Multiuser Museum Interactives for Shared Cultural Experiences: an Agent-based Approach

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ABSTRACT

Multiuser museum interactives are computer systems installed in museums or galleries which allow several visitors to interact together with digital representations of artefacts and information from the museum's collection. WeCurate is such a system, providing a multiuser curation workflow where the aim is for the users to synchronously view and discuss a selection of images, finally choosing a subset of these images that the group would like to add to their group collection. The system presents two main problems: workflow control and group decision making. An Electronic Institution (EI) is used to model the workflow into scenes, where users engage in specific activities in specific scenes. A multiagent system is used to support group decision making, representing the actions of the users within the EI, where the agents advocate and support the desires of their users e.g. aggregating opinions, proposing interactions and resolutions between disagreeing group members and choosing images for discussion.

Categories and Subject Descriptors

I.2 [**Artificial Intelligence**]: Distibuted Artificial Intelligence—*Intelligent agents, Multiagent systems*

General Terms

Algorithms, Experimentation

Keywords

Multiagent system, Collective decision making

1. INTRODUCTION

In recent times, high tech museum interactives have become ubiquitous in major institutions. Typical examples include augmented reality systems, multitouch table tops and

virtual reality tours [9, 12, 21]. Whilst multiuser systems have begun to appear, e.g. a 10 user quiz game in the Tate Modern, the majority of these museum interactives do not perhaps facilitate the sociocultural experience of visiting a museum with friends, often being designed for a single user. At this point, we should note that mediating and reporting the actions of several 'agents' to provide a meaningful and satisfying sociocultural experience for all is challenging, requiring multiple criteria decision making. Another trend in museum curation is the idea of community curation, where a community discourse is built up around the artefacts, to provide different perspectives and insights [20].[1] This trend is not typically represented in the design of museum interactives, where information-*browsing*, not information-*generation* is the focus. However, museums are engaging with the idea of crowdsourcing with projects such as 'Your Paintings Tagger' and 'The Art Of Video Games' [10, 4]. Again, controlling the workflow within a group to engender discussion and engagement with the artefacts is challenging, especially when the users are casual ones as in a museum context.

In this paper we propose a first of its kind multiuser museum interactive which uses a multiagent system to support community interactions and decision making and an electronic institution to model the workflow. Our aim is not only to make use of agent technology and electronic institutions as a means to implement a multiuser museum interactive, but also to relate agent theory to practice in order to create a usable system that will help us to answer the following research questions. Do agent technology and electronic institutions enable users to share online experiences in a way that was not possible before? Are decision making capabilities and aggregation operators defined in the literature suitable for enhancing the experience of users?

To this end, we specify a community curation session in terms of the scenes of an electronic institution for controlling community interactions. We support system's and users' decisions by means of personal assistant agents equipped with different decision making capabilities. We make use of a

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[1]Edmond de Goncourt's opinion that 'A painting in a museum hears more ridiculous opinions than anything else in the world' not withstanding.

multimodal user interface which directly represents users as agents in the scenes of an underlying electronic institution and which is designed to engage casual users in a social discourse around museum artefacts. We describe a method for evaluating such systems which combines data driven analysis with user feedback.

The system described here is an improvement of a previous version trialled in May 2012. This second version is due to be installed for two weeks at a major London museum in November 2012 with the plan of creating a permanent exhibit and then moving the technology onto other museums.

The paper is organised as follows. Section 2 presents several works that relate to ours from different perspectives. Section 3 describes the WeCurate workflow and the underlying system. Section 4 discusses some preliminary results we obtained in the trials of a previous version of the system and outlines the evaluation scheme we aim to use to validate the current version. Finally, Section 5 draws some conclusions and envisions some of the ideas we have in mind to improve the current system.

2. RELATED WORK

Many systems exist that enable realtime personalised experience and multiuser collaboration in virtual workspaces, both in industry and in academia. In industry, web conferencing software such as Adobe Connect allows complex media and text driven interactions; shared document editors such as Google Drive enable co-editing of office-type documents. However, the user interfaces are perhaps too complex for a casual user in a museum and it is not possible to enforce specific workflows with specific goals with these systems as required by our group curation scenario. Further, agreement technologies such as group decision making are not explicitly supported, e.g. consider the scenario where users are co-editing a presentation using Google Drive and they need to select an appropriate image.

In academia, enhancing the users' experience in museums has already been addressed in different ways. For instance, in the PEACH project, researchers focused on the creation of online personalised presentations to be delivered to the visitors for improving their satisfaction and personalised visit summary reports of suggestions for future visits [13]. Their focus was mainly the modeling of preferences of single users but the importance of social interactions in visiting a museum was investigated in the PIL project, an extension of the research results of the PEACH project, and in the ARCHIE project [14, 15]. ARCHIE aimed to provide a more socially-aware experience to users visiting a museum by allowing visitors to interact with other visitors by means of their mobile guides. User profiles were used to tailor the information to the needs and interests of each individual user and, as such, no group decision making was necessary. A cultural heritage application was proposed in [6] where agents are able to discover users' movements via a satellite, to learn and to adapt user profiles to assist users during their visits in Villa Adriana, an archaeological site in Tivoli, Italy.

On the other hand, in a system aiming to create a multiuser museum interactive, it is not only important to model users (by means of agents) and their preferences but also to assist them in taking decisions. For example, the system could decide which artefact is worthy to be considered by merging users' preferences [23]; or it could decide whether the artefact is collectively accepted by a group of users by considering users' valuations about certain criteria of the artefact itself like in multiple criteria decision making [17]; or assist users in reaching agreements by arguments' exchange like in argument-based negotiation [1]. These cases, that correspond to different decision making problems can be solved by defining different decision principles which take the preferences of the single users into account and compute the decision of the group as a whole. One way to define a decision principle is by means of an aggregation operator. Several operators for aggregating data have been proposed in the literature [3, 22, 19].

In [3], a bipolar fusion operator for merging users' preferences has been studied in the possibilistic logic setting. According to this approach, the problem of deciding what is collectively accepted can be handled by means of an aggregation function on the whole set of positive and negative preferences (represented in terms of possibility distributions) of a group of agents. The Ordered Weighted Average (OWA) operator [22] allows to weight values in relation to their ordering. In this way, a system can give more importance to a subset of the input values than to another subset, e.g. extreme values versus central ones. A generalisation of both the weighted mean and the OWA operator is the Weighted Ordered Weighted Average (WOWA) operator [19]. WOWA allows the system to weight the importance of a value (as in the weighted mean), and the values in relation to their relative position (as in the OWA operator). The choice of the operator to be used usually depends on the type of experience the system aims to provide to its users.

A multiuser interactive is a typical example of a system in which users (and thus their respective agents) can enter and leave the system and they behave according to *norms* that are appropriate for that specific society. A convenient way to model social interactions and their norms is by means of an Electronic Institution (EI) [2].

An EI makes it possible to develop programs according to a new paradigm, in which the tasks are executed by independent agents, that are not necessarily designed specifically for the given program and that cannot be blindly trusted. An EI is responsible for making sure that the agents behave according to the *norms* that are necessary for the application. Therefore, the EI paradigm allows a flexible and dynamic infrastructure, in which agents can interact in an autonomous way within the norms of the cultural institution.

EIs have usually been considered as centralised systems [16, 8, 7]. Nevertheless, since users can be physically in different places, it is desirable to run an EI in a distributed manner to enable a flexible and dynamic structure, which is characteristic to human social communities.

3. IMPLEMENTATION

WeCurate is a museum interactive which provides a multiuser curation workflow where the aim is for the users to synchronously view and discuss a selection of images, finally choosing a subset of these images that the group would like to add to their group collection. In the process of curating this collection, the users are encouraged to develop a discourse about the images in the form of weighted tags and comments as well as a process of bilateral argumentation. Further insight into user preferences and goals is gained from data about specific user actions such as image zooming and general activity levels. The activity has been defined as an electronic institution, with agents operating
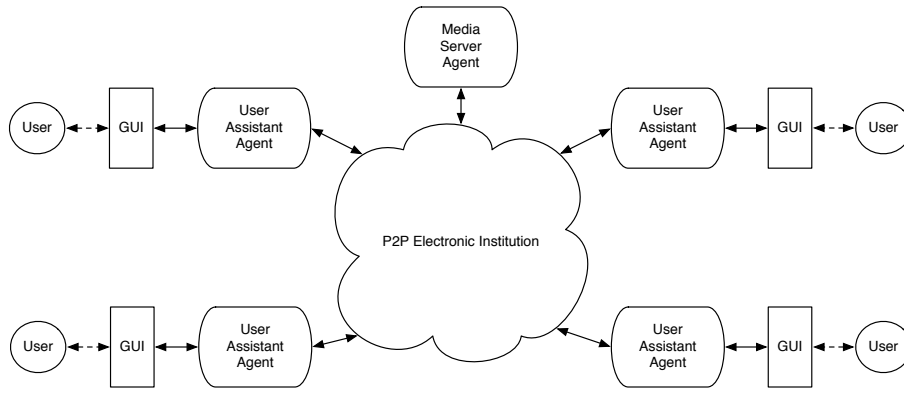
Figure 1: The WeCurate system architecture, here showing 4 simultaneous users.

within it to represent the activities of the users and to provide other services. The users interact with the system using an animated user interface. An overview of the system architecture, showing the electronic institution, agent and user interface components is provided in figure 1.

In the following sections, we deal first with the way we have modelled the WeCurate workflow using an electronic institution. Then we describe the agents that enact the workflow, with particular emphasis on user representation and group decision making. The user interface is presented, with images of the different scenes in the workflow. The system architecture is described, including the connections between EI, agents and UI. Finally, the adopted technologies used to implement the system are briefly explained.

3.1 WeCurate workflow

The WeCurate workflow is defined as an EI consisting of 5 scenes, with associated rules controlling messaging and transitions between scenes. An overview of the workflow is provided in figure 2. The scenes are as follows:

- **Login and lobby scene**: this allows users to login and wait for other users to join. The EI can be configured to require a certain number of users to login before transition to the selection scene can take place.

- **Selection scene**: its purpose is to allow a quick decision as to whether an image is interesting enough for a full discussion. Users can *zoom* into the image and see the zooming actions of other users. They can also set their *overall preference* for the image using a like/dislike slider. The UI is shown in figure 3a.

- **Forum scene**: if an image is deemed interesting enough, the users are taken to the forum scene where they can engage in a full *discussion* of the image. Users can add and delete tags, they can resize tags to define their opinions of that aspect of the image, they can make comments, they can zoom into the image and they can see the actions of the other users. They can also view images that were previously added to the collection and choose to argue with another user directly. The aim is to collect community information about the image. The UI is shown in figure 3b.

- **Argue scene**: here, two users can engage in a process of *bilateral argumentation*, wherein they can propose

aspects of the image which they like or dislike, in the form of tags. The aim is to convince the other user to align their opinions with yours, in terms of tag sizes. For example, one user might like the 'black and white' aspect of an image, whereas the other user dislikes it; one user can then pass this tag to the other user to request that they resize it. The UI is shown in figure 3c.

- **Vote scene**: here, the decision is made to add an image to the group collection or not by *vote*. The UI is shown in figure 3d.

3.2 Institutional and other agents

This electronic institution itself is executed by several institutional agents, including a *SceneManager* which runs the scene instances, an *EIManager* which admits agents to the EI and instantiates scenes and several *Governors* which control message passing between agents. This first non-institutional agent is the *MediaAgent*, which provides access to the media archive. The users are represented by *UserAssistant* agents. Each time a new user joins a curation session, a new UserAssistant is enrolled into the EI. The actions of the users are passed down to their representative agents which then send messages to each other via the EI. An agent's Governor will check if a given message can be sent, based on the state of the current scene and the role of the sender. The state of a scene might change as a result of a message being sent. For example, a user clicking on the 'go to forum' button in the selection scene will generate a message which will trigger a count down timer at the Scene-Manager level, giving the other users a limited time in which to complete their examination of the image before a scene transition occurs. Other messages might not affect the state of the scene, but instead will provide information to other agents about the actions of a user, e.g. zooming into an image or changing a tag preference. This information might be used later on to make decisions, for example.

In the following section, the decision making criteria used in the WeCurate workflow are described.

3.3 Agent supported decision making

The UserAssistant agents are involved in several automatic decisions and calculations. These are described in the following subsections.
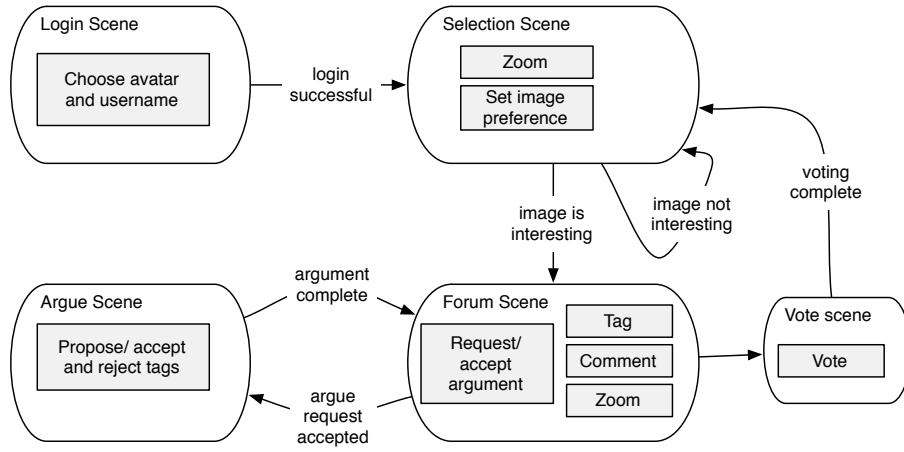
Figure 2: The WeCurate workflow: white boxes represent scenes, grey boxes represent users' actions, and arrows denote scenes' transitions.

3.3.1   Selection scene

In the selection scene, if the image is deemed sufficiently interesting, the agents (and therefore their users) are taken to the forum scene. *Image interestingness* of an image takes the image preferences of all the users into account and it is computed in different ways.

Image interestingness based on average.

The *image preference* of a user is a value belonging to a finite bipolar scale $\mathcal{S} = [-1, -0.9, \ldots, +0.9, +1]$ where -1 stands for "discard" and $+1$ stands for "keep". Given a group of users $\{u_1, u_2, \ldots, u_n\}$, let us denote the image preference of a user u_i w.r.t an image im by $r_i(im) = v_i$ with $v_i \in \mathcal{S}$.

Each UserAssistant agent also stores the zoom activity of its user. Clearly, the zoom activity is a measure of the user's interest in a given image and, as such, it should be taken into account in the calculation of the image interestingness. Let us denote the number of *image's zooms* of user u_i w.r.t. an image im as $z_i(im)$. Then, we can define the total number of zooms for an image im as $z(im) = \sum_{1 \leq i \leq n} z_i(im)$. Based on $z(im)$ and the z_i's associated with each user, we can define a weight for the image preference r_i of user u_i as $w_i = z_i/z(im)$.

The *image interestingness* of n users w.r.t an image im, denoted by $\overline{r(im)}$, can be defined as:

$$\overline{r(im)} = \frac{\sum_{1 \leq i \leq n} r_i w_i}{\sum_{1 \leq i \leq n} w_i} \qquad (1)$$

Then, a decision criterion for the interestingness of an image im is defined as follows:

$$\mathtt{int}(im) = \begin{cases} 1, & \text{if } 0 \leq \overline{r(im)} \leq 1 \\ 0, & \text{if } -1 \leq \overline{r(im)} < 0 \end{cases} \qquad (2)$$

Therefore, the system proceeds with a forum scene when $\mathtt{int}(im) = 1$, while the system goes back to a select scene when $\mathtt{int}(im) = 0$.

Image interestingness based on WOWA operator.

An alternative criterion for deciding whether an image is interesting or not can be defined by using a richer aver-

age operator such the Weighted Ordered Weighted Average (WOWA) operator [19].

The WOWA operator is an aggregation operator which allows to combine some values according to two types of weights: i) a weight referring to the importance of a value itself (as in the weighted mean), and ii) an ordering weight referring to the values' order. Indeed, WOWA generalizes both the weighted average and the ordered weighted average [22]. Formally, WOWA is defined as [19]:

$$f_{wowa}(r_1, \ldots, r_n) = \sum_{1 \leq i \leq n} \omega_i r_{\sigma(i)} \qquad (3)$$

where $\sigma(i)$ is a permutation of $\{1, \ldots, n\}$ such that $r_{\sigma(i-1)} \geq r_{\sigma(i)} \ \forall i = 2, \ldots, n$, ω_i is calculated by means of an increasing monotone function $w^*(\sum_{i \leq i} p_{\sigma(j)}) - w^*(\sum_{j < i} p_{\sigma(j)})$, and $p_i, w_i \in [0, 1]$ are the weights and the ordering weights associated with the values respectively (with the constraints $\sum_{1 \leq i \leq n} p_i = 1$ and $\sum_{1 \leq i \leq n} w_i = 1$).

We use the WOWA operator for deciding whether an image is interesting in the following way. Let us take the weight p_i for the image preference r_i of user u_i as the percentage of zooms made by the user (like above). As far as the ordering weights are concerned, we can decide to give more importance to image preference's values closer to extreme value such as -1 and $+1$, since it is likely that such values can trigger more discussions among the users rather than image preference' values which are close to 0. Let us denote the sum of the values in $\mathcal{S}$ as s. Then, for each image preference $r_i(im) = v_i$ we can define an ordering weight as $w_i = r_i(im)/s$. Please notice how the p_i's and w_i's defined satisfy the constraints $\sum_{1 \leq i \leq n} p_i = 1$ and $\sum_{1 \leq i \leq n} w_i = 1$.

Then, a decision criterion for the interestingness of an image im based on $f_{wowa}(r_1, \ldots, r_n)$ can be defined as:

$$\mathtt{int}_{\mathtt{wowa}}(im) = \begin{cases} 1, & \text{if } 0 \leq f_{wowa}(r_1, \ldots, r_n) \leq 1 \\ 0, & \text{if } -1 \leq f_{wowa}(r_1, \ldots, r_n) < 0 \end{cases} \qquad (4)$$

3.3.2   Forum Scene

The main goal of the users in a forum scene is to discuss an image, which has been considered interesting enough in

a select scene, by pointing out what they like or dislike of the image through tags. During the tagging, the *overall image preference per user* is automatically updated. Whilst tagging is the main activity of this scene, a user can also choose to argue with another user in order to persuade him to adopt his own view (i.e. to "keep" or to "discard" the image). In such a case, a list of *recommended argue candidates* is retrieved. Finally, when a user is tired of tagging, he can propose the other users to move to a vote scene. In this case, an automatic *multi-criteria decision* is taken in order to decide whether the current image can be added or not to the image collection without a vote being necessary.

Overall image preference per user.

In order to update the overall image preference of a user *user* in an automatic way, all the tags which the user has been specifying w.r.t. an image must be taken into account. An *image's tag* (or image's argument) t for an image im is represented as $(\langle id, v, w \rangle, im)$ where id identifies a certain feature of the image, such as "blue", "sea" etc., $v \in \mathcal{S}$ is the tag's value and $w \in \{0, 0.1, \ldots, 0.9, 1\}$ is the tag's importance.

Let $\mathcal{T}_{im}^i = \{t_1, t_2, \ldots, t_m\}$ be the set of image's tags specified by a user u_i w.r.t. an image im. Then, the *aggregate* or *overall image preference* of a user u_i given $\mathcal{T}_{im}^i$ denoted by $r_i^*(im)$ is defined as:

$$r_i^*(im) = \frac{\sum_{1 \leq j \leq m} v_j w_j}{\sum_{1 \leq j \leq m} w_j} \qquad (5)$$

When a user rates the image im by specifying of a new tag or by updating a tag already specified, his overall image preference is automatically updated by computing $r_i^*(im)$.

Argue Candidate Recommender.

In order to recommend an ordered list of argue candidates to a user willing to argue, the distance between the overall image preferences per user (Eq.5) can be taken into account.

Let u_i be a user willing to argue and $r_i^*(im)$ be his overall image preference. Then, for each u_j (such that $j \neq i$) we can define the *image preference distance* of user u_j w.r.t. user u_i, denoted by $\delta_{ji}(im)$, as:

$$\delta_{ji}(im) = \{\texttt{abs}(r_j^*(im) - r_i^*(im)) | (r_j^*(im) < 0 \wedge r_i^*(im) \geq 0) \\ \vee (r_j^*(im) \geq 0 \wedge r_i^*(im) < 0)\} \quad (6)$$

Then, an argue candidate for user u_i for an image im is $cand_i(im) = \{u_j \mid \max\{\delta_{ji}(im)\}\}$. The ordered list of argue candidates can be defined by ordering the $\delta_{ji}(im)$'s.

Multi-criteria decision.

When users in a forum scene decide to move to a vote scene, first, an automatic decision process to decide whether the image can be added or not to the image collection is run. The problem of deciding whether to add the image is a *multi-criteria decision problem* in which different users can have different criteria (their image's tags). The main idea behind this decision step is to first obtain the overall image preference of each user, and, then, to take the image's preferences into account in order to define a decision criterion.

The overall image preference of each user can be computed according to Eq.5. Then, a decision criterion for deciding whether to add an image im or not to the image collection

can be defined as:

$$\texttt{add}(im) = \begin{cases} 1, & \text{if } \forall u_i, 0 \leq r_i^*(im) \leq 1 \\ 0, & \text{if } \forall u_i, -1 \leq r_i^*(im) < 0 \\ undefined, & \text{otherwise} \end{cases} \qquad (7)$$

Therefore, an image im is automatically added to the image collection if it has been unanimously accepted by the users. On the contrary, the image is discarded if it has been unanimously rejected. Finally, if $\texttt{add}(im) = undefined$, then the system is unable to decide and the final decision is taken by the users in a vote scene.

3.3.3 Argue Scene

The main goal of two users running in an argue scene is to try to reach an agreement about to "keep" or to "discard" an image im by exchanging image's tags (image's arguments). The argue scene defines a bilateral argumentation protocol. The formal protocol was presented in [1] and it works as follows:

- the two users tag the image im by means of image's tags (like in the forum scene), but, they can also propose their image's tags to the other user:
  - while tagging, their overall image preferences are automatically updated;
- a user proposes an image's tag to the other user who can either accept or reject it:
  - if the user accepts the image's tag proposed, then their overall image preferences are automatically updated:
    * if an *argue agreement* is reached, then the argue scene stops,
    * otherwise, the argue scene keeps on;
  - if the user rejects the image's tag proposed, then the argue scene keeps on;

Both users can also decide to leave the argue scene spontaneously.

Overall image preference per user.

The overall image preference of a user in an argue scene is automatically updated by computing $r^*(im)$ (see subsection 3.3.2).

Argue Agreement.

Informally, an *argue agreement* is reached when the image preferences of the two users agree towards "keep" or "discard". Let $r_i^*(im)$ and $r_j^*(im)$ be the image's preferences of user u_i and u_j respectively. Then, a decision criterion for deciding whether an argue agreement is reached can be defined as:

$$\texttt{argue}(im) = \begin{cases} 1, & \text{if } (0 \leq r_i^*(im) \leq 1 \wedge 0 \leq r_j^*(im) \leq 1) \vee \\ & (-1 \leq r_i^*(im) < 0 \wedge -1 \leq r_j^*(im) < 0) \\ 0, & \text{otherwise} \end{cases}$$

$$(8)$$

Therefore, an argue scene stops when $\texttt{argue}(im) = 1$. Instead, while $\texttt{argue}(im) = 0$, the argue scene keeps on until either $\texttt{argue}(im) = 1$ or the two users decide to stop arguing.

3.3.4 Vote Scene

The main goal of the users running in a vote scene is to decide by vote to add or not an image to the image collection. This decision step occurs when the automatic decision process at the end of the forum scene is unable to make a decision.

In a vote scene, each user's vote can be "yes", "no", or "abstain" (in case that no vote is provided). Let $v_i \in \{+1, 0, -1\}$ be the vote of user u_i where $+1 =$ "yes", $-1 =$ "no", and $0 =$ "abstain" and let $\mathcal{V} = \{v_1, v_2, \ldots, v_n\}$ be the set of votes of the users in a vote scene. Then, a decision criterion for adding an image or not based on *vote counting* can be defined as:

$$\texttt{vote}(im) = \begin{cases} 1, & \text{if } \sum_{1 \leq i \leq n} v_i \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

Therefore, an image im is added to the image collection if the number of "yes" is greater or equals than the number of "no". In the above criterion, a neutral situation is considered as a positive vote.[2]

3.4 User interface

The user interface provides a distinct screen for each scene, as illustrated in figures 3a, 3b, 3c and 3d. It communicates with the UserAssistant agent by sending a variety of user triggered events which are different in each scene. The available user actions in each scene are shown in figure 1. The state of the interface is completely controlled by the UserAssistant agents, which send scene snapshots to the interface whenever necessary, e.g. when a new tag is created. Some low level details of the method of data exchange between interface and agents are provided in the adopted technologies section below (3.5).

The interface is the second iteration of a shared image browsing interface, designed to include desirable features highlighted by a user trial of the first iteration [11]. Desirable features include standard usability such as reliability, speed and efficiency etc., awareness of the social presence of other users and awareness of the underlying workflow. Given the social nature of the system, social presence, where users are aware of each others' presence and actions as well as a shared purpose and shared synchronicity is of especial interest. The detailed concepts behind the design are beyond the scope of this paper and will be reported elsewhere.

3.5 Adopted technologies

The physical museum installation includes 4 iPads allowing 4 simultaneous users to use the system. There is a large panel displaying a summary of what is going on or information about the exhibit, during inactive periods. A local network connects the iPads to a local server, which executes the agents and EI, as well as driving the information screen. The institutional and other agents are implemented as independent Java programs and they discover and communicate with each other and the components of the EI using a FreePastry P2P network[18]. This means the agents and EI system can be run in a distributed fashion if necessary. The user interface is implemented using Javascript drawing to an HTML5 canvas element, which is a cross platform and plug-in free solution. The downside is that the interface cannot

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[2]This assumption is made to avoid an *undecided* outcome in this decision step.

communicate directly with the agents since it is not a part of the FreePastry network. Instead, the interface sends events formatted as JSON to a queue stored on an HTTP server. The agents poll the server and pick up the event queue, then in turn generate scene snapshots in JSON format which are sent to the HTTP server. The interface polls the HTTP server for the latest snapshot, which is then used to define the state of the interface.

One advantage of this queued event and snapshot model with regard to evaluation is that all interface events and interface state snapshots are stored on the server for later inspection. This allows a complete, interactive reconstruction of activity of the users and the agents for qualitative analysis as well as providing a lot of data for quantitative analysis. The evaluation scheme section (4) describes how this data will be used.

4. PREVIOUS EVALUATION

In the evaluation of a previous version of the system [23], the user interface (UI) is tasked with establishing the users' awareness of the shared experience, including the presence and actions of other members of the community and the state and norms of the shared environment. The evaluation focused on measuring the effectiveness of the prototypical UI in these regards and the eliciting of user feedback as to how future interfaces might better deliver an engaging, shared experience. To this end, 4 pairs of friends were asked to conduct two tasks. They first had to collaboratively sort a set of printed photos into like and dislike piles. Then they were asked to use the first version of our system for 20 minutes. Finally, they were interviewed in a loosely structured way, focusing on: i) Brief explanation and comparison of current practices of sharing image with friends online, ii) Use, conceptual understanding and opinion of our system, and iii) Ideas for expansion of features, functionality and visualisation of the system's and user's actions.

They were filmed during the activities and their interactions with the system was recorded in timestamped logs. Data was gathered and cross referenced from adhoc observation of the trials themselves, inspection of the video footage, transcription of the interviews and the UI log files. Analysis of the data focused on users' engagement with the community browsing task, their awareness of the nature and activity of the system, the social dynamic and practices and their awareness of the social presence of the other user and of a shared conceptual space. In the following section, each of the 3 foci listed above will be addressed in turn.

4.1 Results

Engagement with the task: The users enjoyed the curation experience, and none of them found a 20 minute session to be too long. They were not happy with non-editable tags as a means of expressing opinions about the image. Some would be interested to try the system with a stranger, as it was an interesting way to find out about someone.

System awareness: Users were aware of the similarity of images as an online image recommender was used to select images that matched the tag preferences of two users, but this did not necessarily enhance the browsing experience. In fact, one user actively chose tags to thwart the converging effect. They seemed aware of the simple norms of the EI and had no problem interacting in the correct way.

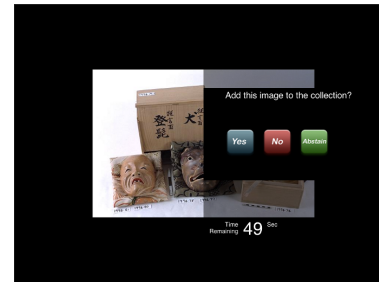*Social dynamic and social presence*: Users talked constantly

(a) The selection scene for rapid selection of interesting images

(b) The forum scene for in-depth discussion

(c) The argue scene for bilateral argumentation

(d) The vote scene for deciding to add images to the group collection

Figure 3: The WeCurate user interface. Bubbles represent tags and are resizable and movable; icons visible on sliders and images represent users.

during the paper based exercise, but communication became sparse, with only very terse and efficient conversation during the session. This suggests the system-mediated, shared experience was quickly assimilated into the social interaction. As for the tagging actions of the other user, they reported that their awareness of this abated over time. A low correlation was observed between tag actions, i.e. one user liking a editing tag preferences resulted in another user editing their preference for the same tag immediately afterwards.

4.2 Evaluation Scheme

The current system will be trialled with members of the public in situ in a major London museum which receives around 3.000 visitors on a busy day. It is anticipated that at least 100 curation sessions will be logged in the system during the 2 week trial period. The evaluation will be based on 3 types of data: direct observations of people using the system, logged activity data and a survey tool with open and closed questions. The observational data will be coded using a grounded theory approach where a code schema emerges from behaviours and opinions as opposed to being pre-ordained [5]. The logged activity data will be used in support of the observations but will also provide a numerical method of assessing the success of different types of agent decision models. For example the image interestingness measures will be compared by calculating the correlation between the interestingness and the level of activity in the subsequent forum scene; i.e. do images selected by the WOWA operator receive greater activity that those selected by the simple average? By trying different decision models and algorithms on different days, it will be possible to assess their success or otherwise. Interactional patterns will also be extracted from the numerical data, e.g. is creation of a new tag followed by its modification by other users?

The survey tool will allow assessment of usability and self reported measures of social presence and other aspects of the experience.

5. CONCLUSION AND FUTURE WORK

A first of its kind multiuser museum interactive which uses a multiagent system to support community interactions and decision making and an Electronic Institution (EI) to model the workflow has been described. Its multimodal user interface which directly represents the scenes in an underlying EI and which is designed to engage casual users in a social discourse around museum artefacts has also been described. An evaluation scheme has been proposed, which will assess the success of the system as a museum interactive as well as the finer grained goals of trialling various group decision making algorithms and engaging users in a social, cultural discourse.

This line of research looks promising. Previous results have shown that the use of agent technology and EIs can enhance users' social dynamics and users' social presence. On one hand, EIs can facilitate the regulation of the behavior of autonomous agents and can capture the social structures of community curation. On the other hand, agents technology can be employed to enhance the social experience of users. Further results of our new evaluation scheme will help us to better understand whether agent technology and electronic institutions enable users to share online experiences in a way that was not possible before.

In terms of future work, the analysis of the data from the museum user trial will be the next major undertaking. Based on those results, the design of the system at all levels will undergo a further iteration, with an aim to improving users' social engagement and the efficacy of the agent ar-

chitecture in supporting the curation task. We also wish to revisit an idea that was in our earlier prototype [23], where an online image recommender was used to select images that matched the tag preferences of two users. The idea of recommending images in this way was rejected for the WeCurate system after several users reported frustration at receiving a series of similar images. A smarter method would be to extract a representation of images based on their potential for discussion by the group, as opposed to a simplistic, tag based metric. For example, which parts of the images were users zooming into? Which types of image engendered the most active discussion? Beyond that, the technology has been designed to easily transfer to a web or mobile app, and the distributed agent execution model is designed to scale; and we see great potential in the concept of agent supported, workflow driven, synchronous image discussion and curation taken to the mass audience on the open web.

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7. REFERENCES

[1] L. Amgoud, R. Confalonieri, D. D. Jonge, M. d'Inverno, K. Hazelden, N. Osman, H. Prade, C. Sierra, and M. Yee-King. Sharing Online Cultural Experiences: An Argument-Based Approach. In V. Torra, *et. al.*, editors, *Modeling Decisions for Artificial Intelligence - 9th Int. Conf., MDAI 2012*, vol. 7647 of *LNCS*, pages 282–293. Springer, 2012.

[2] J. L. Arcos, M. Esteva, P. Noriega, J. A. Rodríguez-Aguilar, and C. Sierra. Engineering open environments with electronic institutions. *Eng. Applications of Art. Int.*, 18(2):191–204, 2005.

[3] S. Benferhat, D. Dubois, S. Kaci, and H. Prade. Bipolar possibility theory in preference modeling: Representation, fusion and optimal solutions. *Information Fusion*, 7(1):135–150, 2006.

[4] C. Barron, The Washington Post. The Art of Video Games, Apr. 2012.

[5] K. Charmaz. *Constructing grounded theory: A practical guide through qualitative analysis*. Sage Publications Limited, 2006.

[6] S. Costantini, L. Mostarda, A. Tocchio, and P. Tsintza. DALICA: Agent-Based Ambient Intelligence for Cultural-Heritage Scenarios. *IEEE Intelligent Systems*, 23(2):34–41, Mar. 2008.

[7] M. d'Inverno, M. Luck, P. Noriega, J. A. Rodríguez-Aguilar, and C. Sierra. Communicating open systems. *Artificial Intelligence*, 186:38–94, 2012.

[8] M. Esteva. *Electronic Institutions: From Specification to Development*. PhD thesis, Technical University of Catalonia, 2003.

[9] A. Gaitatzes and M. Roussou. Reviving the past : Cultural Heritage meets. In *Proc. of the 2001 conference on Virtual reality, archeology, and cultural heritage*, pages 103–110, 2002.

[10] A. Greg. Your paintings: public access and public tagging. *Journal of the Scottish Society for Art History*, 16, 2011.

[11] K. Hazelden, M. Yee-King, L. Amgoud, M. d'Inverno, C. Sierra, N. Osman, R. Confalonieri, and D. D. Jonge. WeCurate: Designing For Synchronised Browsing And Social Negotiation. In S. Ossowski, F. Toni, and G. A. Vouros, editors, *Proc. of the 1st Int. Conf. on Agreement Technologies, AT 2012*, volume 918 of *CEUR Workshop Proceedings*, pages 168–179. CEUR-WS.org, 2012.

[12] E. Hornecker. "I don't understand it either, but it is cool" - visitor interactions with a multi-touch table in a museum. In *2008 3rd IEEE Int. Workshop on Horizontal Interactive Human Computer Systems*, pages 113–120, 2008.

[13] T. Kuflik, C. Callaway, D. Goren-Bar, C. Rocchi, O. Stock, and M. Zancanaro. Non-intrusive user modeling for a multimedia museum visitors guide system. In L. Ardissono, P. Brna, and A. Mitrovic, editors, *Proc. of the 10th Int. Conf. on User Modeling*, vol. 3538 of *LNCS*, pages 236–240. Springer, 2005.

[14] T. Kuflik, O. Stock, M. Zancanaro, A. Gorfinkel, S. Jbara, S. Kats, J. Sheidin, and N. Kashtan. A visitor's guide in an active museum: Presentations, communications, and reflection. *J. Comput. Cult. Herit.*, 3(3):11:1–11:25, Feb. 2011.

[15] K. Luyten, H. van Loon, D. Teunkens, K. Gabriels, K. Coninx, and E. Manshoven. ARCHIE: Disclosing a Museum by a Socially-aware Mobile Guide. In Proc. of the 7th Int. Symp. on Virtual Reality, Archaeology and Cultural Heritage (VAST 2006), 2006.

[16] P. Noriega. *Agent Mediated Auctions: The Fishmarket Metaphor*. PhD thesis, Autonomous University of Barcelona, 1997.

[17] R. A. Ribeiro. Fuzzy multiple attribute decision making: a review and new preference elicitation techniques. *Fuzzy Sets Syst.*, 78(2):155–181, Mar. 1996.

[18] A. Rowstron and P. Druschel. Pastry: Scalable, decentralized object location, and routing for large-scale peer-to-peer systems. In *Middleware 2001*.

[19] V. Torra. The weighted owa operator. *International Journal of Intelligent Systems*, 12(2):153–166, 1997.

[20] C. Turner. Making Native Space: Cultural Politics, Historical Narrative, and Community Curation at the National Museum of the American Indian. *Practicing Anthropology*, 33(2):40–44, Apr. 2011.

[21] R. Wojciechowski, K. Walczak, M. White, and W. Cellary. Building virtual and augmented reality museum exhibitions. In *Proceedings of the ninth international conference on 3D Web technology*, pages 135–144. ACM, 2004.

[22] R. R. Yager. On ordered weighted averaging aggregation operators in multicriteria decisionmaking. *IEEE Trans. Syst. Man Cybern.*, 18(1):183–190, 1988.

[23] M. Yee-King, R. Confalonieri, D. D. Jonge, N. Osman, K. Hazelden, L. Amgoud, H. Prade, C. Sierra, and M. d'Inverno. Towards Community Browsing for Shared Experiences: The WeBrowse System. In S. Ossowski, F. Toni, and G. A. Vouros, editors, *Proc. of the 1st Int. Conf. on Agreement Technologies, AT 2012*, vol. 918 of *CEUR Workshop Proceedings*, pages 201–202. CEUR-WS.org, 2012.