Prototyping by Moving for Virtual Reality

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Figure 1: Examples of VR experiences created with InteractML. Clockwise from top left: (1) dancing influences the appearance of an abstract visual space. (2) hand gestures controlling particle systems (3) an interactive VR experience based on Bangladeshi street dance.

Abstract

Movement interaction is now placed firmly within contemporary digital culture and the creative domain, particularly performance, interactive and immersive media. However, though there has been considerable work on embodied ideation for movement interaction, implementation tools have lagged behind. We present a design methodology that incorporates a bespoke implementation toolkit (InteractML) with an embodied ideation methodogolody. The ideation methodology was developed specifically for creative practitioners in designing embodied interaction for immersive creative work, particularly in virtual reality.

Index Terms: Virtual Reality, Machine Learning, Movement Interaction, Prototyping

1 Introduction

Movement is a key part of interaction in Virtual Reality. Rather than interacting with a flat screen, virtual reality (VR) users step into an entire virtual world and the experience is most effective if users interact with their whole bodies, something that is reflected in the prevalence of motion controllers and hand and body tracking in VR systems. In Slater's [19] theory of presence, movement plays a central role in the experience of virtual reality. He introduce the concept of Place Illusion, the feeling of being in a virtual place different from the space you physically inhabit. This happens when the sensorimotor contigencies supported by a virtual reality device match those experienced in the real world. Sensorimotor contigencies[16] are the relationships between movement and sensory input that characterise human perception, for example how our field of view changes as we turn our head. Virtual Reality Head Mounted Displays are able to mimic this relationship between head turning and viewpoint, thus resulting in a strong sense of place illusion. Slater also introduces the concept of Plausibility Illusion, in which events happening in virtual reality feel real. This is in large part caused by events in the world responding to users' behaviour as they would in the real world. This implies that people should intearct with virtual reality in the same way as the real world: through they whole body movement.

For there to be good movement interaction for VR, designers have to be able to effectively design, prototype and test movement interaction. However, this challenges existing interaction design techniques based on 2D representations like sketching. In this paper we will describe how new design approaches centering the body are better suited to movement interaction design than traditional approaches. In addition we present our software platform InteractML

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which uses interactive machine learning to enable rapid prototyping of movement interaction for VR.

2 RELATED WORK

2.1 Embodied Design Approaches

As our interactions with technology feature more frequently and are further embedded in our daily lives, the requirement that these interactions provide enriching experiences has become the motivation behind recent user-centric human-computer interaction (HCI) design approaches [2]. Third wave HCI has seen the context to which technology is used in our lives expanded towards more cultural, personal, emotional and aesthetic domains. To address this shift, HCI approaches have turned to phenomenology, embodied cognition and affect research to better place interaction design in line with our everyday embodied experiences[10]. This viewpoint places emphasis on our bodily ways of experiencing and understanding the world, with a particular focus on how movement is central to our thinking and cognition [11].

Out of these embodied design paradigms techniques such as 'bodystorming' [17] or 'embodied sketching' [13] have been developed that have designers physically enact and explore their movement designs. By prototyping with the body, designers use physical activity to get an immediate sense of the tacit knowledge of how movements feel. By acting out the movements designers benefit from a first-person perspective on their designs. This allows a consideration the changing experience of movement over time and encourages cycles of refinement based on this experience [10]. Enactment in this way focuses the designer towards their own lived experience, invoking an awareness of the felt qualities of embodied experience [15]. Designing by moving can greatly improve the design of movement interaction through embodied knowledge. However, when it comes to creating working prototypes, standard tools do not support embodied approaches[8]. Implementing working prototypes means sitting at a desk and coding using a game engine or similar platform. What is needed is an approach that supports prototyping by moving.

2.2 Interactive Machine Learning

Human movement is complex and nuanced, and our knowledge of it is tacit and embodied. This makes it very difficult to implement movement interaction using traditional programming methods [8]. However, machine learning is a valuable approach because it makes it possible implement movement interaction techniques by supplying examples of movement, rather than by explicit programming. Machine learning is therefore often used for movement interaction [6, 7]. However, traditional approaches to machine learning do not support creative practitioners. They generally rely on machine learning engineers who have high levels of technical expertise, but are unlikely to be creative practitioners or experts in movement practice. It is also a batch process that relies on gathering large amounts of data ahead of training. This is not well suited to the more iterative, exploratory methods used by creatives and designers. As we have argued elsewhere [8] a more appropriate approach is Interactive Machine Learning.

Interactive machine learning (IML), a term originally coined by Fails and Olsen[5], centers on human interaction to improve supervised learning systems by allowing the user to use their expert knowledge to guide the learning process[1]. A significant advantage to IML is that it is meant to be easily used by non-machine learning experts. This is becoming increasingly important as machine learning techniques are being applied in a variety of research disciplines, such as HCI. IML centres on an interactive, iterative loop of training and testing. Users begin training by supplying a smaller number of examples to train an initial model which they can quickly test. This use of small training sets and rapid training is more suited to simpler algorithms such as k-nearest neighbours (kNN) than slow and data intensive deep learning methods (though IML can be used with transfer learning, for example training a kNN on the output of a deep learning feature extractor). Once an initial model has been trained, designers can rapidly test and iterate. They refine the model by adding (and sometimes removing) training data and re-testing. Fiebrink *et al.* [7] found that creative practitioners using IML tended to focus on curating smaller data sets, with a focus on example chosen to represent particular cases, rather than the type of large scale identically and independently distributed data samples used in traditional machine learning. Another difference is that creative designers work in an exploratory way. They do not start with a pre-defined concept that must be modelled accurately, but develop their ideas through interaction with sketches and prototypes[18, 4]. Their design evolves throughout the process of design resulting in the need to continuously evolve the concept being learned[7, 12]. The rapid, iterative approach of Interactive Machine Learning makes this possible by allowing creatives to rapidly test prototype models without the outlay and commitment required to gather large datasets.

3 PROTOTYPING

We propose a new design methodology for movement interaction in virtual reality that places movement at both the design and implementation process using interactive machine learning. Inspired by the 'designing by doing and moving' ideation methodologies advocated by research as outlined in section 2.1 as a starting point, we aimed to offer a design methodology that retains all the benefits of design by moving approaches, but extending the design process to allow creators to immediately reflect on the pairing between their embodied interaction designs and how their system's respond to them by incorporating a demonstration based implementation tool-InteractML[9]. Interactive machine learning allows creators to prototype movement interactions by performing examples of movements i.e. prototyping by moving. Not only this, it supports an iterative process in which designers can gradually refine interaction prototypes through testing and providing more examples, and via full body movement.

3.1 InteractML

InteractML is a plugin to the Unity game engine, built on the RAPID-MIX API [3] that enables developers to interactively train machine learning models within the Unity Editor. It is the software platform that underlies our prototyping by moving aporach. The following sextions will describe the steps in using InteractML.

3.1.1 Model Definition

InteractML uses a node-based scripting interface for setting up the learning model (Figure 2). This represents the model as a graph whose nodes are the different stages of the learning model. Users can add inputs to the system from the game engine. In most cases these will be Game Objects which include transforms having position and orientation. This works well as most standard VR tracking devices (including the head and hand trackers included with Head Mounted Displays) are represented in the engine as Game Objects. It is, however, possible to import other inputs, for example our residency participant, Bushra Burge, used specially designed, Arduino-based input devices and was able to add them to InteractML.

The next stage is feature extraction (the term stages refers to the stages of the learning process, participants could build the graph in any order). Features are the numerical representation of the inputs that are used as input to the machine learning model. The choice of features is well known as a challenge within IML[14]. Features can be directly taken from the input, such as the position or rotation of the game object, or derived features that are calculated from these basic inputs such as the velocity (rate of change) or a feature or the difference between two features (e.g. the distance between two

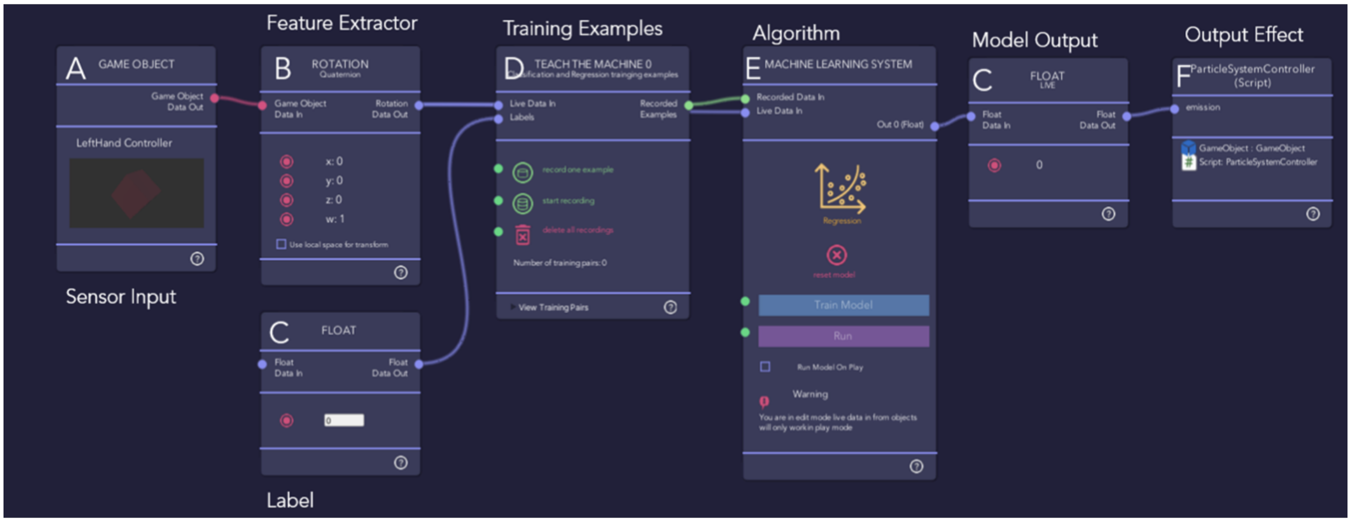

Figure 2: The InteractML node based scripting interface.

objects). These feature extractors can be chained together using the node based interface to calculate more complex features (e.g. the difference between the rotational velocities of two objects).

The next step is to select a machine learning algorithm to use. In this study the options were:

- **Classification:** a k-nearest neighbour algorithms is used to classify inputs into a set of discrete outputs.
- **Regression** maps inputs to continuous outputs using a Neural Network (Multi-layer Perceptron).
- **Dynamic Time Warp:** an algorithm that classifies sequences of data as they change over time, rather than single frames of data. This was particularly suited to complex gestures.

The final stage is using the outputs of the model within the game engine. The outputs can be exposed as variables within the game engine or can be piped to scripts which can interface them to other game actions. This allows for great flexibility this allows the full feature set of the game engine to be used on the resulting outputs.

3.1.2 Interactive Training

Once the model has been set up, participants can train the model. This is an iterative process consisting of adding data by performing movements, training the model and then testing it, again by performing movements and observing the outputs.

Participants record data by selecting "training" mode and performing a number of examples of the movement in VR. They can select the "train" button which runs the learning algorithm. Once this is done they can switch to "run" mode which performs inference on new inputs and generates outputs. This allows them to test the model in real time. This is done in an embodied way by performing movements an observing whether the the outputs are correct. If the result is not what the participant was intending, they can further refine the model by adding new training data (or possibly adjusting the graph). There is a VR interface which allows participants to perform all stages of training (with the exception of editing the graph) within VR, to allow them to have a seamless training workflow. It is also possibly to do the training with two people: one person performs the movement in VR while the other controls the learning process via the desktop interface.

3.2 User Studies

We performed a series of long term user studies in which participants used InteractML and our methodology over a time period of hours, days or weeks. These included a number of multi-day hackathons and three residencies in which participants used InteractML over a period of 6 weeks to create an immerisve art work. Figure 1 shows some examples of work produced by our participants, many of which would have been difficult or impossible to prototyping using pure code or standard methods such as colliders.

Participants appreciated the design by moving approach, particularly those with a dance background. They felt that it would not have been possible to design movements effectively through coding *"for artists who work in movement in it will never work to just code it you need to understand that by actually doing"*. The tools also enabled an exploratory, iterative workflow that fitted well with creative work. A full analysis of these studies will be published in future.

4 Conclusion

This paper has argued that current techniques are not sufficient for prototyping movement interaction in VR. We have instead, proposed an approach based on interactive machine learning, and described a tool, called InteractML, which enables prototyping by moving using machine learning. This tool has been used in a number of creative projects and has shown potential to enable types of movement that would have been difficult to prototype in other ways. We hope that this will lead a greater interest in prototyping movement interaction and therefore a greater range of more creative approaches to movement in VR.

Acknowledgments

This research was partially supported by the UK Engineering and Physical Sciences Research Council grant "4i: Immersive Interaction Design for Indie Developers with Interactive Machine Learning" (EP/S02753X/1).

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