A User-Adaptive Interface Agency for Interaction with a Virtual Environment

Britta Lenzmann and **Ipke Wachsmuth**
University of Bielefeld
Faculty of Technology
AG Knowledge-based Systems
D-33501 Bielefeld, Germany
{britta,ipke}@techfak.uni-bielefeld.de

Abstract

This paper describes an approach to user adaptation realized in a multiagent interface system for interaction with a virtual environment. Single agents of the interface system adapt to users' individual preferences by learning from direct feedback. The core idea is that agents that were successful in meeting the user's expectations are given credit while unsuccessful agents are "discredited." Communicating credit values, agents organize themselves so that the overall behavior of the interface agency gradually adapts to the individual user as the session is proceeding.

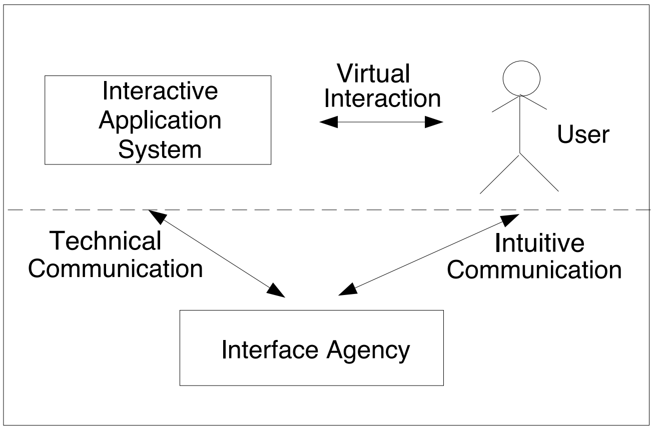

Figure 1: Agent-mediated interaction

1 Introduction

Enabling a flexible, robust, and effective system design, agent systems have proven especially useful in the design of more intelligent user interfaces. Acting as mediator between the user and the application system, they can add comfort in human-computer interaction by allowing more human-like communication forms [Laurel, 1990]. Thus, the user can instruct the application system by way of abstract commands (virtual interaction) since the interface agency interprets them (intuitive communication) and transmits the results to the application system via technical communication (see figure 1).

While communication between humans is situated naturally, the interface system must be able to meet varying conditions to enable an effective human-computer interaction. Thus, incorporating adaptation facilities in the agent system becomes necessary. In our work, we distinguish two aspects regarding adaptation: adaptation in respect to individual differences among users and adaptation to varying situation circumstances.

In this paper we focus on the first aspect, i.e., user adaptation. A prominent approach is to build user-adaptive interface agents by applying machine learning techniques [Maes and Kozierok, 1993] such as learning from example, learning from feedback, or learning through experience. For example, [Maes, 1994] has realized a learning personal assistant for electronic news filtering which accumulates knowledge about tasks and habits of its users to act on their behalf. Similar agents have been built for meeting scheduling, such as calendar managing [Mitchell *et al.*, 1994]. Common to these works is that a solitary interface agent is used which adapts to individual user preferences by aquiring user data and changing its internal functionality. A visual agent gives advice to the user by expressing facial emotions or by prompting suggestions.

In our approach, we consider a system of interface agents which adapts to user preferences by learning from direct feedback. The user gives feedback by way of correcting solutions offered by single agents until the agent generating the preferred solution is negotiated in the system-user interaction. Thus, internal functionalities of agents remain unchanged but individual agents are preferred among a variety of task-specific interface agents. The core idea is that agents which were successful in meeting the user's expectations are given credit while unsuccessful agents are "discredited." By this, the overall behavior of the interface agency gradually adapts to the individual user as the session is proceeding.

Our approach is realized in a multiagent interface system for interaction with a virtual environment, which is carried out in the VIENA project. We start with explaining the VIENA system, describe then our approach to user adaptation by a multiagent system and, in concluding, discuss our ideas and sketch future work.

2 VIENA: Interaction with a Virtual Environment by a Multiagent System

VIENA[1] ("Virtual Environments and Agents") is a research project concerned with the interactive manipulation of high-quality 3D graphical scenes by way of agent-mediated user interaction [Wachsmuth and Cao, 1995]. A multiagent system translates qualitative verbal communications of the user to quantitative commands that are used to update the visualization scene model. To this end, the multiagent system has to solve different tasks which are distributed among a number of specialized agents. A parser agent translates an instruction to an internal deep-level representation which outputs to the mediating agents. A bookkeeping agent is authorized to access and modify the augmented data base to supply current situation information to agents on request. A space agent translates qualitative relations such as 'left of' to appropriate scene coordinates. Other agents, in similar ways, take special responsibilities in mediating an instruction (figure 2).

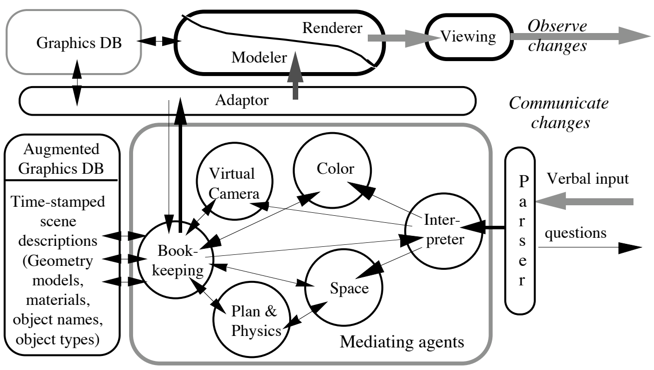

Figure 2: The architecture of the VIENA system (after [Wachsmuth and Cao, 1995]).

For computing the entire solution of a user's instruction agents have to communicate and cooperate with each other. Defining agents as autonomous, heavyweight processes exchanging messages, communication is realized by using the RPC mechanism. The cooperation method is basically characterized by a negotiation process similar to the contract-net approach; in addition, a master-slave-type of behavior can be modeled by allocating tasks directly (for detail cf. [Lenzmann *et al.*, 1995]).

The multiagent system is used in a prototype scenario with various items of furniture as well as color and light impressions of a virtual office room which can be changed interactively. The practical experience with the system has shown that the computed solutions do not always meet the expectations of the user. More precisely, we observed variations of individual preferences among users (cf. section 3). To cope with this, the VIENA system accepts corrections such as 'a bit more' which modify the previous solution accordingly by inspection of the current and the previous scene models. In this way, the semantics of instructions is negotiated in the system-user interaction; we refer to this as "negotiated semantics."

However, frequent corrections are uncomfortable for the user. This gave rise to the idea of incorporating adaptation facilities in the interface agency. In section 3, we explore this idea in more detail and describe an approach where user adaptation is achieved by learning from direct feedback.

3 User-Adaptation in a Multiagent Interface System

In VIENA spatial transformations of scene objects are communicated by way of qualitative spatial descriptions, as in "move the palmtree to the left." The semantics of such spatial instructions may depend on different perspectives: from the user's point of view (deictic perspective) or from the point of view of an object which has a prominent front (intrinsic perspective). Figure 3 illustrates the two alternative solutions when an object located on a desk is to be moved to the left.

We assumed that, depending on their individual preferences, users may choose one of either perspective. For verification of this claim, we carried out an empirical study. A total of 64 probands were asked to perform the instruction "Move the object to the left" in a simplified setting of the one presented in figure 3. The study shows that 36% of the probands used the intrinsic perspective (solution 1), whereas 64% used the deictic perspective (solution 2). Hence, we are confirmed that designing space agents able to adapt to users' preferences for different spatial reference frames is a useful goal.

Consequently, we conceptualized two instances of a space agent that are similar in the way they compute spatial transformations, and different with respect to the reference scheme they take on. More concrete, we have implemented one space agent embodying the user's reference frame (deictic reference) and one space agent embodying an externally anchored reference frame (intrinsic reference).

[1] The VIENA project is part of the "Artificial Intelligence and Computer Graphics" research program at the University of Bielefeld which is partly supported by the Ministry of Science and Research of the Federal State North-Rhine-Westphalia under grant no. IVA3-107 007 93.

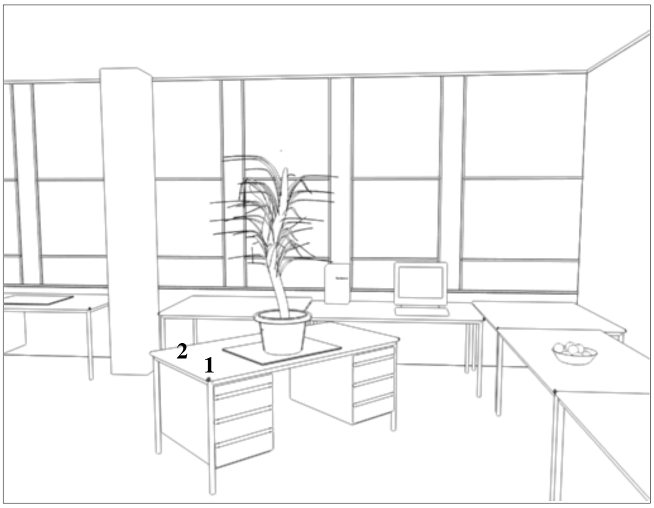

Figure 3: Example scene from the VIENA test application: The palmtree located on the desk can be moved to the left from an intrinsic perspective (1) or from a deictic perspective (2).

3.1 Learning from direct feedback

Instructing the system with a spatial transformation, one of both space agents offers a possible solution. In case the visualized solution does not meet the expectation, the user can correct the system ("wrong"). The other space agent then generates a offer which modifies the previous solution. By this, adaptation to a user's preferred reference scheme is achieved by direct user feedback.

Regarding from the system internal point of view, the adaptation process is achieved by a form of reinforcement learning [Kaelbing, 1993]. This means in more detail, that both space agents have credit values corresponding to their quality at discrete periods of time. When the user demands a change incorporating a spatial transformation, both space agents are informed by receiving a corresponding task posting. Depending on the task description, each agent generates a bid which includes its actual credit value. Bids are evaluated by comparing credit values. The agent offering the best bid (that is the bid with the highest credit) will get the task, whereas the bid of the other agent is rejected. Figure 4 illustrates a detail of the VIENA coordination structure where both agents compete with each other to compute an optimal solution regarding a user's expectation.

For adapting to users' preferences, agents have to adjust their credit values dynamically. This takes place if, e.g., the deictic space agent has worked out the task but, preferring the intrinsic perspective, the user corrects the system. Being informed about the correction, the deictic space agent will reduce its credit value. The intrinsic agent is then able to generate the best bid and is allocated the task (cp. figure 4). In this way, adaptation to dynamically changing preferences can be realized.

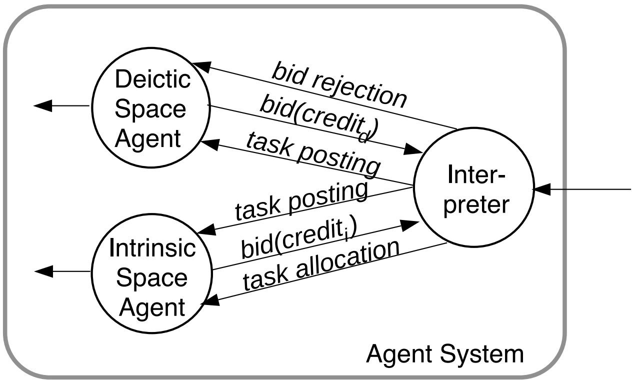

Figure 4: A detail of the VIENA coordination strategy: the deictic and the intrinsic space agent make offers qualified by their credit values; the space agent generating the better bid gets the task, whereas the bid of the other space agent is rejected.

Speaking metaphorically, increasing (or reducing) credit values induced by being successful (or nonsuccessful, resp.) in meeting the user's expectations corresponds to being more or less selfconfident. Based on their selfconfidence, agents are able to organize themselves in the way individual users' preferences call for without the need to accumulate explicit user models. Avoiding explicit user modeling seems a desirable goal because explicit user models have found critique with respect to privacy of user data [Norman, 1994].

4 Discussion and Future Work

In this paper we have presented an approach to user adaptation by a multiagent system for interacting with a virtual environment. Learning from direct feedback is used to adapt the interface agency to users' individual preferences. More successful individual agents within the agency are preferred. Agents organize themselves by communicating credit values which represent their amount of selfconfidence. Depending on their success in the preceding session, agents adjust their credit values dynamically to meet the user's expectations. The system's knowledge of users' preferences is expressed in adjustments of agents and is distributed across agents. Thus, user adaptation is achieved without accumulating explicit user models.

We have illustrated our approach by focusing on users' preferences for different spatial reference frames. As further preferences which the agent system could adapt to, differences in color perception as well as differences in strength regarding transforming or scaling objects will be investigated. Furthermore, we have considered the interaction with a virtual environment as an example application but, in our view, the approach is also applicable to other scenarios where a multiagent interface is used to mediate between users and an application system.

So far, first steps have been taken to implement the adaptation method described above. Besides of testing and further implementing, we think of measures to optimize the adaptive behavior of the interface agency. On the one hand, frequent corrections at starting time of a session could be avoided by appropriate initializations of agents' credit values. Our idea is that "anonymous user profiles" could evolve, and be pooled, as the system becomes experienced. Resembling correlations among agents' credits, such profiles could be used to enhance adaptation speed by more global adjustments. On the other hand, we plan to investigate in which form users' individual preferences depend on actual situation circumstances. Regarding the example illustrated in figure 3, users' preferences for spatial reference frames may depend on the orientation of the desk given in the actual situation. Therefore, actual scene data would have to be integrated in the adaptation process. By this, we consider adaptation to users' preferences as well as adaptation to varying situation parameters to be realized by multiagent systems.

References

[Kaelbing, 1993] L.P. Kaelbing. *Learning in Embedded Systems.* The MIT Press, 1993.

[Laurel, 1990] B. Laurel. Interface agents: Metaphors with character. In B. Laurel, editor, *The art of human-computer interface design*, pages 355–365. Addison-Wesley, 1990.

[Lenzmann *et al.*, 1995] B. Lenzmann, I. Wachsmuth, and Y. Cao. An intelligent interface for a virtual environment. Paper submitted to the 19th German Annual Conference on Artificial Intelligence – KI-95, September 1995.

[Maes and Kozierok, 1993] P. Maes and R. Kozierok. Learning interface agents. In *Proceedings of the Eleventh National Conference on Artificial Intelligence (AAAI-93*, pages 459–465. AAAI Press/The MIT Press, 1993.

[Maes, 1994] P. Maes. Agents that reduce work and information overload. *Communications of the ACM*, 37(7):31–40, 1994.

[Mitchell *et al.*, 1994] T. Mitchell, R. Caruana, D. Freitag, J. McDermott, and D. Zabowski. Experiences with a learning personal assistent. *Communications of the ACM*, 37(7):80–91, 1994.

[Norman, 1994] D.A. Norman. How might people interact with agents. *Communications of the ACM*, 37(7):68–71, 1994.

[Wachsmuth and Cao, 1995] I. Wachsmuth and Y. Cao. Interactive graphics design with situated agents. In W. Strasser and F. Wahl, editors, *Graphics and Robotics*, pages 73–85. Springer, 1995.