are non-verbal and can use assistive technology.

The glove supports two forms of sign language which is used by two groups:

- Deaf or hard of hearing who use BSL
- Non-verbal disability who use Makaton

The glove can also be trained for custom signs and/or hand gestures.

Duration of study: 3 months

Location of study: The glove is to be used for daily communication in real-life situation and in the participants' natural environments. School, park, outings and at home with their families.

Data Collection:

- Software data collection stored locally on the glove's SD card
- Feedback from participants
- Feedback from care givers, family members and teacher
- Observation and video documentation

Timeline:

April - May >>> Setting up study outline

- Set up study outline with the local council
- Identify collaborative schools
- Ethics Clearance and DBS checks

June >>>

- Recruit study participants:
    - Age, Size, Interests
    - Sign language library used
- Submit gloves parts order (can take up to10 weeks to arrive)
- Finalise permission documents and clearance forms with all parties involved

July >>> Textiles / Software

- Design custom glove textiles to match participants' interests
- Update gloves software to accommodate schools' requests for customization

August >>> Product Manufacturing

- *Gloves manufacturing (Takes 3 weeks)*

September >>> Usability study launch

- Initial meetings with parents and teachers on school premises
- Train study participants, family members and teachers
- Leave gloves with participants/schools

October to December >>> Study active

- Set up a schedule for regular visits and data collection
- School visits up to twice a week and based on special requests
- Interview teachers and families once midway through the study (November)

January >>> Study data collection and analysis

- Document feedback from teachers, parents and participants
- Families to keep the gloves and get access to support

March >>> Study write up for publication

Appendix D

Consent Forms

D.1 School Consent Forms

SCHOOL CONSENT FORM

Project Title: BrightSign Technology Usability Study
Research Investigator: Hadeel Ayoub Email: [redacted]
Project Supervisor: Mick Grierson Email: [redacted]
Department of Computing, Goldsmiths, University of London

Please tick the box for each statement and complete the details below.

☐ I confirm that I have the authority to give permission for my school to take part.

☐ I agree that the research project named above has been explained to me to my satisfaction and I agree for the students in my school to take part.

☐ I am happy with the contact hours that the researcher has proposed and I confirm this will not adversely affect the students' school study.

☐ I understand that the students' and the school's participation is voluntary and that we are free to withdraw at any time without giving a reason and without penalty.

☐ I understand that information about my school may be used in a published academic paper and that confidentiality and anonymity will be maintained.

☐ I agree to provide the use of a suitable location in which to conduct study meetings.

☐ I agree to allow the lead researcher to visit the school for data collection and observation during school hours in accordance with a pre-approved visits schedule.

☐ I acknowledge that only children with parental/guardian consent will be allowed to take part in the study.

☐ I understand that I am free to discuss any questions or comments I might have with the points of contacts provided to me on the information sheet.

Name:... Signed:...

School:.. Date:..

D.2 Parent Consent Forms

PARENT CONSENT FORM

Project Title: BrightSign Technology Usability Study
Research Investigator: Hadeel Ayoub Email: [redacted]
Project Supervisor: Mick Grierson Email: [redacted]
Department of Computing, Goldsmiths, University of London

Circle As Applicable

1. Have you read the information sheet about this study?	YES / NO
2. Have you had an opportunity to ask questions and discuss this study?	YES / NO
3. Have you received satisfactory answers to all your questions?	YES / NO
4. Have you received enough information about this study?	YES / NO
5. Do you understand that you are free to withdraw your child from this study at any time and without giving a reason for withdrawing?	YES / NO
6. Do you agree for your child to take part in this study?	YES / NO
7. I understand that the information collected from this study may form part of a scientific publication and I will be sent a copy. Confidentiality and anonymity will be maintained, and it will not be possible to identify me or my child from any publications.	YES / NO
8. I agree to be contacted throughout the duration of the study by the lead researcher for data collection and follow up meetings.	YES / NO
9. I understand that I will have to return the glove if I leave the study before it is concluded.	YES / NO
10. I understand that it is my responsibility to follow the technology safety guidelines outlined in the user manual received with the glove	YES / NO
11. I understand that the glove should be used under adult supervision at all times.	YES / NO

I, ______________________the parent and/or legal guardian of ____________________

PRINT NAME HERE PRINT CHILD'S NAME HERE

consent to the processing of our personal information for the purposes of this study only and that it will not be used for any other purpose. I understand that such information will be treated as strictly confidential and handled in accordance with the provisions of the Data Protection Act 1998 and the GDPR regulations.

If you have any concerns about your role in the project, please contact the Chair of the University's Research Ethics and Integrity Sub-Committee, Professor Simon McVeigh, via the REISC Secretary on [redacted] */ email* [redacted]

Signed_______________________________ Date_____________________________
Name of Parent/Legal Guardian ____
Name of Investigator____
Signature of Investigator____

Appendix E

Surveys

E.1 Parents Entry Survey

BrightSign Usability Study

Entry Survey – Parents

Please Answer these questions about your child who will be taking part in this study:

Name:
Age:
Gender:
Age started signing:
Sign language library: BSL - Makaton - Signalong - Other …………………..
Level of signing: Beginner - Intermediate - Advanced
Study Group: 1 - 2 - 3

Has your child been part of previous studies for assistive technology?

- Yes
- No

Has your child ever used assistive technology for communication ?

- Yes: an app on tablet
- Yes: other………………………………………………………………………………
- No

Who covers, or would cover, the cost of assistive technology for your child:

- Health insurance
- Government aid
- The school (Education aid)
- Device loan from accessibility platform (CENMAC, LGFL, etc)
- Yourself

How does your child communicate in public ?

- Family, friend translate
- Sign language
- Smart device
- Other:……………….

What is the primary reason you registered your child in this study ?

- Improve signing skills
- Promote communication independence
- Enhance social interaction
- Support assistive technology development
- Other:

Please rate the study evaluation criteria in the order of importance to your child:

- Technology Development
- Social Behaviour
- Education Support
- Early adopter of BrightSign

Which of the following supplementary features of BrightSign can be beneficial to your child? *Tick all that applies elaborating on why you would use it*

- Customising sign language (Training for personal versions of sign language)
  ……
- Customising speech voice (Child, a friend, family member.. .etc)
  ……
- Translating speech to other languages (French, Indian ..etc)
  ……
- Personalized textile design (favourite character, colour ..etc)
  ……

Would you like to keep BrightSign when the study is concluded?

- Yes
- No

Please write in your own words what do you hope your child will gain from this study?

Thank you for completing BrightSign entry survey ☺

E.2 Participants Profiles (Teachers)

BrightSign Usability Study

Participants Profiles
Teachers

School	
Teacher	
Class/Age	
Sign Language	
Names of study participants in your class	
Study Group	
Top 3 group songs in class:	

Most used phrases in class by students:

1.
2.
3.
4.
5.
6.
7.
8.
9.
10.
11.
12.
13.
14.
15.
16.
17.
18.
19.
20.

Appendix F

Patent

F.1 GB2590502 - Method and system for gesture recognition

Intellectual Property Office

Ipsum - Online Patent Information and Document Inspection Service

New Search View on Espacenet

GB2590502 - Method and system for gesture recognition

Case Details

Application Number	GB1919046.1
Application Source	Form 1
Publication Number	GB2590502
Status	Granted
Filing Date	20 December 2019
Publication Date	30 June 2021
Grant Date	Grant of Patent (Notification under Section 18(4)): 16 November 2021
Application Title	Method and system for gesture recognition
Grant Title	Method and system for gesture recognition
Compliance Date (Section 20 Date)	20 June 2024
Address for Service	MARKS & CLERK LLP 15 Fetter Lane London EC4A 1BW United Kingdom [ADP Number 09973496001]
Applicant / Proprietor	BRIGHTSIGN TECHNOLOGY LIMITED 2104 Distillery Tower 1 Mill Lane London SE8 4HP United Kingdom [ADP Number 12616447001]
Inventors	HADEEL DIAAELDIN AYOUB, BRIGHTSIGN TECHNOLOGY LIMITED 2104 Distillery Tower 1 Mill Lane London SE8 4HP United Kingdom [ADP Number 12616454001] EDWARD RICHARD HILL Oakham House Tong Road Brenchley Tonbridge TN12 7HT United Kingdom [ADP Number 12616462001]

Appendix G

Supplementary Online Content

G.1 Videos

These links provide access to example video documentation for each of the case studies' glove prototype testing sessions, as well as a demonstration of the final commercial system:

- Pilot Study: Jeddah Autism Centre, Saudi Arabia, 2016 (Section 4.1)

  https://resources.brightsignglove.com/pilot_study

- Iterative Case Study A: IBM AI Hackathon, South Korea, 2016 (Section 4.2.4)

  https://resources.brightsignglove.com/ibm_study

- Iterative Case Study B: No Barriers Summit, USA, 2017 (Section 4.2.4)

  https://resources.brightsignglove.com/no_barriers_study

- Iterative Case Study C: CENMAC Conference, UK, 2018 (Section 4.2.4)

  https://resources.brightsignglove.com/cenmac_study

- Longitudinal Case Study: SEN School, UK, 2019 (Chapter 5)

  https://resources.brightsignglove.com/essex_study

- BrightSign Glove Promo Video, 2020 (Section 9.3)

  https://resources.brightsignglove.com/brightsign_demo

G.2 Participants Profiles and Surveys

This link provides access to participants' profiles and entry surveys filled out by parents and teachers for the 11 participants who took part in the longitudinal case study (Chapter 5):

https://resources.brightsignglove.com/study_surveys