International Workshop, in conjunction with UMAP 2010, on
Adaptation and Personalization in E-B/Learning using Pedagogic Conversational Agents (APLeC)
Hawaii, June 20-24, 2010

APLeC
UMAP 2010

1ˢᵗ International Workshop on

Adaptation and Personalization in E-B/Learning using Pedagogic Conversational Agents (APLEC 2010)

Hawaii, U.S.A.
June 21ˢᵗ 2010

Online Proceedings

Diana Pérez-Marín
Ismael Pascual-Nieto
Susan Bull (Eds.)

PREFACE

The benefits of the personalization and adaptation of computer applications to each user have been widely reported in recent decades. Educational applications are not an exception, both in e-learning, i.e. the use of electronic media to teach or assess, and in b-learning (blended learning), i.e. to combine traditional face-to-face instruction with electronic media.

Pedagogic Conversational Agents (PCAs) can be defined as virtual characters, which can teach or be taught by students in a domain, and even to serve as learner companions to avoid the so-called isolation problem of computer-based education. PCAs can be animated, and may consist only of a face, or have a full body (embodied conversational agents).

The first International Workshop on Adaptation and Personalization in E-B/Learning using Pedagogic Conversational Agents (APLEC) took place on 21st of June 2010, in Hawaii, U.S.A. in conjunction with the International Conference on User Modeling, Adaptation and Personalization (UMAP) to answer the following question: *How does the use of Pedagogic Conversational Agents in e-b/Learning systems permit better personalization and adaptation?*

Ten submissions were received to provide an answer to that question, and after a double-blind peer-review process, five papers were accepted (50% acceptance rate). Two papers come from Europe and three from U.S.A.

This volume contains the proceedings of the workshop. In particular, the first paper entitled '*Generation of Dialogs Adapted to the Student Knowledge for Pedagogic Conversational Agents*' has been chosen as the introductory paper of this book because it introduces the notion of PCA. Moreover, the paper focuses on one of the possibilities of allowing better personalization and adaption in PCAs through the use of Natural Language Processing techniques: the generation of adapted dialogs to each student model.

The second paper entitled '*Characters that Help You Learn: Individualized Practice with Virtual Human Role Players*' discusses how the adjustment of the behavior of the virtual humans to meet the specific learner needs is able to provide individualized practice to each student. That way, students are expected to improve their communicative skills.

The third paper entitled '*A Teachable Agent Game for Elementary School Mathematics promoting Causal Reasoning and Choice*' presents a different type of PCA. In this case, the agent does not assume the role of teacher, but the role of a student (i.e. a teachable agent) who needs to be taught to play a math game by elementary school-children. That way, students are expected to improve their causal reasoning and choice-making skills among others focusing on their special needs.

The fourth paper entitled '*Turning Cognitive Tutors into a Platform for Learning-by-Teaching with SimStudent Technology*' presents an on-line game-like environment in which SimStudent (a teachable agent too) learns how to solve algebra equations as helped by the particular information provided by the students.

Finally, the fifth paper entitled 'Adaptive Agents for Promoting Intercultural Skills' focuses on the possibility of developing adaptive agents for intercultural

communication skills. The adaptation feature to the culture and needs of the students is presented as a key element to facilitate the intercultural communication skills.

We would like to thank the authors for their paper submissions, our Programme Committee members for their reviews and the UMAP workshop chairs for their advice and guidance during the APLEC workshop organization. We would also like to thank our sponsors: the Spanish Ministry of Science and Technology, project TIN2007-64718 and the Department of Computing Languages and Systems I from the Universidad Rey Juan Carlos.

May 2010

Dr. Diana Pérez-Marín
Dr. Ismael Pascual-Nieto
Dr. Susan Bull
Editors
APLEC Organizers

COMMITTEES

Organizing Committee

Diana Pérez Marín, Universidad Rey Juan Carlos, Spain

Ismael Pascual Nieto, Universidad Autónoma de Madrid, Spain

Susan Bull, University of Birmingham, United Kingdom

Program Committee

Gautam Biswas,Vanderbilt University, U.S.A.

Federica Cena, University of Torino, Italy

Alice Kerly, The Open University, U.K.

Max Louwerse, University of Memphis, U.S.A.

José Antonio Macías, Universidad Autónoma de Madrid, Spain

Liliana Santacruz, Universidad Rey Juan Carlos, Spain

Olga C. Santos, Universidad Nacional de Educación a Distancia, Spain

Dimitris Spiliotopoulos, University of Athens, Greece

Carlo Strapparava, FBK-irst, Italy

Kate Taylor, Sanger Institute, U.K.

George Veletsianos, University of Texas, U.S.A.

TABLE OF CONTENTS

Generation of Dialogs Adapted to the Student Model for Pedagogic Conversational Agents

Cristóbal Hermida-Portales[1], Diana Pérez-Marín[1], Ismael Pascual-Nieto[2]

[1] Computing Languages and Systems I Department, Universidad Rey Juan Carlos
[2] Computer Science Department, Universidad Autónoma de Madrid, Spain
c.hermida@alumnos.urjc.es, diana.perez@urjc.es, ismael.pascual@uam.es

Abstract. Conversational agents can be defined as computer programs which can have an animated face and/or body, understand natural language and respond in natural language to a user request. Pedagogic Conversational Agents are a subset specifically designed for educational purposes. Some of the existing conversational agents provide predefined answers irrespectively of the student model. In this paper, our hypothesis is that the use of Natural Language Processing techniques would allow the generation of dialog templates adapted to each student model and that it would improve the perceived quality and trustworthiness of the Pedagogic Conversational Agent. In order to support that hypothesis, an initial module of a more complete system to generate dialog templates has been implemented and it is described with some initial results.

Keywords: generation of dialog templates, adaptation to the student model.

1 Motivation

Conversational agents can be defined as computer programs which can have an animated face and/or body (embodied conversational agent), understand natural language and respond in natural language to a user request [1].

ELIZA was the first conversational agent, based on a simple pattern matching technique [2]. Since then, more and more conversational agents have appeared based on different techniques and implementations [3].

Regarding the interface, the simplest form of conversational agent could be a text area in which users type the sentences and read the written answer of the agent. While the most sophisticated form could be an agent with an animated face and body able to make gestures according to the dialogue in natural language (e.g. a smile on the face when the mood of the conversation is happy).

Conversational agents can be applied to multiple domains such as e-commerce, web assistance to help users navigating among the pages or retrieving information, training and education.

However, currently many of the existing conversational agents provide predefined sentences. Therefore, the generated dialogue is quite similar for different users, irrespectively of their preferences and needs. For instance, conversational agents that

answer just the same when asked about where some information in a web page is or to book a travel.

The reason for not generating a more adapted dialogue in natural language could be found in a perceived difficulty of using Natural Language Processing (NLP) tools, or the fear that NLP tools still make many mistakes that could lead to a more confusing dialogue instead of a more sophisticated interaction.

However, we believe that not generating and using student models for conversational agents supposes a main drawback since it means that they loss believability and trustworthiness. Both of them important factors to create realistic dialogues.

This is particularly relevant for the training and education domain providing benefits both for teachers and students. For teachers, the task of creating a course would not be so complex, and for students, the questions would not only be presented in different order but with different sentences adapted to them.

For instance, if instead of asking teachers to type the questions for a course, teachers would only need to type information about the course and the questions were generated from that information, it would be possible that the agent could generate questions about different concepts and their relationships depending on the course information and adapted to each student.

That way, if the agent asks the student about a certain concept and the student gives a correct answer, the agent could use that concept to create more complex questions taking into account that the previous concept has been assimilated according to the Meaningful Learning Theory of Ausubel [4].

It is therefore expected that the interaction would not only be more natural, but also more efficient, based on a dialogue more focused on the specific conceptual difficulties of each student.

In this paper, we propose an ongoing work on the creation and implementation of a procedure to automatically generate dialogs from the information of a course domain and a student model to adapt and personalize the interaction and contents to each student. That way, it is expected to increase the perceived quality and trustworthiness of the Pedagogic Conversational Agent.

The organization of the paper is as follows: Section 2 briefly reviews related work; Section 3 focuses on the description of the proposal and its current implementation; Section 4 provides some preliminary results attained; and, finally Section 5 ends the paper with some lines of future work.

2 Related Work

Natural Language Interaction is a multidisciplinary research area that combines techniques from Natural Language Processing [5] and Human-Computer Interaction [6]. One of its main benefits is that it can help bridging the digital gap by letting users without computer knowledge interact with computers in natural language.

However, it is still not possible to allow users to "talk" to the computer in the same way that they talk to other human because of the difficulty of automatically processing natural language (not only understanding natural language but generating

it) [5]. On the other hand, the progress made in NLP in the last decades and the creation of more resources have made possible to create conversational agents able to keep a dialogue on a certain domain with a specific goal [3].

In particular, Pedagogic Conversational Agents (PCAs) can be defined as virtual characters which can teach or be taught by students in a domain, trying to focus the attention of the student to the topic under study rather than deviating their attention to how to use the e-b/learning platform. Three main types of PCAs can be distinguished according to their role with the students [7]:

− *PCAs that serve as tutors*. For instance, AutoTutor [8] that has successfully been used with university students of literature and physics. Furthermore, AutoTutor keeps a student model to improve the didactics of the tutoring process [9].
− *PCAs that serve as students*. For instance, Betty [10] that has been used with school science students. The pedagogic strategy here is different because the agent is not supposed to be the source of knowledge but to be taught by the student.
− *PCAs that serve as companions*. For instance, MyPet [11] that is an animated dog or cat whose aim is just to be in the system to motivate the student.

3 Proposal

Following the work reported in [9], our hypothesis is that the use of Natural Language Processing techniques would allow the generation of dialog templates adapted to each student model and that it would improve the perceived quality and trustworthiness of the Pedagogic Conversational Agent.

In order to test that hypothesis, we are in the process of building a complete Pedagogic Conversational Agent from the core engine of the Willow free-text scoring system [12]. Willow is able to keep a student model with an estimation of the level of knowledge that a student has on the concepts of a course. Currently, the questions of the course and the key concepts have to be specified by the teacher of the course in the Willow's authoring tool, but our aim is that Willow will be able to generate its own questions to dialogue with the student and focus on the less known concepts.

The architecture of Willow would change as shown in Figure 1. In this paper, a first implementation of the module 'Generator of dialogue templates from the student model' is presented. The module is shadowed in the architecture.

As can be seen it gets as input the student model in the form a conceptual model such as the one shown in Figure 2 and currently produces a question in the form 'Is X a kind of Y?' where X and Y are two related concepts in the student's conceptual model. Furthermore, X is a precedent concept according to he Meaningful Learning Theory of Ausubel and it should be learnt before Y. For instance, in an English Learning Course, a teacher could have identified 'apple' and 'fruit' as two key concepts and the module could generate the question 'Is an apple a kind of fruit?'

That way, teachers would not need either to type those taxonomic relationships questions in their course or to type their answers. It is because from the information in the domain model, it is trivial to automatically identify that those concepts are related and thus, Willow would expect an affirmative question for them and vice versa.
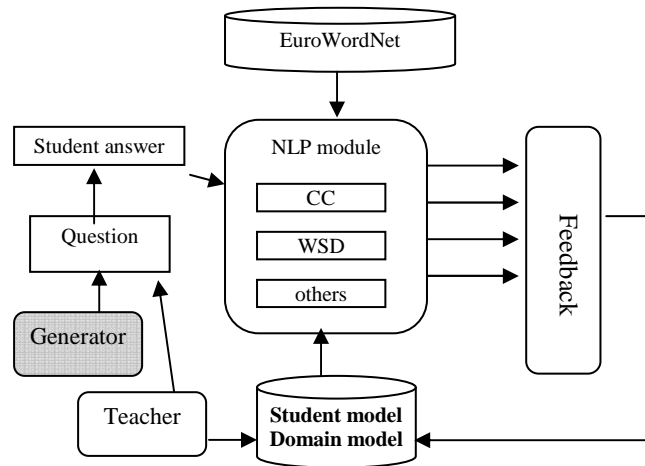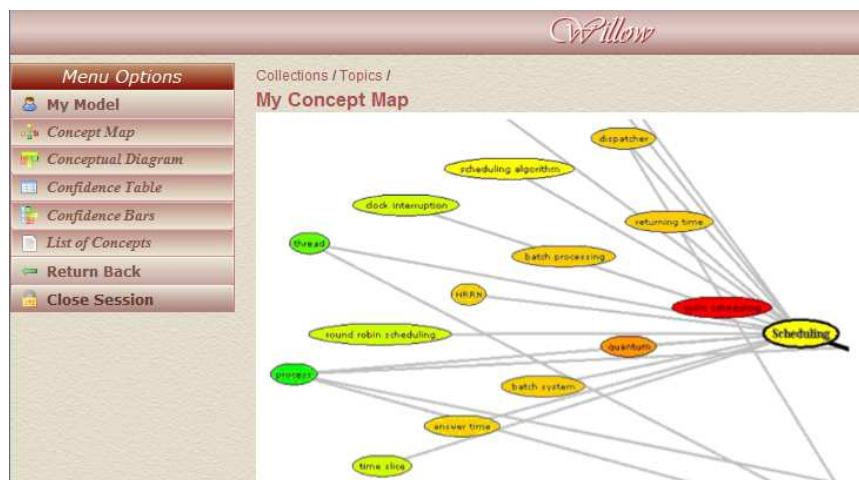
Fig. 1 High-level Architecture of Willow

Fig. 2. Sample Student Model in Willow

4 Results

The generator for the taxonomic questions has already been implemented in Java. An independent web system from Willow has been deployed to test the module. The input files provided to the module has been extracted from the students' conceptual and domain models in Willow. In particular, Table 1 shows 5 runs tested with 5 different students' conceptual models ranging from 2 up to 15 concepts. As can be seen, the number of different questions that can be automatically generated is quite high.

Table 1. Number of questions generated according to the number of concepts.

Number of concepts	Number of questions
2	1
5	6
11	30
13	36
15	40

5 Discussion and Future Work

Given the preliminary nature of the results in this paper, it is still early to provide evidence to support any hypothesis. Nevertheless, the simple fact that 40 questions can be generated from a student conceptual model with 15 questions without the involvement of the teacher and adapting the relationships between the concepts to the level of knowledge automatically is encouraging enough to keep working in this line of research.

It is our intention to keep working in the generator module so that it is not limited just to taxonomic relationships questions, but it is also able to generate more complex questions from the information extracted in the students' answers provided to Willow and the conceptual model kept by the system.

Furthermore, once the implementation is finished, we will carry out an experiment with university students to test whether the use of Willow (being able not only to automatically evaluate the students' answer but also to generate the questions) produces a statistically significant higher perception of quality in the dialogue and trustworthiness to use the system.

Other line of future work that is to be researched with Willow is in the field of personalization. Currently, Willow is represented by an owl. In the last experience with Willow we introduced a first change in that respect and asked the students to use a different avatar for Willow from a set provided.

However, many students did not use that feature. We think that it could be due to the limitation of choosing just among the avatars provided. Therefore, in the next experiment, we will separate the test students who will use the agent Willow into two subgroups: subgroup A will be able to use any figure from Internet or their local disk to personalize Willow's avatar and their own, while subgroup B will not have those possibilities and will remain with the typical Willow's avatars as shown in Figure 3.
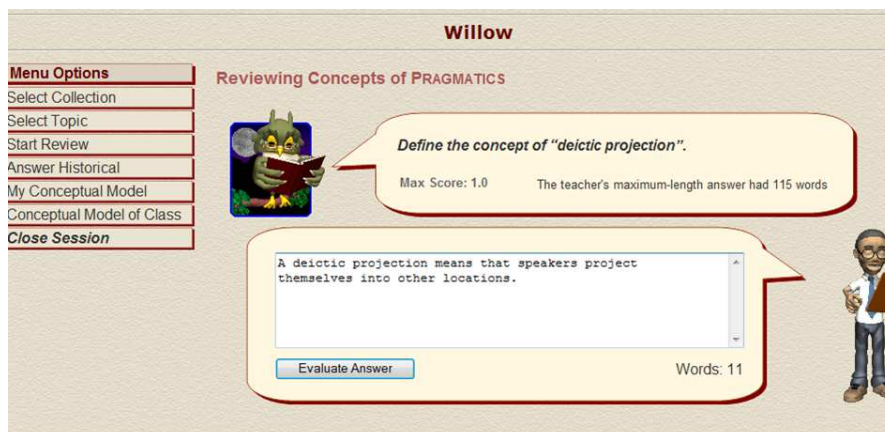
Fig. 3. Snapshot of the Willow interface

References

1. Macskassy, S., Stevenson, S.: A conversational agent. Rutgers University (1996)
2. Weizenbaum, J.: Eliza, a computer program for the study of natural language communication between man and machine. Communications of the ACM 9, 26-45 (1966)
3. Lester, J., Brandy, K., Mott, B.: The Practical Handbook of Internet Computing. Chapman & Hall, chapter Conversational Agents, 220-241 (2004).
4. Ausubel, D.: The Psychology of Meaningful Verbal Learning. NY: Grune & Stratton (1963)
5. Mitkov, R.: The Oxford Handbook of Computational Linguistics, Oxford Press (2003).
6. Baecker, R.M. Buxton, W.: Readings in human-computer interaction: A multidisciplinary approach. Morgan Kaufmann Publishers, CA (1987)
7. Kerly, A., Ellis, R., & Bull, S.: Conversational Agents in E-Learning, Applications and Innovations in Intelligent Systems XVI - Proceedings of AI, Springer, London (2008).
8. Graesser, A., Person, N.; Harter, D. Teaching tactics and dialog in AutoTutor, International Journal of Artificial Intelligence in Education 12, 3, 23-29 (2001).
9. Jackson, T., Mathews, E., Lin K., Olney, A., Graesser, A.: Modeling Student Performance to Enhance the Pedagogy of AutoTutor. LNCS 2702, Springer, UM (2003)
10. Wagster, J., Kwong, H., Segedy, J., Biswas, G., Schwartz, D.: Bringing CBLEs into Classrooms: Experiences with the Betty's Brain System. IEEE ICALT, 252-256 (2008).
11. Chen, Z., Liao, C., Chien, T. & Chan, T.: Animal Companion Approach to Fostering Students' Effort-Making Behaviors, in 'Artificial Intelligence in Education' (2009).
12. Pérez-Marín, D., Alfonseca, E., Rodríguez, P. & Pascual-Nieto, I. Willow: Automatic and adaptive assessment of students free-text answers, in 'Proceedings of the 22nd International Conference of the Spanish Society for the Natural Language Processing (2006).

Characters that Help You Learn:
Individualized Practice with Virtual Human Role Players

H. Chad Lane

Institute for Creative Technologies
University of Southern California
lane@ict.usc.edu

Abstract. This paper describes how virtual humans can be used as role players in for communicative tasks that require modification of one's social skills. Examples are discussed, including systems for intercultural communication and doctor-patient interviewing, and we conclude with a discussion of the challenges of providing individualized practice by dynamically adjusting the behaviors of virtual humans to meet specific learner needs.

Keywords: virtual humans; social skills; pedagogical experience manipulation

1 Introduction

Pedagogical agents are most often designed to play the role of tutor or peer in virtual learning environments [1]. In these roles, the agent works alongside the learner to solve problems, ask questions, hold conversations, and provide guidance. Over the last decade or so, a new breed of pedagogical agents has emerged that do not play the role of expert or peer, but rather act as the *object* of practice. That is, instead of helping on the side, it is the interaction itself (with the agent) that is intended to have educational value. Here, the agent is usually a *virtual human* that is playing some defined social role in an interaction. To "succeed", the learner must apply specific communicative skills. For example, to prepare for an international business trip, one might meet with a virtual foreign business partner to negotiate a contract agreement.

The technological goal is to simulate an authentic social context for the practice and learning of new communicative skills. In describing the challenges of modeling human reasoning and emotion related to building virtual humans, Gratch and Marsella [2] state that "The design of these systems is essentially a compromise, with little theoretical or empirical guidance on the impact of these compromises on pedagogy" (p.215). What are the implications of the pedagogical demands on virtual human design? How could virtual humans facilitate learning? In this paper, we explore some methods for providing guidance *through* the virtual human role players. Inspired by anecdotal statements from expert human role players who reported adjusting their behaviors based on observations of learners, we outline the dimensions of what is adjustable in virtual and discuss some examples of how virtual human role players might similarly adapt to meet specific learner needs.

2   Virtual human role players

Live role playing has a long history in education [3] and because it is interactive and situated, is a common strategy for teaching social interaction skills [4]. There are problems, however, with the approach. Role playing in classrooms or offices is not situated in a realistic context, and when done with peers, raises authenticity concerns. Expert human role players are generally the best option, but are not cost-effective and can be prone to inconsistency (between different role players and due to fatigue). Virtual humans that exist in authentic, virtual environments, are beginning to emerge that address some of these problems.

Cultural learning, interpersonal communication, and language learning are popular targets for virtual human-based training systems. For example, BiLAT [5] is a serious game that situates the learner in a narrative context to prepare and meet with a series of virtual humans to solve problems. A similar structure is used in the Tactical Language family of serious games where the focus is on conversational language, communicative, and intercultural competence [6]. Another prominent domain for virtual humans is clinical training. Virtual "standardized" patients have been used to train psychiatric students in the classification of post-traumatic stress disorder (PTSD) cases [7] as well for the practice of positive non-verbal behaviors during clinical interviewing, such as body positioning and eye gaze [8]. Virtual humans have been used in countless other social contexts, including for police officer training [9], teaching coping behaviors for bullying in schools [10], and demonstrating healthy play for children with autism [11]. Across the wide spectrum of these applications, most of the individualization that occurs is (1) at the learner's discretion, and (2) at the scenario level (e.g., to select appropriate characters to meet with). In the sections that follow, we discuss how the level of individualization might be pushed down into the dynamic behaviors of the characters themselves.

3   What can be tailored in a virtual human?

The efficacy of virtual humans to support intercultural and social skill learning has been shown in numerous studies [12-14]. In each case, character models were developed based on analysis of human-human data and input from experts with realism taking highest priority. What counts as "realistic" is therefore based primarily on expert opinion and subject to great amount of variance given the often inconsistent nature of human behavior. People with the same cultural background may possess very different opinions about a certain cultural value because of regional or personality differences, for example. Stories for characters can be easily constructed that lead to different outcomes (e.g., "the character is having a bad day"). Thus, different reactions to the same action – either between characters, or even from the same character at a different time or place – are entirely plausible. It seems there is a vast (and to date, unarticulated) space of communicative experiences that we might consider "realistic". This section describes a few of the more prominent dimensions in which current virtual humans communicate.

Fig.1. Expressions of anger, skepticism, appreciation, and umbrage by ICT virtual humans [15]

Nonverbal behaviors. Observable, nonverbal behaviors during interactions with virtual humans are often a primary focus in studies of their communicative competency and fluidity. For example, the role of eye gaze, nodding, and gestures play a significant role in generating feelings of rapport in users [16]. When no attempt is made to align nonverbal behaviors with the utterances of users ("non-contingent" responses), feelings of distraction and disfluency in speech follow. The implication for learning with virtual humans is that if their nonverbal behaviors are unnatural to the point of being a distraction, learning may be hindered.

Nonverbal behaviors play a large part in the expression of emotion and it is possible to convey a great deal of implicit feedback through them. There is staggering complexity that emerges from facial expressions alone, but also through gaze, body positioning and movement, and gesturing (examples are shown Figure1). Such signals also come in varying levels of *intensity*, as measured by onset, duration, and length [17], and so these all represent adjustable parameters that would enable the system to *dampen* or *magnify* nonverbal backchannel feedback from the virtual human.

Content. The information conveyed and the words used to encode a message represent another critical dimension in the space of configurability. A message may have more or less content, more or less meaning, more or fewer emotive words, more or less explanatory content, and so on. The "best" choice of content depends heavily on many factors, including the context of the simulated social situation (e.g., business vs. casual), the culture and personality of the virtual human (e.g., reticent vs. talkative), the familiarity of the character with the user, and more.

Cognitive, communicative, and emotional models. The most sophisticated virtual humans are able to do complex, task-based reasoning and behave based on underlying representations of the dialogue, their intentions, desires, the task domain, and their emotions [15]. Nonverbal and verbal behaviors follow from these basic underlying representations and they are naturally influenced by the incoming utterances of a human user. For example, a threatening utterance might trigger a withdraw intention, which in turn increases terseness and the likelihood of compliance. Speaker intentions may vary greatly from how the message is received. Misunderstandings between a learner and a virtual human role player can have a profound effect on the learner's evolving understanding of the skills being practiced.

4 Towards adaptive virtual human role players

Dynamic tailoring can be understood as influencing or overriding the standard behaviors of a simulation, as it is running, for pedagogical reasons [18]. In domains like human behavior, where there is significantly more freedom in what may be considered realistic than in many other domains (like physics), the idea is to select actions within this range of acceptability that will have the most pedagogical benefit. Given the dimensions of adjustability discussed in the previous section, some pedagogical goals dynamic tailoring could be used to achieve are:

1. support *recognition* when errors are committed or ideal actions taken
2. provide an *explanation* for observed reactions and emotional state changes
3. suggest a *repair* for how a learner might revise their beliefs

These are the same broad goals typically addressed by explicit feedback from a human or computer tutor [19]. The difference is that these goals are achieved through the character, by modifying utterances, beliefs, or behaviors, while maintaining the narrative context and not detracting from the perceived realism of the experience.

Achieving these pedagogical goals is more complicated than it is with explicit feedback. To alter behavior, it is necessary to both select what dimension to tailor (e.g., nonverbal, content, model) and how to do it. Further, a method for ensuring fidelity (acceptability, believability, etc.) should be included in the form of preconditions on modification rules or as a separate filter. Some examples of how a character might achieve the goals of recognition, explanation, or repair include:

1. amplification of virtual human response behavior, such as the intensity of facial expressions or use of emotionally charged vocabulary (recognition)
2. description of a causal link between a user action and a negative (or positive) result via additional content (e.g., "By suggesting X you are essentially blaming me for the problem."; explanation)
3. clarification of a relevant domain concept by including it in the content of an utterance ("In my culture we believe X…"; explanation; repair).
4. suggestion of an alternative communicative action that would have produced a better outcome (e.g., "If I were you, I'd …"; repair)

The central idea behind all of these strategies is to build on the existing feedback already coming from the virtual human, but alter it to address a specific need of the learner. The changes can be generated from shallow modification rules, such as "increase the intensity of facial expressions to enhance feedback" or through deeper, model-based adjustments like "increase the cultural pride of the character, which will produce longer utterances that explain beliefs and/or values."

We have completed a prototype system that modifies the content of character utterances to both amplify feedback and provide explanations [18]. The system, built as a supplemental component to BiLAT [5], tracks meetings with characters and augments character utterances when errors are made and when a specific knowledge component (cultural knowledge, in this case) is first encountered. For example, if an error is made by a beginner, the character might bring up the underlying cultural difference in their response (a content adjustment). Other learners would get the standard simulation response. Currently, the system uses a rudimentary student model to track learner's progress and studies of the system effectiveness are being planned.

For virtual human role players to adapt based on pedagogical aims, it is likely that more sophisticated learner models will be necessary. Building learner models for domains such as cultural learning and interpersonal skills is no simple task, but even crude distinctions can be helpful. Of course, a key question is whether such adaptations threaten fidelity and the implications of that. If learners figure out the characters are secretly "helping", does it ruin the fantasy? How does this affect learner affect and motivation to engage? Also, what if realism is breached – does this necessarily hinder learning? Future studies will need to address these questions as well as determining if support from pedagogical experience manipulation can be as effective (or complementary to) explicit help from a tutoring system.

References

1. Johnson, W.L., Rickel, J., Lester, J.C.: Animated Pedagogical Agents: Face-to-Face Interaction in Interactive Learning Environments. International Journal of Artificial Intelligence in Education **11** (2000) 47 - 48
2. Gratch, J., Marsella, S.: Lessons from emotion psychology for the design of lifelike characters. Applied Artificial Intelligence **19** (2005) 215-233
3. Kane, P.E.: Role Playing for Educational Use. Speech Teacher **13** (1964) 320-323
4. Segrin, C., Givertz, M.: Methods of social skills training and development. In: Greene, J.O., Burleson, B.R. (eds.): Handbook of Communication and Social Interaction Skills. Routledge, New York, NY (2003) 135--176
5. Kim, J.M., Hill, R.W., Durlach, P.J., Lane, H.C., Forbell, E., Core, M., Marsella, S., Pynadath, D.V., Hart, J.: BiLAT: A Game-based Environment for Practicing Negotiation in a Cultural Context. International Journal of Artificial Intelligence in Education (in press)
6. Johnson, W.L., Valente, A.: Tactical language and culture training systems: using artificial intelligence to teach foreign languages and cultures. Proceedings of the 20th national conference on Innovative applications of artificial intelligence - Volume 3. AAAI Press, Chicago, Illinois (2008) 1632-1639
7. Kenny, P., Parsons, T., Gratch, J., Rizzo, A.: Virtual humans for assisted health care. Proceedings of the 1st international conference on PErvasive Technologies Related to Assistive Environments. ACM, Athens, Greece (2008) 1-4
8. Johnsen, K., Raij, A., Stevens, A., Lind, D.S., Lok, B.: The validity of a virtual human experience for interpersonal skills education. Proceedings of the SIGCHI conference on Human factors in computing systems. ACM, San Jose, California, USA (2007) 1049-1058
9. Hubal, R.C., Frank, G.A., Guinn, C.I.: Lessons learned in modeling schizophrenic and depressed responsive virtual humans for training. Proceedings of the 8th international conference on Intelligent user interfaces. ACM, Miami, Florida, USA (2003) 85-92
10. Sapouna, M., Wolke, D., Vannini, N., Watson, S., Woods, S., Schneider, W., Enz, S., Hall, L., Paiva, A., Andre, E., Dautenhahn, K., Aylett, R.: Virtual learning intervention to reduce

bullying victimization in primary school: a controlled trial. Journal of Child Psychology and Psychiatry **51** (2010) 104-112

11. Tartaro, A., Cassell, J.: Playing with virtual peers: bootstrapping contingent discourse in children with autism. Proceedings of the 8th international conference on International conference for the learning sciences - Volume 2. International Society of the Learning Sciences, Utrecht, The Netherlands (2008) 382-389

12. Surface, E.A., Dierdorff, E.C., Watson, A.M.: Special operations language training software measurement of effectiveness study: Tactical Iraqi study final report. Special Operations Forces Language Office (2007)

13. Lane, H.C., Hays, M.J., Auerbach, D., Core, M.: Investigating the relationship between presence and learning in a serious game. In: Kay, J., Aleven, V. (eds.): 10th International Conference on Intelligent Tutoring Systems. Springer-Verlag (in press)

14. Johnsen, K., Raij, A., Stevens, A., Lind, D.S., Lok, B.: The validity of a virtual human experience for interpersonal skills education. Proceedings of Computer Human Interaction 2007 (2007) 1049-1058

15. Swartout, W., Gratch, J., Hill, R.W., Hovy, E., Marsella, S., Rickel, J., Traum, D.: Toward virtual humans. AI Magazine **27** (2006) 96-108

16. Gratch, J., Wang, N., Gerten, J., Fast, E., Duffy, R.: Creating Rapport with Virtual Agents. Proceedings of the 7th international conference on Intelligent Virtual Agents. Springer-Verlag, Paris, France (2007) 125-138

17. Ekman, P.: Facial expression and emotion. American Psychologist **48** (1993) 384-392

18. Wray, R., Lane, H.C., Stensrud, B., Core, M., Hamel, L., Forbell, E.: Pedagogical experience manipulation for cultural learning. In: Blanchard, E. (ed.): Proceedings of the 2nd Workshop on Culturally Aware Tutoring Systems at the 14th International Conference on Artificial Intelligence in Education (2009) 35-44

19. Shute, V.: Focus on Formative Feedback. Review of Educational Research **78** (2008) 153-189

A Teachable Agent Game for Elementary School Mathematics promoting Causal Reasoning and Choice

Lena Pareto

Media Produktion Department, University West, Sweden.
lena.pareto@hv.se

Abstract: We describe a mathematics computer game for children designed to promote causal reasoning, choice-making, and other higher-order cognitive activities. The game consists of a choice-based board game, enhanced with a conversational, teachable agent, taught to play the game, by the child, through demonstrations and questions. Game design is motivated by causal reasoning theory and educational psychology. The game is currently evaluated in an ongoing large-scale study that seeks to investigate the game's effects on the players' abilities to reason and make productive choices. The study involves 20 elementary-school classes at different levels.

Keywords: Teachable agent, intelligent game, mathematics, elementary school, causal reasoning, choice, metacognition

1   Introduction

Educational games have documented potential effects on learning and motivation [1,2,3], but their delimitations regarding developed skills and competencies, attitudes towards a subject, and understanding of symbolic content are less understood [4].

The purpose of our research is to show that educational games are effective for the development of higher-order cognitive and metacognitive skills. The paper presents an educational game designed to develop such skills in the context of elementary mathematics, e.g., ability to reason over, reflect over, and invent strategies for solving mathematical problems. In the game, players take turns by choosing a card (representing a number) and placing it on a game board (also representing a number). The game challenge is to make as good as possible choices with respect to cards at hand and the game goal in question. Each card may yield points and its strategic value depends on the situation, so the choices give opportunity to reason. We have found the game to give substantial training of *causal reasoning* and *choice* which are basic cognitive processes that underpin all higher-order activities [5], and which are regarded as essential to train by educational psychologists [3]. Empirical research on instructional methods for supporting causal reasoning is scarce [5].

The game relies on two threads of research: the "Squares Family" microworld for understanding arithmetic concepts of the author [6]; the teachable agent of Biswas, Schwarz et al. [7,8]. The first version of the game was developed in 1998 and field-

tested in schools in 1999. The game presented in this paper is the result of a decade of evaluation and evolution of the initial game using an iterative, user-centric approach to development. The most recent addition is a teachable agent that starts out with no knowledge about mathematics but which has a built-in ability to learn it from the child, using the teach-by-guidance model [9]: the agent learns by observing the child's game playing behavior and by posing reflective questions about the choices. In this way, the teachable agent paradigm provides *structural guidance* and *reflection techniques* [10] known to help learners achieve deep understanding [11,12,13,4].

We are currently conducting large-scale studies of learning and motivational effects of the game using experimentation, observation, and inquiry in situations where students play the game as part of their regular education. Experiments involve playing and control conditions with pre-post tests, and game log analysis. Observations are concerned with behavior and social interaction in-class. Inquiries are concerned with end-user perceptions and attitudes towards the game. The game was evaluated in 9 classes in 2009, and is being evaluated in 20 classes during 2010.

The paper's focus is on the *design of a conversational, teachable agent as a mean to stimulate causal reasoning and productive choice strategies*. The agent presented has undergone several iterations of field tests to become "smart enough" to learn game playing strategies discovered by children. The contribution over past research [9] is a *knowledge model* that also involves *choice-strategy knowledge* and a *reasoning-oriented dialogue* based on that model.

2   The Teachable Agent Math Game

The game environment consists of combined card and board games, with a variety of levels and goals. We illustrate it by a few steps from a simple game (see Figure 1):
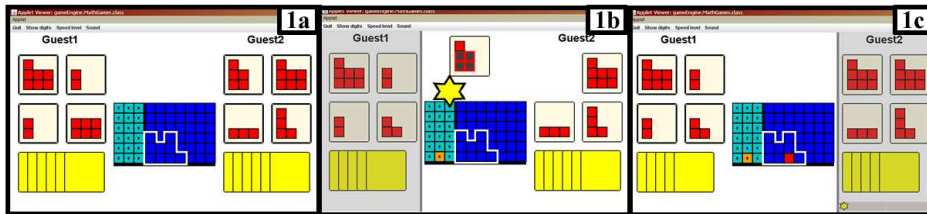

Fig. 1. Game play scenario: start (1a), during 2nd turn (1b), after 2nd turn (1c)

Two players on each side of a common game board receive 10 cards each: 4 face-up; 6 face-down. In Fig 1a the left player has received the cards 7, 2, 2 and 6 and the right player 5, 7, 3 and 4; the game board is empty and represents 0. The left player starts by choosing card 6 (bottom-right), causing 6 squares to be added to the board (not shown). The right player then chooses the card 5 (top-left of her cards), which causes a packing operation: 10 (i.e. 6+4) squares are packed into a *square-box* which is then placed in the board's leftmost compartment; the right player is awarded a point indicated by a flashing star (Fig 1b); in the same turn, the remaining square is placed on the board (Fig. 1c). This has illustrated that 6+5=11.

How well did the players do in this scenario? A better first choice for the left player would have been the card 2, since the right player's largest card is 7, and thus not enough for a carry-over: choosing 2 would have blocked the right player from scoring; further, choosing 2, neither of the right player's cards would have prevented the first player from scoring. Could the right player have made a better choice than 5, when the game board was 6? Three of the original cards would score (4, 5 and 7) whereas 3 would not so that 3 would have been a bad choice. However, card 4 is slightly better than 5, since 6+4 is 10, and no 1-digit number would yield a carry-over when added to 10. In this particular scenario the left player cannot score in either case with a board of 10 or 11, but keeping the 5 instead of the 4 might make a difference in later turns.

Already in this simple game, making good choices involve reasoning on several levels. Other games are more challenging: 3-digit cards can generate between 0-3 points per turn, and each digit in the result may allow or block the opponent to score in that position. There are games that include negative numbers, other operations than addition and have goals that are more difficult to fulfill than carry-overs. Players can choose to either compete or collaborate, and the strategies for playing well differ.

2.1 The Conversional Teachable Agent

Besides playing self, children can teach an agent how to play and watch the agent play. The agent performs according to its current knowledge level, which depends on how well it is taught. There are two ways to teach: by showing the agent how to play (show-mode); by letting the agent try and then accept or reject the agent's choice (try-mode). In both modes the agent will ask multiple-choice questions to its teacher, concerning the choice(s) just made (see Figure 2a).

The questions asked depend on several factors: the game's state (the chosen card, the board, and the players' hands), the teaching mode, whether players compete or collaborate, and the agent's current knowledge level.

The agent's knowledge level is estimated from a trace of the child's actions and from a record of her responses, as is explained in [9]. The general idea is that we keep track of positive indications (scoring rules and strategic values of chosen cards or correctly answered questions) as well as negative indications (missed rules in better choices or incorrect answers) and calculate a knowledge level from these indications.

Our current model includes knowledge in five categories 1) the game idea, 2) how the graphical model behaves, 3) how to score, 4) how to choose the best card considering own cards, and 5) how to choose the best card considering the other player's cards too. Categories 1-3 represent mathematical knowledge; while 4-5 represent strategic and choice-making knowledge.

During the game, the agent's knowledge is shown using 5 knowledge meters (see Figures 2b, 2c, 3d and 3e). Taken together, the knowledge meters reflect a progression in *sophistication of choice*: from knowing what the game is about, to consideration of all possible paths 2 steps ahead.
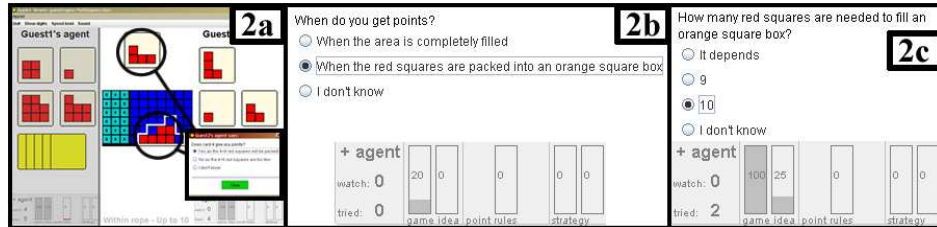
Fig. 2. Game UI (2a), game idea question (2b) and graphical model question (2c)

Questions difficulty level advance with the agent's knowledge. The simple question in Figure 2b is asked when the agent knows very little (the meters are low) and the more difficult question in 2c, later in the game, when the agent knows more. Questions are chosen to be slightly above the agent's knowledge level to allow progression towards the child's level; when the child's level is reached, the child is challenged by reflective questions. If progression stops, so will the advancement of questions. This follows the idea of Vygotskij's zone of proximal development [14].

Fig. 2 gives examples of advanced questions. Question 3a is from show-mode, where the child has chosen a card and the agent has made a hypothetical choice according to its knowledge, which is reflected in the question: "I also thought of card 4..." (the agent's choice was the same as the child's). Question 3b is from try-mode, where the child accepted the agent's choice: "So I made a good choice, right?" Question 3c occurs in either mode, and compares the child's and the agent's choice: "Why is card 2 better than card 4?". Alternative responses reflect the choice sophistication level: being able to distinguish between 1) different scores, 2) general strategic value of same-score cards and 3) situation-specific strategic value of same-score cards. Question 3d is raised when the agent's scoring knowledge is high (the middle meter is almost full), so the question considers both scoring and the strategy to leave few squares (general strategy). Question 3e is the most challenging type of questions which involves both scoring and blocking the opponent in the next turn (situation-specific strategy). To be sure of the correct response: "It's obviously the best one! It gives 1 point and it's the only card that blocks the opponent", the child must predict and distinguish between 16 alternative paths: each own card composed with any of the opponent's cards.
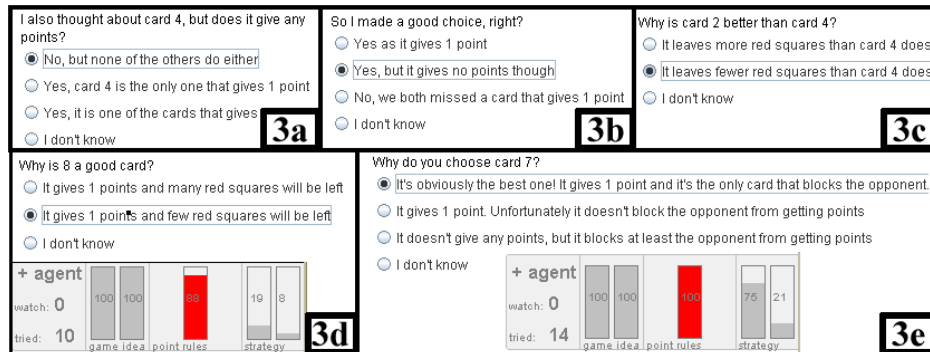

Fig. 2. Five examples (3a-3e) of questions from scoring and strategic categories

Our approach is related to the programming by demonstration principle [15,16] in the sense that the user demonstrates examples of desired behavior and the system generalizes the examples to rules. However, the agent-teaching extends the principle with reflective dialogue, it targets mathematical and strategic knowledge rather than programming, and the agent can perform (i.e., play the game) at any knowledge level.

3   Promoting Causal Reasoning and Choice

Our game is designed to promote causal reasoning and choice. In particular, it fosters the following sub-forms of causal reasoning identified by Jonassen and Ionas [5]: *prediction*, *implication*, *inference,* and *explanatory explanations*.

Prediction is defined as reasoning about possible future states on the basis of a given set of states and possible effects. Players of our game need to predict the effects of cards regarding point generation and strategic value (to play well).

Implication is defined as hypothesizing state-effect relationships. Players of our game do not know how cards score a priori, but successively discover this through hypothesizing the cards' effects on the score (while making the choice), and by observing the played card's actual effect (once the choice has been made).

Inference is defined as backwards reasoning from effect to cause. This form of reasoning occurs when a player starts from a game goal (e.g., producing a carry-over in a compartment), then decides what is needed (e.g., a card greater than or equal to 7), and finally checks for a matching of such card at hand.

Explanation in this context is defined as being able not only to induce causal relations, but also to explain them. Players of our game are prompted with reflective, explanatory questions of the agent, and thereby encouraged to reason about and verbalize *why a choice is good*.

Our game fulfills Jonassen and Ionas's recommendations on using *explorations in microworlds* and *explanatory questions* as means of achieving such reasoning skills [5]. The game relies on a microworld of arithmetic; the agent's interaction with the user relies on questions in which the child explains her choices in relation to alternatives.

The ability to make good choices is fostered by the game as a whole: the incentive of the causal reasoning, illustrated in the examples above, is to make good choices; good choice is the only way to perform well in the game. Our notion of good is captured by a context dependent *goodness value* for each possible card. The goodness value reflects the card's score and its strategic value, and is used in the assessment of the player's level of knowledge.

4   Discussions and Future Work

Schwartz and Arena argue that *choice-making* will be an important skill in the 21st century that should be practiced and assessed in education [3]. Our game gives opportunity to practice choice-making in a playful way, within a well-defined domain (arithmetic) with immediate feedback and progress, and with few choices (four cards).

Guided learning has repeatedly been shown to be superior to unguided learning [13]. The teachable agent provides implicit guidance through reflective questions that direct the player's attention to discriminating properties of the choices: each choice is assessed to give a goodness value; this allows us to study progression of choice-making, and players to value their performance (irrespective of their luck with cards).

Observations and previous studies [17] show that children quickly learn to play well, but that the degrees to which they challenge themselves vary. This is a matter of motivation; and teachable agents have increased motivation in other contexts [18].

With our new agent and with extrinsic incentives (medals, meters, high-scores, and statistics) we hope to motivate students to further engage in learning productive choice strategies. This is investigated in our current study: i.e., players' abilities to reason and make productive choices, progression paths, choice-patterns, and learning- and motivational effects compared to traditional mathematical instruction.

Finally, we think that our game mediates that mathematics is not merely a matter of right and wrong – computation is – but mathematics is much more than computation.

References

1. Ke, F: Alternative goal structures for computer game-based learning. International Journal of Computer-Supported Collaborative Learning vol 3:429--445 (2008)
2. Vogel, J.F. Vogel, D.S. Cannon-Bowers, J. Bowers, C.A. Muse, K. & Wright, M.: Computer gaming and interactive simulations for learning: A meta-analysis. Journal of Educational Computing Research, 34(3) 229--243 (2006)
3. Schwartz, D. L., & Arena, D. A.: Choice-based assessments for the digital age. [White paper]. Retrieved from http://aaalab.stanford.edu. (2009)
4. Moreno, R. & Mayer, R. E.: Role of guidance, reflection and interactivity in an agent-based multimedia game. Journal of Educational Psychology, 97(1), 117--128 (2005)
5. Jonassen, D., & Ionas, I.: Designing effective supports for causal reasoning. Educational Technology Research and Development, 56(3), 287--308 (2008)
6. Pareto, L: The Squares Family: A Game and Story based Microworld for Understanding Arithmetic Concepts designed to attract girls. In World Conference on Educational Multimedia, Hypermedia and Telecommunications, Issue 1, pp. 1567--1574 (2004)
7. Biswas, G,T. Katzlberger, J. Brandford, D. Schwartz & TAG-V: Extending intelligent learning environments with teachable agents to enhance learning. In Artificial Intelligence in Education, J.D. Moore et al. (Eds.) IOS Press, 389--397 (2001)
8. Schwartz, D.L. Blair, K.P., Biswas, G. Leelawong, K. & Davis, J.: Animations of thought: Interactivity in the teachable agents paradigm. In R. Lowe & W. Schnotz (Eds). Learning with Animation: Research and Implications for Design. UK: Cambridge Univ. Press (2007)
9. Pareto, L: Teachable Agents that Learn by Observing Game Playing Behavior. In proceedings of the Workshop on Intelligent Educational Games at the 14th International Conference on Artificial Intelligence in Education (AIED), pp 31--40 (2009).
10 Schwartz, D. L Chase, C. Wagster, J. Okita, S. Roscoe, R. Chin, D. & Biswas, G.: Interactive metacognition: Monitoring and regulating a teachable agent. In D. J. Hacker, J. Dunlosky, and A. C. Graesser (Eds.), Handbook of Metacognition in Education. (in press)

11 Kirschner, P. A, Sweller J. & Clark, R. E.: Why minimal guidance during instruction does not work: an analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. Educational Psychologist, 41(2), 75--86 (2006)

12 Manske, M & Conati, C.: Modelling Learning in Educational Games. Proceedings of the International Conference on Artificial Intelligence in Education, 411—418 (2005)

13 Mayer, R. E.: Should there be a three-strikes rule against pure discovery learning? The case for guided methods of instruction. Educational Psychologist, 59, 14--19 (2004)

14 Vygotskij, L. Tänkande och språk (eng. Thought and Language), Göteborg: Daidlos (2001)

15 Cypher, A.: Watch What I Do: Programming by Demonstration. MIT Press (1993)

16 Dey, A.K., Hamid, R, Beckmann, C, Li, I, & Hsu, D: a CAPpella: Programming by Demonstration of Context-Aware Applications. CHI Letters **6**(1): pp. 33--40 (2004)

17 Pareto, L., Schwartz, D.L. & Svensson, L.: Learning by Guiding a Teachable Agent to Play an Educational Game. In Proceedings of the International Conference on Artificial Intelligence in Education,. IOS press, pp 662--664 (2009).

18 Chase, C; Chin, D.B; Oppezzo, M, & Schwartz, D.L. Teachable agents and the protégé effect: Increasing the effort towards learning. Journal of Science Education and Technology, 18(4), 334--352 (2009)

Tuning Cognitive Tutors into a Platform for Learning-by-Teaching with SimStudent Technology

Noboru Matsuda[1], William W. Cohen[1], Kenneth R. Koedinger[1], Gabriel Stylianides[2], Victoria Keiser[1], Rohan Raizada[1]

[1]Carnegie Mellon University
5000 Forbes Ave. Pittsburgh PA, 15213
[2]University of Pittsburgh
5517 Posvar Hall, Pittsburgh PA 15260 USA
[noboru.matsuda, wcohen, koedinger, keiser, rohanr]@cs.cmu.edu
gstylian@pitt.edu

Abstract. To study cognitive and social factors that facilitate the tutor-learning effect, we have developed an on-line game-like environment where students learn algebra equation solving by teaching a computer agent, called SimStudent. SimStudent is a first pedagogical teachable agent that commits to genuine inductive learning and studied in authentic classroom settings. Our Learning by Teaching (LBT) environment is also designed to be highly modular and domain independent. Furthermore, the tutoring interface used in the proposed LBT environment is automatically extracted from a Cognitive Tutor authored with Cognitive Tutor Authoring Tools. Thus, it is fairly easy to build a LBT environment for a new subject domain.

1   Introduction

It is well known that students learn by teaching others [1], and there is a school of researchers studying such an *effect of tutor learning* using a cutting-edge technology of pedagogical computer agent. The advanced agent technology enables us to conduct fine-grained controlled studies to investigate cognitive and social factors that facilitate tutor learning.

One of the challenging issues to study the effect of tutor learning is that the tutor learns at the tutee's expense. The tutee might not learn much from the tutor who is also learning the subject. It is also difficult to conduct control studies to explore the facilitators for the tutor learning in such a real peer-learning context. To address these issues, we have developed a pedagogical machine-learning agent, called SimStudent [2] that inductively learns cognitive skills from worked-out examples or through tutored problem-solving in the context of learning by teaching, which is the primary focus in the current paper. Using the SimStudent technology, we developed

an on-line game-like learning environment where students learn algebra equation solving by teaching SimStudent.

The purpose of this paper is to introduce an overview of SimStudent and the Learning by Teaching (LBT) environment. We discuss a various aspects of the teachable agent and summarize advantages and disadvantages of SimStudent as a research tool to study the effect of tutor learning. One of the unique characteristics of our LBT environment is that it is designed to use a tutoring interface taken from a Cognitive Tutor, which is authored by Cognitive Tutor Authoring Tools (CTAT) [3]. Coupling CTAT and SimStudent strikingly makes it affordable to build a new LBT environment with customized study variables to advance the theory of tutor-learning effect.

2 Teachable Agent Technologies

A *teachable agent* is a peer learner that students can teach. Using a teachable computer agent in an educational context is not a new idea. There have been a number of different teachable agents developed so far for different purposes and hence with different roles.

One of the most controversial issues is whether a teachable agent should actually learn knowledge from students or it could just dissimulate its learning capability. Math Concept Learning System (MCLS) [4] is an early example of the teachable agent that engages in *inductive learning* from examples. Our SimStudent also falls into this category. A set of background knowledge is given to compose the hypotheses from given examples. Since this type of teachable agent has the ability to learn correct or incorrect knowledge based on the student's input, it can be used to see if students learn from errors made by the teachable agent, the so-called effect of corrective self-explanation. The other type of teachable agent does not actually commit to learning, but rather solicits tutoring activities from the student [5]. There has been no direct control study comparing teachable agents that commit genuine learning vs. pseudo learning. Such a comparison would clarify the importance of the behavioral characteristics of the teachable agent for tutor learning.

Sometimes, the domain principles are conveyed directly by the student using the exact knowledge representation used by the teachable agent. Other teachable agents create such domain principles by themselves using their own knowledge representation that may be different from the students' mental models. Betty's Brain [6] is an example of the teachable agent that shares the knowledge representation with the student. When teaching Betty's Brain, the student draws a concept map representing a causal network in a natural system (e.g., ecosystem). Given the concept map, Betty's Brain then derives a causal inference. When Betty's Brain makes an incorrect inference, the student must identify a flaw in the concept map and correct it by redrawing the map. DENISE [7] is another example of sharing a knowledge representation to learn a causal qualitative model of economics. Since MCLS and SimStudent both learn production rules, the student does not exactly know what the teachable agent has learned. Such a gap between the student's input and the teachable agent's output then gives the student more challenge to remediate the incorrect knowledge acquired by the teachable agent. Thus, the formative assessment becomes

more natural and essential in the tutoring context. This issue is also related to the visibility of the acquired knowledge discussed in the next section.

Would it facilitate the student's learning if the student could directly peek at the knowledge that the teachable agent has learned? Diagnosing the proficiency of the tutee and providing an adaptive instruction is an essential aspect of tutoring. If the student could directly itemize what the teachable agent knows, it might facilitate the tutoring processes. In some systems, such a direct observation happens quite naturalistically. Obayashi et al. [8] developed a virtual classroom environment where multiple teachable agents, after being tutored by individual students, solve problems. The students observe the answers made by the teachable agents (not only their own agents, but also others), and reflect their own knowledge. The subject domain used for their study was psychophysiology, and hence the student and the teachable agent shared the knowledge representation. Betty's Brain is another example in which the student can directly browse the knowledge acquired by the teachable agent (which in this case is exactly what the student has drawn).

3 SimStudent – General Overview

SimStudent is a machine-learning agent that inductively learns cognitive skills for solving procedural problems from examples. It is a realization of *programming by demonstration* with an underlying technology of *inductive logic programming*. There are two essential learning strategies implemented for SimStudent – learning from worked-out examples and learning by tutored-problem solving. In either case, there must be a *tutor agent* that provides examples and feedback to SimStudent.

When SimStudent is engaged in the former learning strategy, SimStudent attempts to generate a set of hypotheses that explain demonstrated solutions. The hypotheses are represented as production rules. This type of learning is passive and only *positive examples* are explicitly given (in the form of worked-out examples) to SimStudent. A closed world assumption applies here, so a positive example of a particular skill K implicitly serves as a *negative example* for all other skills than K.

When SimStudent commits learning by tutored-problem solving, it is given a series of problems to solve. While solving problems, SimStudent gets feedback from the tutor agent on the correctness of the step performed. The feedback on the correctness simply shows whether the step performed is correct or not. SimStudent may commit alternative attempts until the step is performed correctly. When SimStudent cannot perform a step correctly, then SimStudent asks the tutor agent for a hint on what to do next. The tutor agent then responds to the request by actually performing the step. Details of SimStudent can be found elsewhere [2].

4 Learning by Teaching Environment

Figure 1 shows a screenshot of the LBT environment. Although the underlying system architecture is domain independent, the current system is built for algebra linear equations. SimStudent is visualized as an avatar at the lower left corner, and

Lucy is the name of the avatar in the current version of the system. The tutor agent in this learning environment obviously is a student who tutors Lucy.

There is a Tutoring Interface in the LBT environment that the student and Lucy share to solve problems. The student enters a problem for Lucy, and Lucy attempts to solve it. A step performed by Lucy is shown in the Tutoring Interface. The student then provides feedback on the correctness of the step performed. In Figure 1, Lucy divided the equation $3x+2=5$ by 3, thus entered "divide 3" in the Transformation cell. Lucy then asked the student if such a move was a good move or not. The student provides feedback by clicking the [Yes]/[No] button. Since the student is learning the equation solving, he/she may provide incorrect feedback. The "correctness" of Lucy's performance is determined merely by the student's feedback.

The goal for the student in this LBT environment is to have Lucy pass the quiz. The system developer prepares the quiz items. When the [Quiz Lucy] button is clicked, Lucy takes the quiz. The results are then summarized in a separate window as shown in Figure 2.

Since SimStudent is capable of inductive learning, we can control SimStudent's learning ability by manipulating SimStudent's background knowledge and, thus,
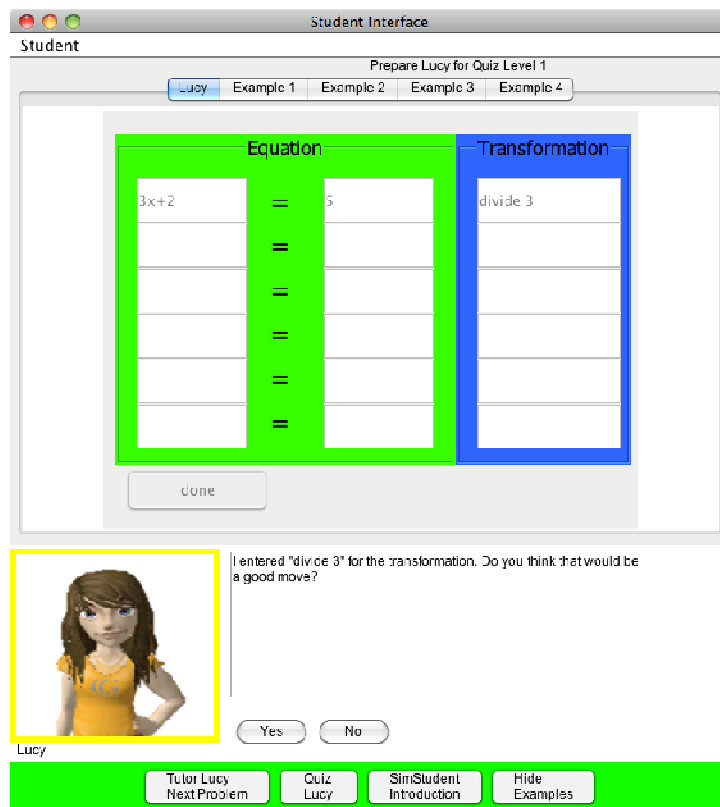

Fig. 1. Screenshot of the Learning by Teaching Environment. SimStudent is visualized as an avatar at the lower left corner and names as Lucy.

incorporate in SimStudent specific misconceptions that will yield certain errors when solving problems [9]. We have analyzed errors that students commonly make and successfully trained SimStudent to make the same errors when it is first launched. This gives us the opportunity to examine how students deal with these errors as they come up when they tutor Lucy.

5   Authoring Learning by Teaching Environment

Applying SimStudent teachable agent and the LBT environment to other domains is easy and quick. Basically, to build a new LBT environment, one needs to create a Tutoring Interface and write the necessary background knowledge for SimStudent. The entire authoring process is rapid and easy, because SimStudent is originally developed as an intelligent plug-in component for Cognitive Tutor Authoring Tools (CTAT) [3] to help novice authors build their own Cognitive Tutors without heavy programming [2].

The Tutoring Interface used in the LBT environment is automatically taken from a Cognitive Tutor authored by CTAT. Depending on the subject domain to which the LBT environment is applied, additional background knowledge

Fig. 2 Summary of quiz. The red steps are incorrect steps whereas the green steps are correct.

may need to be written with Java. There are some domain dependent components, such as examples and quiz items. These components are specified in a plane test file with fairly intuitive syntax. Interested readers can refer to the SimStudent project website (www.SimStudent.org) to learn more about how to apply SimStudent teachable agent to a new domain.

6   Discussion and Concluding Remarks

SimStudent is an inductive learner who genuinely acquires problem-solving skills from examples. The skills are represented as production rules, which is not directly sharable with the student who tutors SimStudent. The student must gauge SimStudent's proficiency in solving problems by observing SimStudent's behavior during problem solving. The student needs to diagnose SimStudent's errors and determine what problem should be posed next to remedy particular errors and/or reveal more errors. We anticipate that such meta-level monitoring skills would enhance tutor learning. A preliminary lab study showed the effectiveness of learning equation solving by teaching SimStudent [10].

Our LBT learning environment provides researchers with an infrastructure to conduct a various controlled studies to explore the effect of tutor learning. We can, for example, test if the self-explanation effect applies to the tutor learning. We modify SimStudent so that it prompts the student to justify his/her tutoring activities. We can
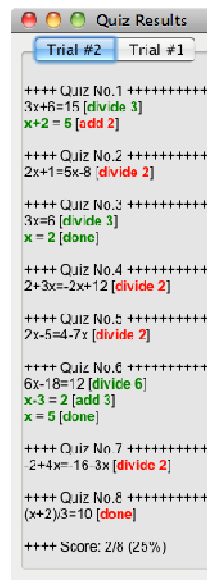
also test if an intervention of *meta-tutor* would facilitate the tutor learning. The impact of the initial proficiency level (and/or the learning capability) of SimStudent on tutor learning is another important factor that should be studied.

Using the proposed LBT learning, the researchers can various controlled studies to explore the effect of tutor learning easily and rapidly. Learning by teaching is a promising style of learning hence should be studied rigorously to establish robust cognitive theories of the tutor-learning effect.

Reference

1. Roscoe, R.D. and M.T.H. Chi, Understanding tutor learning: Knowledge-building and knowledge-telling in peer tutors' explanations and questions. Review of Educational Research, 2007. **77**(4): p. 534-574.
2. Matsuda, N., W.W. Cohen, and K.R. Koedinger, Applying Programming by Demonstration in an Intelligent Authoring Tool for Cognitive Tutors, in AAAI Workshop on Human Comprehensible Machine Learning (Technical Report WS-05-04). 2005, AAAI association: Menlo Park, CA. p. 1-8.
3. Aleven, V., et al., The Cognitive Tutor Authoring Tools (CTAT): Preliminary evaluation of efficiency gains, in Proceedings of the 8th International Conference on Intelligent Tutoring Systems, M. Ikeda, K.D. Ashley, and T.W. Chan, Editors. 2006, Springer Verlag: Berlin. p. 61-70.
4. Michie, D., A. Paterson, and J.E. Hayes, Learning by teaching, in Proc. of Second Scandinabian Conference on Artificial Intelligence. 1989: Tampere, Finland. p. 413-436.
5. Chan, T.-W. and C.-Y. Chou, Simulating a learning companion in reciprocal tutoring systems, in Proceedings of the first international conference on Computer support for collaborative learning. 1995. p. 49-56.
6. Leelawong, K. and G. Biswas, Designing Learning by Teaching Agents: The Betty's Brain System. International Journal of Artificial Intelligence in Education, 2008. **18**(3).
7. Nichols, D., Issues in designing learning by teaching systems, in Proceedings of East-West Conference on Computer Technologies in Education, P. Brusilovsky, et al., Editors. 1994.
8. Obayashi, F., H. Shimoda, and H. Yoshikawa, Construction and evaluation of CAI system based on learning by teaching to virtual student, in Proceedings of the World Multiconference on Systemics, Cybernetics and Informatics. 2000. p. 94-99.
9. Matsuda, N., et al., A Computational Model of How Learner Errors Arise from Weak Prior Knowledge, in Proceedings of the Annual Conference of the Cognitive Science Society, N. Taatgen and H. van Rijn, Editors. 2009, Cognitive Science Society: Austin, TX. p. 1288-1293.
10. Matsuda, N., et al., Learning by Teaching SimStudent: Technical Accomplishments and an Initial Use with Students, in Proceedings of the International Conference on Intelligent Tutoring Systems, J. Kay and V. Aleven, Editors. 2010 to appear, Springer: Heidelberg, Berlin.

Adaptive Agents for Promoting Intercultural Skills

W. Lewis Johnson and Alicia Sagae

Alelo Inc., 12910 Culver Bl., Suite J, Los Angeles, CA 90066 USA
ljohnson@alelo.com, asagae@alelo.com

Abstract. Pedagogic conversational agents can be effective in promoting the acquisition of language and intercultural skills, both as virtual coaches and virtual conversational partners. This paper gives an overview of a framework for utilizing conversational agents to promote acquisition of intercultural communication skills. Adaptation plays an important and increasing role, in creating courses that are adapted to the needs of particular learners, as well as pedagogic agents that adapt to the skills of the learner and the conversational context. In our current work we are developing agents with explicit models of culture, which may be used to create agents with adaptable levels of intercultural sensitivity. This makes it possible to adapt practice scenarios to the skills of the individual learner.

Keywords: Virtual coaches, virtual conversational partners, second language learning, adaptation

1 Introduction

Animated pedagogical agents have shown significant potential for promoting learning [5]. A number of recent studies have identified benefits from using them (e.g., [1]). However other studies have produced mixed results [9], or have suggested that agent features such as voice [6], language style [7], and adherence to politeness norms [8] are more important than having an animated persona. For the domain of language learning, however, animated agents offer obvious benefits, if they are designed and utilized properly. Animated agents that can engage in face-to-face conversation can give learners rich opportunities to develop and practice their language skills.

This paper gives an overview of a framework for utilizing animated pedagogical agents to promote intercultural skills, implemented in a deployed suite of learning products. The characteristics of the domain (second language learning) and the teaching method (game-based learning) necessitate an approach centering on the use of virtual conversational partners and virtual coaches, in contrast to the tutor-centric approach which is common in intelligent tutoring systems. We then discuss the general issue of adaptation in our courses, and the specific issues involved in tracking the learner's application of communication skills and adapting agent responses accordingly. Finally, we discuss current work aimed at incorporating explicit cultural models into conversational agents, which will make it possible to create agents with varying degrees of intercultural sensitivity, affecting the difficulty of the scenario.

2   Background: Intercultural Skill Learning Environments

Fig. 1. Operational Indonesian language and culture training system.

Figure 1 shows an example learning environment, Operational Indonesian. In this course learners can learn the basic skills necessary to engage in overseas operations such as humanitarian assistance. They practice their skills in interactive game scenarios. In this scenario the learner's character (center left) is engaged in a conversation with the local military commander (center right) about providing aid. The learner communicates with the non-player characters by speaking in Indonesian into a microphone, and selecting accompanying nonverbal gestures as appropriate. The goal is to get learners to the point where they can engage in conversation without hints or assistance, but until they get to that point they can refer to a list of hints of what to say, either in English (top left), or in Indonesian.

The courses cover the language and cultural knowledge and skills necessary to be effective in the target missions and situations. Curricula employ a stepwise process of knowledge acquisition and skill development. Lessons introduce the relevant phrases, vocabulary, cultural knowledge, and linguistic knowledge, and then give learners opportunities to practice applying this knowledge. Learners practice individual conversational turns, and then progress to more extended conversations, as in Fig. 1.

Approximately 100,000 people around the world have used these courses to date to learn about foreign languages and cultures [3]. We have developed a major language learning Web site that has over 10,000 registered users around the world, and many more guest users. Feedback from this user base has contributed to the development of the ideas presented here.

3   Conversational Partners, Coaches, and Scaffolds

Conversational agents in these courses fall into two main categories: conversational partners and virtual coaches. Conversational partners respond to the learner's spoken utterance and nonverbal actions, in a manner that is appropriate for the culture, the partner's social role, and the social context of the conversation. For example in Fig. 1 the conversational partners represent officers in the Indonesian Army, and the learner should address them in a manner appropriate each officer's social standing. The manner in which the agents respond provides learners with cues as to how well they are performing. For example, conversational partners may express approval then learners speak in a courteous and culturally appropriate manner, or may express offence when they commit a faux pas and say something inappropriate. This helps to make feedback become an intrinsic part of the interaction of the practice scenarios. We find that such intrinsic feedback is generally more salient and memorable than extrinsic feedback such as critiques and commentary of the learner's performance. For example, if a learner says something that is culturally offensive and inappropriate, learners will be more likely to remember and learn from their mistake if they can see the conversational partner display offence at the learner's actions.

For scenarios designed as final learning assessments, the feedback from the learner comes only from the conversational partners. In such cases the learner should be able to decide to say and do based only on what the non-player characters say, and if they require help beyond that they will receive deductions in their performance score. For practice scenarios however learners typically require more feedback than what the conversational partners provide. The agent's reaction to the learner may be subtle or ambiguous, just like in real intercultural situations, where people often avoid showing offence, out of politeness. Reactions to faux pas may be subtle and easily overlooked by someone who is not familiar with the culture. And even when learners recognize that they have made a mistake, they may not understand what exactly they did wrong or understand why it is a mistake. We therefore often find it useful to scaffold practice dialogs with hints and additional feedback and explanations.

Virtual coaches play an important role in providing this scaffolding. They help present and explain the cultural and linguistic knowledge that they will require, providing voiceover narrations of learning materials. They introduce conversational exercises, preparing learners cognitively for the exercise (by reminding them of communication skills that they will need to employ during the exercise) and preparing them affectively as well (by encouraging attitudes and affective states conducive to successful conversation). After the exercise is complete, the coach provides the learner with feedback on how they performed, so they understand what they did wrong and why. It may also give advice on which skills the learner ought to practice to perform better in the future. However we deliberately avoid developing coaches that engage in extended tutorial dialogs, so that the learners can focus attention on culturally appropriate interactions with conversational partners.

Figure 2 illustrates how a conversational partner and a virtual coach are combined in a single exercise. The learner is requested to ask his friend Matt (on the left) whether he wants to stop for a burger. The learner has attempted to make the request, but got it wrong, and so the coach has come in and explained what the learner should have said.
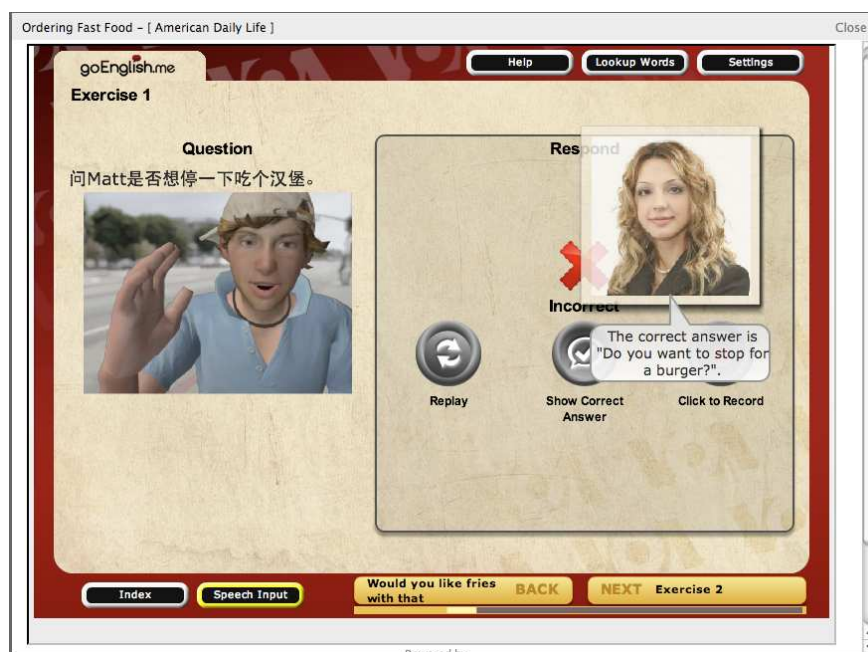
Fig. 2. Combined conversation and tutorial feedback.

One disadvantage of using a virtual coach or tutor is that the coach's intervention can disrupt the flow of the scenario and distract the learner from the conversation. Therefore during ongoing scenarios we use subtler scaffolding cues instead. We employ simple auditory signals (earcons), as graphical symbols (green plusses and red minuses) to signal when the learner has done something particularly good or bad. These alone are usually sufficient to make the learner aware of what they have done and help them adjust their behavior. Then when the scenario is done the virtual coach can come in and explain what exactly the learner did wrong and why.

4 Adaptation

It is useful to adapt the level of difficulty of practice scenarios according to the skill level of the learner. This is currently accomplished by adjusting the amount of additional scaffolding that is provided in the scenario. Depending upon the level of difficulty selected the symbols and earcons that signal a change in the agent's attitude and reaction can be disabled, and subtitles and translations can be removed.

The most important type of adaptation is in making the behavior of the conversational partners adapt in real time to the level of communicative skill of the learners, in the course of the conversations between the learners and the agents. Each agent has a level of rapport with the learner, which increases when the learner says culturally appropriate things and decreases when the learner says culturally inappropriate things. In more complex scenarios agents may include additional

dynamic social variables, such as the agent's level of trust of and fondness toward the learner. The agent's response to the learner is dependent in part upon the levels of rapport and other social variables that have been established to that point. This is particularly important when modeling relationship-oriented cultures, where it is important to establish a personal relationship with one's counterpart before getting down to business.

Agent processing is organized in a pipeline. The agent first interprets the meaning of the learner's speech and gestural inputs as a communicative act, i.e., a generalization of the concept of speech act. The agent then selects a communicative act to perform in response. Finally, it generates a combination of speech and body movements to realize the communicative act. In our currently deployed learning environments, such as those illustrated in Figures 1 and 2, agent communicative act selection is implemented using finite state machines, where state transitions may be conditioned by predicates over the social variables. We have recently developed a new architecture, called VRP (Virtual Role Player) [4], which incorporates explicit representations of the physical and social environment, and rules governing agent behavior.

We have also been experimenting with dynamic learner models that track the learner's ability to use words and phrases in conversation. The learner model tracks and records each attempt on the part of the learner to say a particular phrase. We intend to use this information to filter the curriculum, to focus on learning activities that require learners to practice the phrases that they are having difficulty with.

5 Explicit Models of Culture and Cultural Sensitivity

In our current work we are extending our VRP agent architecture to increase the level of flexibility and adaptability that is supported. This provides additional opportunities for adapting agent behavior to adjust to the skill level of the learner. By making these representations part of a shared state across multiple dialog instances, we can create agents whose behavior adapts over a series of episodes to the learner's communicative competence, creating practice experiences that are both more realistic and provide learners with an appropriate level of challenge.

A new project named CultureCom is developing formal models of the cultural influences underlying dialog and utilizing them to increase the flexibility and realism of the behavior of non-player characters in training simulations. The work is being conducted in collaboration with Dr. Michael Agar of Ethnoworks and Prof. Jerry Hobbs of the University of Southern California. Cultural and linguistic anthropologists are developing validated sociocultural data sets for Afghanistan and other cultures of interest, consisting of annotated dialogs of cross-cultural interactions. Experts in artificial intelligence then use these data to develop logical models of sociocultural behavior in different cultures, based upon a formal ontology of microsocial concepts underlying interpersonal communication. This in turn is being used to create an enhanced version of the VRP architecture in which agent intent planning utilizes explicit validated models of sociocultural reasoning for different

cultures, which can swapped in and out to enable agents to model a variety of different cultural characteristics.

The following example illustrates how CultureCom cultural models will be developed and used. American culture and Afghan culture differ in the way they express promises and commitments. Afghans sometimes agree to a request as a way of being socially agreeable, without making a firm commitment. In CultureCom we explicitly model for communicative acts what sociocultural inferences can be made from them, such as whether a statement of agreement constitutes a firm promise and commitment. This in turn can be used to ensure that the non-player character's actions consistent with the culture throughout, and can also provide helpful feedback to the learner. For example it can help learners to recognize when intercultural misunderstandings can arise due to different views of what has been promised and agreed to.

References

1. Baylor, A.L., Kim, S.: The Effects of Agent Nonverbal Communication on Procedural and Attitudinal Learning Outcomes. IVA 2008, pp. 208-214 (2008)
2. Graesser, A., Lu, S., Jackson, G.T., Mitchell, H.H., Ventura, M., Olney, A., Louwerse, M.: AutoTutor: A tutor with dialog in natural language. Behavior Research Methods, Instruments, and Computers, 36, 193-202 (2006)
3. Johnson, W.L.: Serious Use of a Serious Game for Learning Foreign Language, IJAIED (in press)
4. Johnson, W.L.: Using Immersive Simulations to Develop Intercultural Competence. In Proc. of the Intl. Conf. on Culture and Computer. Springer-Verlag, Berlin (in press)
5. Johnson, W.L., Rickel, J., & Lester J.: Animated Pedagogical Agents: Face-to-Face Interaction in Interactive Learning Environments. Int. J. of Art. Int. in Education 11, pp. 47--78 (2000)
6. Moreno, R. Mayer, R. E. (2000): Meaningful design for meaningful learning: Applying cognitive theory to multimedia explanations. In Proceedings of 2000 World Conference on Educational Multimedia Hypermedia & Telecommunications 747-752. AACE Press, Charlottesville, VA (2000)
7. Mayer, R., Fennell, S., Farmer, L, & Campbell, J.: A personalization effect in multimedia learning: Students learn better when words are in conversational style rather than formal style. Journal of Ed. Psych. 96(2), 389-395 (2004)
8. Wang, N., Johnson, W.L., Mayer, R.E., Rizzo, P., Shaw, E., & Collins, H. (2007). The Politeness Effect: Pedagogical Agents and Learning Outcomes. International Journal of Human Computer Studies (2008).
9. Woo, H.L.: Designing Multimedia Learning Environments using Animated Pedagogical Agents: Factors and Issues. J. of Comp. Assisted Learning 25 (3), pp. 203—218.