

Multiagent Simulation Meets the Real World

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ABSTRACT

To realize large scale socially embedded systems, this paper proposes a multiagent-based participatory design that consists of steps called 1) *participatory simulation*, where scenario-guided agents and human-controlled avatars coexist in virtual space and jointly perform simulations, and 2) *augmented experiment*, where an experiment is performed in real space by human subjects and scenario-guided extras. In this methodology, we use production rules to describe *agent models* for approximating users, and multiagent scenarios to describe *interaction models* among services and their users. To learn agent and interaction models incrementally from simulations and experiments, we establish the *participatory design loop* with deductive machine learning technologies.

1. INTRODUCTION

Ubiquitous computing systems in the public space often interact with anonymous users and form socially embedded systems. We propose to apply multiagent technologies to the participatory design of ubiquitous computing systems that are to be embedded in society. To this end, we separate agent models from interaction models: the former covers beliefs, desires, intentions and emotions of human users of ubiquitous computing systems, and the latter covers protocol, method, rule or law that guides users when interacting with the ubiquitous computing systems. We view interaction models as behavioral guidelines of human users playing with socially embedded systems; users keep autonomy within the given guidelines. The question is whether or not users will follow the guidelines in an actual ubiquitous environment. The effectiveness of guidelines depends on agent models, which include the personalities of the users (deliberative, reactive, etc.).

We call the descriptions of interaction models *scenarios*. We have developed a scenario description language Q and its processor, which can simultaneously interpret scenarios for a large number of agents [4]. Q has been already connected to Microsoft agents for Web navigation, FreeWalk [8] for digital city experience [3], Cormas for natural resource simulation [1], and Caribbean for a massively multiagent simulation [11]. We have used Q and FreeWalk to conduct crisis management field studies [5,6,7].

In this paper, we pursue *multiagent-based participatory design*

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methodologies (*participatory design* hereafter) to confirm the adequateness of socially embedded systems; the following steps outline our approach.

1. Describe *interaction models* among ubiquitous computing systems and their users so as to define the expected behaviors of socially embedded systems. We use multiagent scenarios for this purpose, while using production rules to describe *agent models* for approximating users.
2. Perform a *multiagent-based simulation* by modeling users under the given interaction protocols. The simulation takes place in virtual space and involves simulated users, i.e. scenario-guided agents, whose internal models are described in production rules. Results of the simulation can predict how the entire system would work in society.
3. Replace some of the simulated users by human-controlled avatars to perform a *multiagent-based participatory simulation* (*participatory simulation* hereafter). The simulation is performed in virtual space, and the avatars are controlled by the humans sitting in front of their desktop computers. From the results of the participatory simulation, we can improve the models of users, as well as the interaction protocols: i.e. both agent and interaction models.
4. Perform experiments in real space to try out the entire system with human subjects. Since the number of human subjects is often limited, the experiment should be augmented by scenario-guided agents in virtual space and scenario-guided human extras in real space. We called this the *multiagent-based augmented experiment* (*augmented experiment* hereafter); note that most participants will be virtual constructs.

2. PARTICIPATORY SIMULATION

In our participatory design methodology, we first conduct multiagent-based simulations. Figure 1(a) illustrates how a multiagent-based simulation is realized. The scenario processor interprets interaction protocols and requests agents in virtual space to perform sensing and acting functions. Note that, since agents are inherently autonomous, though agents are guided by scenarios, there is no guarantee that they will behave as requested.

We can easily extend multiagent-based simulations to yield *participatory simulations* by replacing some of scenario-guided agents with human-controlled avatars. Figure 1(b) illustrates how humans and agents can cooperatively perform a simulation. Just as video games, human subjects can join simulation by controlling avatars by joy sticks, mice or other input devices. To analyze simulation results, we monitor the entire process of the simulation by visualizing the virtual space. In addition of video taping the virtual space, we record how the human subjects control their avatars. Recording human behavior is often useful for analyzing simulation results.

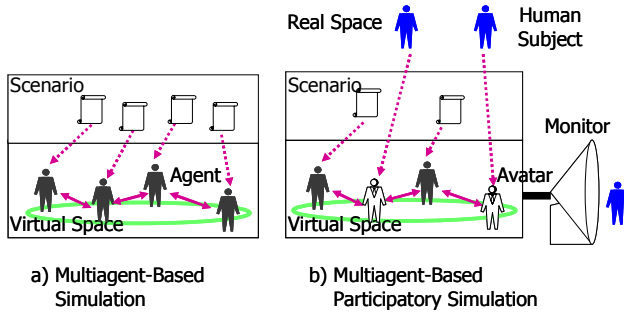


Fig. 1. Participatory Simulation

We conducted a multiagent-based simulation in the evacuation domain. We simulated the controlled experiments conducted by Sugiman [9]. He established a simple environment with human subjects to determine the effectiveness of two evacuation methods: the *Follow-direction method* and the *Follow-me method*. In the former, the leader shouts out evacuation instructions and eventually moves toward the exit. In the latter, the leader tells a few of the nearest evacuees to follow him and actually proceeds to the exit without verbalizing the direction of the exit. Sugiman used university students as evacuees and monitored the progress of the evacuations with different number of leaders. The experiment was held in a basement that was roughly ten meters wide and nine meters long; there were two exits, one of which was not obvious to the evacuees.

Our first evacuation simulation used scenarios with simulated leaders and evacuees in a two-dimensional virtual space. Since the simulation results closely parallel those recorded in Sugiman's controlled experiment, we could conclude that the agents were reasonably well modeled [5]. We then examined the same scenario in the three-dimensional virtual space FreeWalk. One difference between the two-dimensional and three-dimensional simulations is that the latter allowed humans to join the simulation: human subjects can sense their environment and control their avatars in the virtual space.

A participatory simulation was then performed with twelve human subjects: we replaced twelve out of twenty scenario-guided agents by human-controlled avatars. The virtual space is designed so that the human subjects could not distinguish agents from avatars. During the participatory simulation, we found humans behaved differently from their model used in the multiagent-based simulation. We thus adopted machine learning technology to develop agent models from the logs of the participatory simulation. By analyzing the logs and the videos of the simulation, we learned that a) evacuees use their eyes, not their ears, to identify the leaders, b) upon finding a leader, evacuees tend to approach the leader, even if the Follow-direction method is performed, and c) if contact with the leader is lost, they follow other evacuees that are moving in a group.

Once an accurate model is acquired from participatory simulations, it becomes possible to simulate experiments that cannot be conducted in real space. For example, Sugiman's experiment was performed using two or four leaders, but we can vary this number to clarify the relation between the number of leaders and the time required for evacuation. Moreover, we can explore an effective combination of the Follow-me and Follow-

direction methods. Given accurate agent models, participatory simulations are also useful in educating or training people. People can be provided with an experiential learning environment wherein evacuations or other drills can be experienced.

3. AUGMENTED EXPERIMENT

To understand how people behave with socially embedded systems, real-world experiments are often conducted. In the case of video phones, for example, since user behavior in everyday life is not easy to simulate, it is essential to observe how users utilize video phones in real space. In ubiquitous computing, however, because a large number of electronic devices are embedded in public space like railway stations and are continuously in service, it is often impossible to conduct experiments with large number of human subjects. *Augmented experiments* offer ability to perform experiments with a small number of human subjects through augmentation of multiagent-based simulations.

Figure 2 illustrates how augmented experiments are realized. Figure 2(a) represents a real world experiment, where human subjects communicate and perform an experiment in real space. Figure 2(b) shows how we introduce virtual space into a real world experiment. Using sensors in real space, behavior of human subjects are reproduced in virtual space. The sensors can be cameras, RFIDs or GPS depending on the environment. By using virtual space, we can monitor the entire experiment from various viewpoints. Furthermore, we can communicate with human subjects in real space by selecting their avatars in virtual space. *Transcendent communication* is a new monitoring interface, where a visually simulated public space provides a more flexible and consistent view than regular surveillance systems [7].

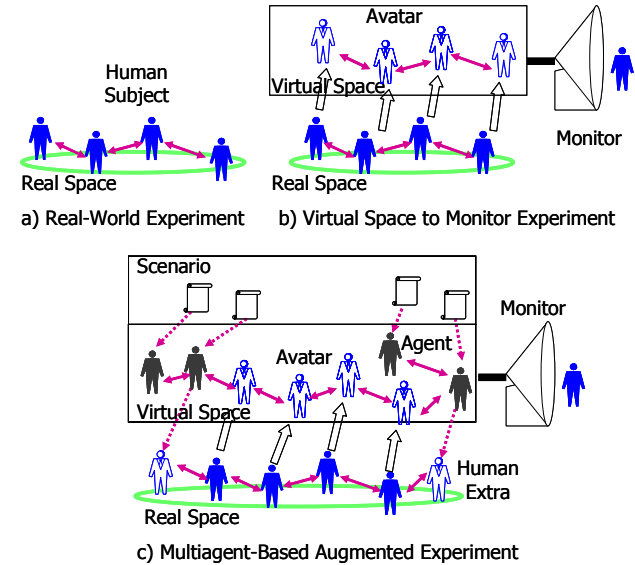


Fig. 2. Augmented Experiment

Figure 2(c) illustrates an augmented experiment. In parallel with a real world experiment, a large scale multiagent-based simulation is conducted in virtual space: the experiment is augmented by the simulation. To combine real and virtual spaces, sensors are used to project human behavior into the virtual space as shown in Figure 2(b). Furthermore, to provide social reality to the human

subjects, scenario-guided extras are placed around the subjects. In contrast to participatory simulations, the human extras do not control avatars: the human extras in the real space are controlled by the scenario-guided agents. For example, we may use human extras acting bus drivers to conduct a demand bus experiment. Conducting an augmented experiment is possible if the real space is equipped with enough sensors. Though we can monitor the experiment via virtual space, video capture of the human subjects in real space is also indispensable for analyzing the entire experiment.

Augmented experiments are needed for testing evacuation methods in railway stations, because there is no other way to conduct experiments with enough reality. To conduct an augmented experiment, we placed twenty eight cameras in Kyoto station, and captured the movements of passengers in real time. Those cameras are specially designed to detect passengers' behavior but not personal features.

We then reproduced the passengers' behavior in virtual space. The evacuees on the station platform are projected into virtual space. The bird's-eye view of real space is reproduced on the screen of the control center so that a leader in the center can easily monitor the experiment [7]. Furthermore the leader can point at particular passengers on the screen, and talk to them through their mobile phones. When the monitor detects pointing operations, a wireless connection is immediately activated between the control center and the indicated passengers. Dragging operations indicating a rectangular area would enable the leader to broadcast an announcement to a group of passengers.

The difficulty with augmented experiments is to provide the human subjects with a sufficient level of reality. To guide extras by scenarios in a timely fashion, the agents must receive sensing information from the corresponding extras. Learning issues are similar to those in participatory simulations, but the evaluation is more difficult, since the behaviors of human subjects in real space are harder to analyze than those in participatory simulations.

4. Future Work

By analyzing the logs of participatory simulations or augmented experiments, we can refine agent and interaction models. The learning process of multiagent-based participatory design consists of two phases: the *normal design loop* and the *participatory design loop*. At first, scenario writers create agent and interaction models and verify their design by multiagent-based simulations. We call this process the normal design loop and have already proposed its detailed steps [5]. After verifying the agent and interaction models, participatory simulations or augmented experiments are performed. The results of which may be different from those of multiagent-based simulations, because human behaviors are often more variable than those of agents modeled by scenario writers. If it is the case, we first refine the agent models to better express the variation seen in human behavior. We then perform the multiagent-based simulations again with the new agent models. If the new simulations fail to produce the expected effects, we then refine the interaction models: modify protocols, methods, rules, and/or laws. After the improved

interaction model is confirmed by multiagent-based simulations, participatory simulation or augmented experiment takes place again. This loop is called the participatory design loop.

At first glance, inductive machine learning technologies can be applied to refine agent models and interaction models. However, it is extremely rare to have a large enough number of human subjects to gather enough data, for inductive learning: deductive methods with domain knowledge are more feasible. To refine agent models, given that the training examples will be limited, explanation-based learning is a reasonable approach. Though variations exist in human behavioral rules such as "escape from crowds" and "follow crowds," observing the behavior of a human-controlled avatar can create a plausible explanation that selects one of the two rules. By combining machine learning technologies with interviews of human subjects, we have successfully refined agent models in several domains [6, 10]. To refine interaction models, if we have enough candidate protocols, we can try them, and select the one that best fits. If we need to invent a new model, however, there is no available technology that can create such an interaction model, while the visualization of simulation processes can support scenario writers in inventing new models.

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