EXAMINING GROUP BEHAVIOR AND COLLABORATION USING ABM AND ROBOTS

PAULO BLIKSTEIN*, Northwestern University, Evanston, IL
WILLIAM RAND, Northwestern University, Evanston, IL
URI WILENSKY, Northwestern University, Evanston, IL

ABSTRACT

Agent-based modeling has been extensively used by scientists to study complex systems. *Participatory simulations* are similar to agent-based models except that humans play the role of the virtual agents. The *Bifocal modeling* approach uses sensors to gather data about the real-world phenomena being modeled and uses that information to affect the model. In this work, we are interested in automatically extracting, analyzing and modeling group behaviors in problem solving. Combining these three systems into one unified platform would be useful for those purposes, since it would facilitate a synthesis of their main affordances: understanding the role of locality, mapping human action to emergent behaviors, and controlling embedded physical objects in noisy environments while receiving sensory feedback. We will demonstrate a technological platform based on the NetLogo/HubNet architecture that supports simulated agents, participatory agents and physical agents. We place this platform within a more general framework that we call Human, Embedded and Virtual agents in Mediation (HEV-M). We have run several studies using an instantiation of this platform that consists of a robot-car with four users who navigate a maze. We believe that this tool has potential for three main reasons (1) it facilitates logging of participant's actions, so as to identify patterns, (2) it offers researchers in the field of computer-supported collaborative learning an easy-to-use tool to design engaging collaborative learning activities and, (3) it foregrounds the role of individual actions within the accomplishment of a collective goal, highlighting the connections between simple individual actions and the resultant macroscopic behaviors of the system.

Keywords: group behavior, agent-based modeling, collaboration, robots

INTRODUCTION

Agent-based modeling has been used by scientists to study phenomena such as the interactions of species in an ecosystem, the collisions of molecules in a chemical reaction, and the food-gathering behavior of insects (Bonabeau, 1999; Troisi, Wong & Ratner, 2005; Wilensky & Reisman, 2006). Typical of agent-based models is that the aggregate patterns or behaviors at the macro level are not premeditated or directly actuated by any of the micro-elements. Participatory simulations are similar to multi-agent simulations except that humans play the role of the virtual agents (Wilensky & Stroup, 2002). As yet another extension to ABM methods, Blikstein & Wilensky (2006) have been exploring the use of physical devices in agent-based modeling, using sensors to gather data about the real-world phenomena under scrutiny (*bifocal modeling*).

* *Corresponding author address*: Paulo Blikstein, Center for Connected Learning and Computer-Based Modeling, 222 Annenberg Hall, 2120 Campus Dr., Evanston, IL 60208; e-mail: paulo@northwestern.edu.

The three aforementioned areas (agent-based modeling, participatory simulations, and bifocal modeling) are concerned with the creation, manipulation, and development of agents in one form or another. In this work, we are particularly interested in automatically extracting, analyzing and modeling group behaviors and collective strategies for problem solving. Combining these three systems into one unified platform would be useful for those purposes, since it would facilitate a synthesis of their main affordances: understanding of the role of locality, mapping human action to emergent collective behaviors, and controlling embedded physical objects in noisy environments while receiving sensory feedback. We will demonstrate a technological platform based on the NetLogo/HubNet architecture (Wilensky, 1999; Wilensky and Stroup, 1999) that supports simulated agents, participatory agents and physical agents (Rand, Blikstein, & Wilensky, 2006). Within this platform, designers can create participatory simulations in which each participant controls one micro-element within a physical system (a car, a mini-factory, etc.), while at the same time interacting with virtual agents. We place this technological platform within a more general framework that we call Human, Embedded and Virtual agents in Mediation (HEV-M). This framework facilitates general discussion about the components of the overall system and their interaction across particular technologies and instantiations.

We have run four studies using an instantiation that consists of a robot-car with four motors, each connected to a robotics interface, the GoGo Board (Sipitakiat, Blikstein & Cavallo, 2004), which communicates with the server. Each user is assigned a motor to control, and turning the car is achieved by activating, deactivating, or reversing the correct wheels. Participants were given the task of moving the robot from a start area to a goal area while avoiding obstacles along the way.

Initial results were intriguing. In our first studies, with university professors and researchers (Blikstein, Rand & Wilensky., 2006; Rand, Blikstein & Wilensky, 2006), before the start of the activity, participants were confident that they could easily accomplish the task. However, as soon as the first turn was necessary, participants started to report increasing frustration[1] with their ability to solve the problem, and we observed the emergence of strategies for optimizing the process, such as delegating leadership to one participant, or formation of two groups acting fairly independently. Also, at the beginning, many participants seemed unaware that an error from *any* of the participants could ruin the group's goal, no matter how well other participants were doing. However, in the present study, with computer science students as subjects, resulted in a diverse set of strategies for managing the task, as we will explain in this paper.

We present the current study as one example of how collaboration with embedded objects can be observed, but the potential of this framework and technology goes beyond this instance. As an example, almost any agent-based model could be recreated using physical agents and human agents interacting with those agents. For instance, traffic simulations in which participants controlled remote control cars, could offer insight into human behavior in traffic systems. The virtual agents in the current study are fairly passive, serving as conduits from the participants to the robot. However, these agents could be given a greater level of interaction, allowing them to interpret and respond to data from both the participants and the robot, and make

[1] It should be noted that the participants found this frustration humorous, since they were amazed that they could not solve such a simple problem.

their own autonomous decisions. This would add another level of complexity to the overall system.

We believe that the framework instantiation presented in this paper has significant potential for three main reasons (1) it facilitates logging of participant's actions, so as to identify patterns and match them to observations, (2) it offers researchers in the field of computer-supported collaborative learning an easy-to-use tool to design engaging collaborative learning activities and, (3) it foregrounds the role of individual actions within the accomplishment of a collective goal, highlighting the connections between simple individual actions and the resultant macroscopic behaviors of the system.

THE HEV-M FRAMEWORK

On a certain abstraction level, human, robotic (also called embedded) and virtual agents can be viewed as equivalent: all of these agents have properties (i.e., descriptions of themselves, and knowledge about the world) and methods (i.e., actions that they can take to achieve goals). In all three cases, the agents, regardless of being human, embedded or virtual, will examine the world around them and their own internal state and decide what action to take on the basis of this input.

Each of these systems, virtual, robotic, and human, present their own challenges. In the case of human agents, the logic that connects the input to the output may not be well known by outside observers, and thus the actions taken may be quite unpredictable. But confusion about the relationship between inputs and outputs is not limited to the human case. Robots can have noisy sensors that affect their perception of the world, and their actuators, also subject to a noisy environment, may not always work perfectly. In addition, there are many challenges to designing virtual agents correctly. Often low-level rules do not result in anticipated emergent patterns. Nonetheless, there are many reasons to motivate the combination of these systems into one integrated platform.

Robotic agents and virtual agents working within a shared model can be complementary. Robotic agents could use virtual agents to plan out routes and to simulate their movements ahead of time, which would assist in the development of some robotic agents, like planetary rovers. However, this is not a simple task. Robotic agents operate within the physical world (which often interferes with the task) and they have noisy sensors and fallible actuators. As mentioned, the integration of virtual systems with robotic systems can present researchers with many difficulties. How does one model the noisiness and inefficiency of the physical world within a virtual system, so that virtual and robotic agents can remain in step with each other? How should virtual agents interpret data from a robotic agent?

In much the same way that robotic agents are different from virtual agents, so are human agents different from virtual agents. The integration of human agents into a unified system also presents many of the same issues that challenge the integration of robotic agents, since they also have noisy sensors and inefficient actuators. Moreover, they present additional problems from a virtual agents' standpoint – human agents can adapt to their surroundings in new and surprising ways, which means that they are less predictable, and can be deliberately obstinate or malicious, attempting to confuse and take advantage of virtual agents. Notwithstanding these challenges, the integration of human and virtual agents within a shared system has a lot of potential. For instance, a model developer can have humans play the role of agents, subsequently capturing and embedding the decisions made by humans into virtual agents, enabling a richer and more elaborate examination of the behaviors employed by the humans (for more information on work on virtual and humans agents using the HubNet platform, see Abrahamson & Wilensky, 2004; Berland & Wilensky, 2006; Wilensky & Stroup, 2002). Alternatively, human agents could work together with virtual agents to accomplish some mutual goal. For instance, in a war simulation, humans could place emphasis on different targets while allowing the virtual agents to take care of the low-level planning. However, all of this requires the development of new protocols – for example, how does one automatically capture human decisions and embed them in agent-based rules? How can human agents express new beliefs, desires and intentions to a virtual agent?

We have been discussing these relationships between human and virtual agents, and robotic and virtual agents as separate entities, but these relationships can also be combined within a unified framework. In this paper, we will explore the combination of all these agents within one integrated platform (Blikstein, Rand & Wilensky., 2006; Rand, Blikstein & Wilensky., 2006). Our unified conceptual framework is the HEV-M framework, which stands for the integration of **H**uman agents, **E**mbedded sensory-enabled robotic agents, and autonomous **V**irtual agents, which communicate via a central **M**ediator (see Figure 3). The three different agent groups may have different goals and even different tasks. The mediator takes messages from any of the three groups of agents, transforms the messages, and relays the information to the other groups within a well-established protocol.

We have previously speculated (Rand, Blikstein & Wilensky, 2006) how this framework might be useful through the use of three hypothetical examples: Widget Factory, Planetary Rover, and Demon Soccer. In Widget Factory humans and virtual agents control simple machines that create parts of widgets. This environment can show, for example, that minor errors in the creation of the parts can dramatically alter the resultant outcome. In Planetary Rover humans cooperate with virtual agents to control a robotic agent. The virtual agents utilize sensory data about their environment to make independent decisions. This environment can enable the exploration of collaborative human-robot protocols. In Demon Soccer, human agents interact with virtual agents to control a soccer ball. The human agents play on opposing teams and attempt to steer the soccer ball in to their opponent's goal. Four different agents control the four wheels. Two of the agents are humans, and two of the agents are demon agents that either malignantly or randomly alter the speed and direction of the wheels. This environment enables the exploration of mediation between hostile agents, and could offer insight into how humans adapt to new and challenging situations.

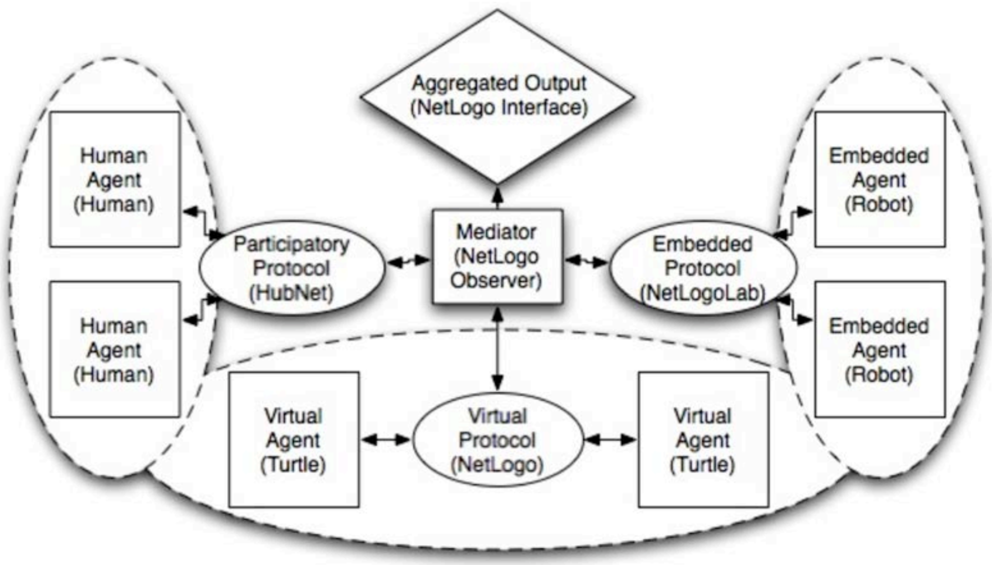

Figure 1: **HEV-M** Framework**.**

TECHNOLOGICAL PLATFORM

In this paper, we describe one technological platform that implements the components of the HEV-M framework. This platform is based on the NetLogo/HubNet modeling environment, and on the GoGo Board, an open-source piece of hardware for interfacing the computer with sensors and actuators. The system has three components:

1. **Robot-car:** the car has four motors, each connected to a wheel and controlled independently. The wheels cannot be steered, thus turning the car is achieved by selectively engaging different wheels in different directions. For example, a slow turn to the left can be accomplished by turning on both of the right wheels, and a faster turn can be accomplished by also turning the left wheels on, but in reverse. The motors have three power levels (high, medium and low), and are connected by long wires to the robotics interface. The interface, in turn, is connected to the server.

2. **Client computers:** each of the four client laptops have a simple interface for wheel control, enabling the user to turn his/her own wheel on and off, set the power level, and toggle the direction of rotation of the wheel.

3. **Server:** the server receives information from the four client computers and controls the robot-car accordingly. It also keeps a log of all the actions performed by the users.

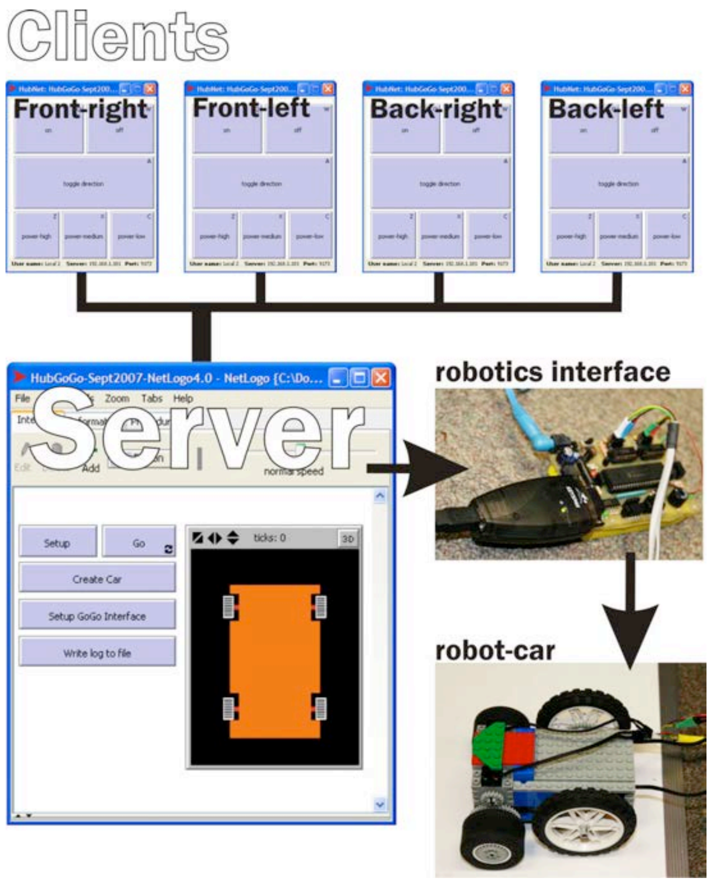

Figure 2 Diagram of the system, with its three components: the client computers, the robot-car, and the server.

EXPERIMENTS

This framework for agent integration is not just hypothetical– we have implemented it in several projects. (Blikstein, Rand & Wilensky, 2006; Rand, Blikstein & Wilensky, 2006). These preliminary prototypes had human and virtual agents working together to guide a robotic agent through a maze.

To extend those preliminary studies, we defined a methodological framework to conduct experiments. First, we standardized the size of the track and generated three fixed mazes. We also implemented a logging feature to capture keystrokes and mouse clicks from the participants. Finally, we defined a sequence of four activities to propose to participants:

Act. 1. **Maze with one obstacle, with communication** – we tell participants that they can talk to each other.

Act. 2. **Maze with two obstacles, without communication** – we tell participants that they should conduct the activity in silence, although they can observe at each other.

Act. 3. **Maze with three obstacles, with leader.** We randomly pick one of the participants and ask them to lead the other ones.

Act. 4. **Maze with three obstacles, randomized.** All wheels are randomized at the beginning, so users don't know beforehand which wheel they control. They have to figure it out during the activity.

Two main sources of data were used: video data and log files of students' interactions. For the video data collection, two cameras were utilized, one fixed, facing the participants, and one mobile, mainly facing the whiteboard and the robot-car. The log files recorded all of participants' interactions with the system.

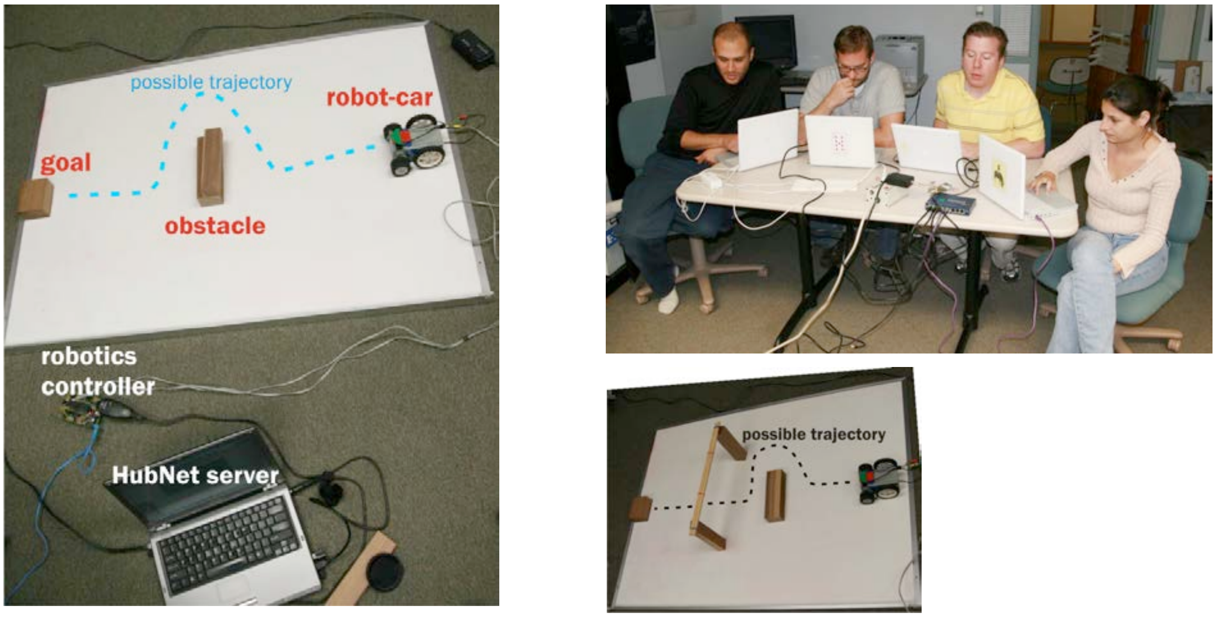

Figure 3 Clockwise from the left: The experimental setup for Act. 1, the four participants, and the experimental setup for Act. 2.

DATA ANALYSIS AND DISCUSSION

In previous work (Rand, Blikstein & Wilensky, 2006), we reported on a group of four university professors and researchers that had great difficulties in successfully completing the maze. We observed that inter-subject communications were confusing and out-of-sync with the required speed of action, and users could not establish clear leadership. The group of professors apparently underestimated the difficulty of the task and over-engineered their own strategies, resulting in poor performance. For that study, however, the logging mechanism was not yet in place, so our understanding of participants' reaction was partial, based on their own utterances and our observations of the robot-car. For the following study, with the logging mechanism in place, a group of four computer science students was selected. We began the study with the hypothesis that, being young students, they would be more spontaneous and communicate extensively; being experts in computer science, they would try to engineer elaborate strategies to control the car. Both of these hypotheses were proved wrong, and other results became apparent from our data analysis, which we will explain below

Fading inter-personal communication patterns

Participants started out communicating extensively during the first activity. The second activity was supposed to be in silence, but even after communication was permitted again, on the third activity, participants did not resume verbal communication: they were paying attention exclusively to the car. Below is the transcript of the dialogue during the first activity, showing that participants were able to devise a successful strategy and orally coordinate their activities:

> **John:** I have a plan: Jim and I don't do anything, you do it all. You guys are the front.
> [after a few second, the car stalls]
> **Marcia:** Uh Oh. More power.
> **John:** Do you think you need us?
> **John:** We need some back…
> **Marcia:** Nice
> **John:** You guys got it, you don't need us.
> **Marcia:** Great success, guys.

However, from the third activity on, there was barely any verbal communication. This was in contradistinction to our initial hypotheses. Somehow the participants developed a personal heuristic as to how to control their wheel which did not require communication. One explanation is that they "read" other participants' states and intentions *through the state of the car*, with no need of explicitly asking questions. As we will show below, this explanation is supported by both the post-interviews that we conducted with the participants and an examination of the log files.

Diversity of personal strategies

Participants' post interviews further corroborate the hypotheses of decreased oral communication, since their self-reported strategies and heuristics did not include talking or asking question of the other participants:

> **Edward:** I was not paying attention to anyone; *I was paying attention to the car*. I was just paying attention to my wheel. If I did something and it went bad, because another person did something else, I would just go back to my previous state.
>
> **Jim:** *I did very little.* I figured that if everyone was hitting buttons and moving forward, the car wouldn't go anywhere, so I waited for opportunities in which I was pretty sure I would make a difference.
>
> **John:** I was back-left, when I was on, the car would go to the right. When my thing is going forward, the car would go right. If my thing is going backwards, the car is going left.
> **Interviewer:** But if the other guy is doing the opposite…
> **John:** Then the car wouldn't go anywhere. [long pause] That's ok.

For John, looking at the car (which was exhibiting behavior that resulted from aggregating each group member's directives) and reacting to it on-the-fly was more efficient than explicitly discussing strategies (which we observed in our previous study with the university professors and researchers). Despite the car's behavior being a collective construction, John was reacting to the resulting emergent behavior of the group, and not discussing every single individual action. Jim had a very different strategy: he realized that, by simply doing nothing, the car would probably achieve the same goal, since there was redundancy in the system – by staying out, he thought he could help the group achieve the goal faster. Edward, conversely, was very active, and devised a strategy of trial-and-error – if his move resulted in undesired behavior, he would just undo the movement, without negotiating every move. In all three of these cases the individual decision criteria is focused on the aggregate behavior of the car, and completely excludes any involvement of the other participants.

Use of the different motor control commands

Additionally, the log files show that, notwithstanding the symmetry of the car, each user had a different approach to their use of the six different commands. One commonality between participants was observed: power-high, medium and low were used very infrequently. Two users (back-right and front-right) realized that just leaving the motor on and using ‘reverse-direction’ during the activity was the most effective strategy. As the log files show, as time went on, these participants employed this strategy with increasing frequency. John, who was controlling the ‘back-right’ wheel, used ‘reverse-direction’, or ‘rd’, almost exclusively toward the end of the study (Activity 3). Comparing the log files and the verbal data, we observed that this learning process took place tacitly, without any oral communication between users. However, John was conscious that he had learned an important technique, since when he was asked to lead the group, on activity 3, he asked everyone to “turn on and just use reverse-direction”. Another surprising observation was that, even after John asked all users to exclusively use ‘rd’, only those users who had had a significant increase in ‘rd’ from activity 1 to activity 2 followed his advice. This can be seen in the ‘rd’ lines on the plots in Figure 4. Compare the ‘rd’ lines of ‘back-right’ [John himself] and ‘front-right’, as opposed to ‘back-left’ and ‘front-left.’ One explanation is that two of the participants employed their own personal theory on how to control the car and were resistant to follow the directions of the leader. This hypothesis is further supported by the aforementioned transcriptions of users’ self-reported techniques for car control.

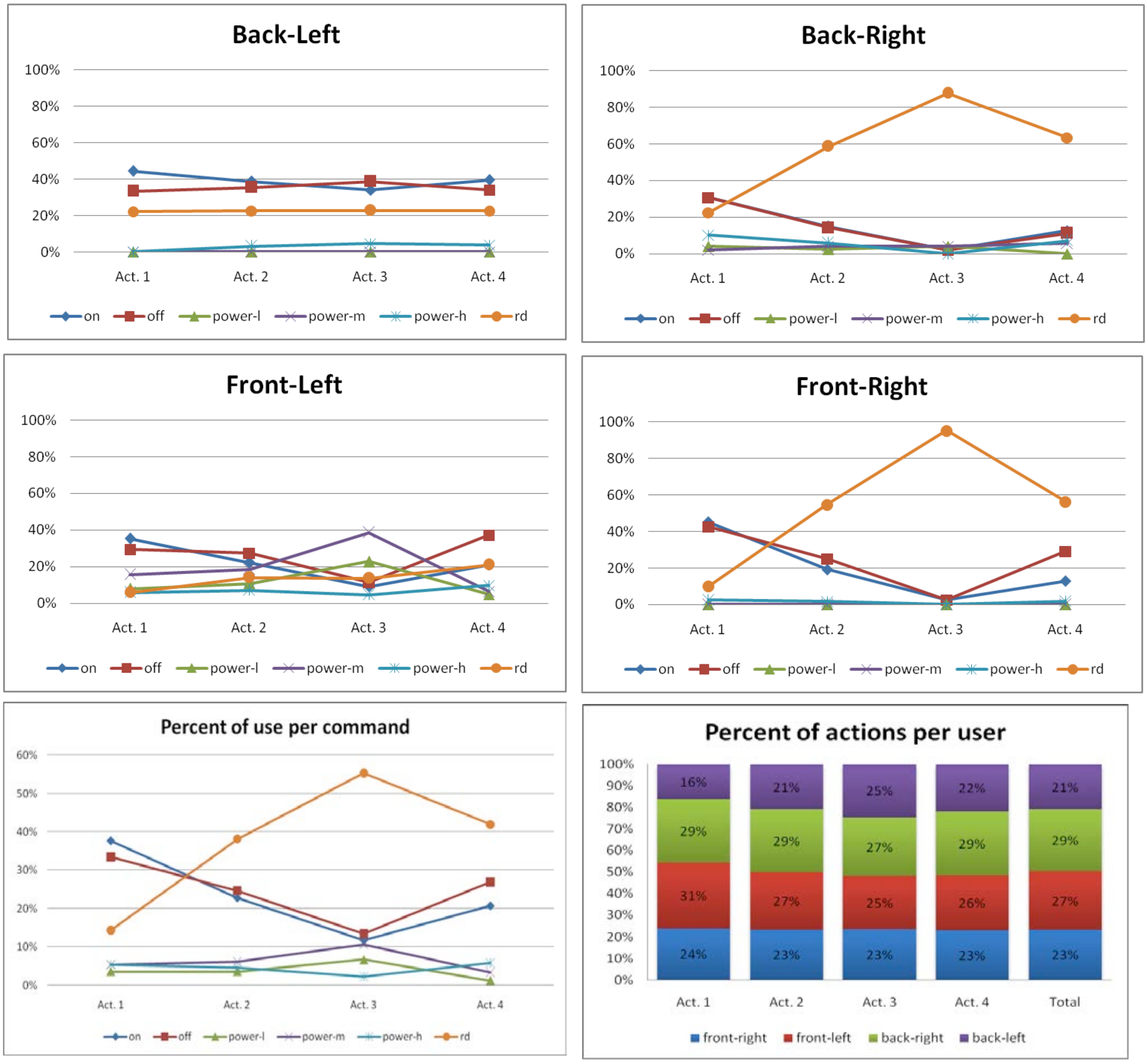

Figure 4 The use of each command over the four activities for each user (first four plots), the overall percent of use per command for all users (bottom left, note the clear increase in the use of reverse-direction), and the percent of actions per user (bottom right), showing an almost uniform distribution, with the exception of user 'back-left'.

CONCLUSION

The HEV-M framework and the implementation described in this paper proved to be a useful tool in exploring the interactions and interoperability among human, virtual and physical agents. We developed data collection tools and techniques that reveal tacit individual and collective strategies for problem solving and communication. The approach of pairing verbal data and log files described in this paper could enable other researchers to unveil unexpected communication and behavior patterns that would otherwise go unnoticed. For example, one behavioral pattern that we observed was that users' final strategy resulted in a focus on the car's actions and movements, instead of observing or communicating with the participants – despite being in the same room. Surprisingly, a simple robot-car ended up mediating interpersonal communication more effectively than oral discourse. Seeing as how the humans involved did not actually communicate and seemed to settle on final strategies quickly, it might have been possible to replace them with virtual agents able to observe the robot-car and make decisions similar to the humans. As we have observed there would need to be different types of virtual agents to represent the different human behavioral styles, but that is a simple task. These results suggest that the nature of the agent controlling the device – human or virtual – could be of less importance than is commonly thought. If this result is confirmed by further research, this could be an important contribution to the study of human-computer interaction within the field of agent-based modeling.

AKNOWLEDGEMENTS

The preparation of this paper was supported by the National Science Foundation (Information & Intelligent Systems Division grant #0713619, "Advancing the Science of Agent-Based Modeling Through Frameworks, Tools, and Pedagogies", PI: Uri Wilensky).

REFERENCES

Abrahamson, D., & Wilensky, U. (2004). *SAMPLER: Collaborative interactive computer-based statistics learning environment.* Paper presented at the 10th International Congress on Mathematical Education, Copenhagen, July 4 - 11, 2004.

Berland, M., & Wilensky, U. (2006). Constructionist collaborative engineering: Results from an implementation of PVBOT. Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Blikstein, P., & Wilensky, U. (2006). The Missing Link: A Case Study of Sensing-and-Modeling Toolkits for Constructionist Scientific Investigation. In *Proceedings of the 6th IEEE International Conference on Advanced Learning Technologies (ICALT 2006),* Kerkrade, The Netherlands, 980-982.

Blikstein, P., Rand, W., & Wilensky, U. (2006). Participatory, Embodied, Multi-Agent Simulation. Paper presented at the AAMAS-06 Conference, 2006.

Bonabeau, E., Dorigo, M., Théraulaz, G. (1999). *Swarm intelligence: From natural to artificial systems.* London: Oxford University Press.

Rand, W., Blikstein, P., & Wilensky, U. (2006). *Widgets, Planets, and Demons: the Case for the Integration of Human, Embedded, and Virtual Agents via Mediation*. Paper presented at the Swarmfest 2006.

Sipitakiat, A., Blikstein, P., & Cavallo, D. P. (2004). *GoGo Board: Augmenting Programmable Bricks for Economically Challenged Audiences.* Proceedings of the International Conference of the Learning Sciences, Los Angeles, USA.

Troisi, A., Wong, V., & Ratner, M. (2005). An agent-based approach for modeling molecular selforganization. *Proceedings of the National Academy of Sciences, 102*(2), 255-260.

Wilensky, U. (1999). NetLogo. Evanston, IL: Center for Connected Learning and Computer-Based Modeling. http://ccl.northwestern.edu/netlogo.

Wilensky, U., & Blikstein, P. (2005). NetLogoLab curriculum. Evanston, IL: Center for Connected Learning and Computer Based Modeling, Northwestern University.

Wilensky, U., & Reisman, K. (2006). Thinking like a wolf, a sheep or a firefly: Learning biology through constructing and testing computational theories -- an embodied modeling approach. *Cognition & Instruction, 24*(2), 171-209.

Wilensky, U., & Stroup, W. (2002). *Participatory Simulations: Envisioning the networked classroom as a way to support systems learning for all.* Paper presented at the Presented at the Annual meeting of the American Research Education Association, New Orleans, LA, April 2002.