A Mixed-Initiative Intelligent Tutoring Agent for Interaction Training

Rob Hubal
Center for Research in Education
rhubal@rti.org

Curry Guinn
Center for Digital Systems Engineering
cig@rti.org

Research Triangle Institute
3040 Cornwallis Road
Research Triangle Park, NC 27709

ABSTRACT
We describe an intelligent virtual tutor for interaction skills training applications. We use agent software to create knowledgeable, emotional, expressive avatars, who populate virtual worlds both as actors within the interaction and as tutors. Our intelligent tutor can be customized by the user and can serve as demonstrator, trainer, coach, mentor, or observer. We are employing the tutor in applications for customer service, interviewing, negotiation, and patient assessment and history-taking.

Keywords
Agent, coach, interaction skills, intelligent tutor, mentor, mixed-initiative.

INTRODUCTION
We employ the set of terms "familiarize, acquire, practice, validate" to describe stages through which students pass in mastering material [11]. Becoming familiarized with to-be-learned material implies gaining declarative knowledge about components or events or procedures. Acquiring a skill is learning to perform techniques and procedures. Practice is an extension of acquisition, during which the student internalizes techniques and procedures and learns strategic knowledge about their application. Skills are validated when students are tested on their ability to perform the skills.

The role of an instructor or tutor changes as students advance in proficiency. Initially a tutor disseminates important information, familiarizing relatively passive students with to-be-learned material. Quickly, though, the students begin constructing and becoming engaged in their learning environments, and tutors transition into facilitators in the learning process. Eventually, the students have acquired the skills and know-how to apply the skills, and the tutors become those who validate skills, and finally mentors for the proficient students. These responsibilities are described as training, coaching, and mentoring [1].

Tutoring can be said to concern two issues, what to say and when to say it, depending on student needs [4,12]. During the acquisition stage, the tutor can demonstrate appropriate techniques and then, as a trainer, hold the student's hands as the student begins practice. Gradually, as the student gains proficiency, the tutor should yield control, providing coaching support but allowing the student to direct the learning. By the end of practice the tutor becomes a mentor, looking over the student's shoulder, prepared to provide guidance or feedback if the student requests, but refraining from interjecting absent an egregious error.

USE OF TECHNOLOGY FOR TUTORING
Good instructional technology that leads to constructive, experiential learning supports tutors in these different roles and even manages some of their responsibilities. We have designed systems for interviewing and interaction skills training that use an agent as tutor, who is able to behave at these multiple levels [10]. This paper describes our determination of both what support the tutor should provide and when to provide it.

Advanced Learning Environments
An advanced learning environment (ALE) [9] integrates enabling technologies such as courseware, animation, video, physical hardware trainers, natural language processing, and virtual reality, as appropriate, forming a multimedia environment well suited for acquiring cognitive skills and knowledge about processes, procedures and sequence of actions necessary to perform an assigned task. An ALE is excellent for training involving equipment that is costly or does not yet exist in quantity, tasks that are dangerous, and intangible concepts such as computation or interaction skills.

Intelligent Tutoring
In the ALE, the actual instructor acting as demonstrator, trainer, coach, mentor, or observer can be supplemented by

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virtual assistance [19]. Meta-analytic studies show how learning increases when instructors adjust their support of learning to individual students [5]. An ALE allows individualization in tutoring to take place, by way of intelligent tutoring systems and instructor support.

An intelligent tutoring system is comprised of a student model, instructor model, expert model, simulation, and user interface [16]. The student and expert models, often acquired through cognitive task analyses [2,18], enable the system to track student knowledge and misconceptions in relation to expert beliefs, and offer relevant remediation. A good instructor model consists of selecting content for the instructional goal that places the student on an appropriate learning path and determining the best delivery method for that content [13,20]. A good instructor takes an active role, noticing differences between student actions and goals and reacting accordingly [6].

Our training applications use our AvaTalk technology (described below) to simulate realistic interactions for the student, incorporating avatars and natural language into the interface. Embedded intelligent tutoring using a virtual tutor (also known as a pedagogical agent [14]) enables on-demand, learning-appropriate help. (If needed, the virtual tutor can have a capability to communicate synchronously or asynchronously with an actual instructor.) Not only are these methods effective at providing learning support, but also they are efficient in providing assistance just-in-time or just-in-place, enabling the student to continue learning immediately.

The ALE provides significant advantages for instruction over traditional learning environments, where instructors cannot play all the roles of demonstrator, trainer, coach, mentor, and observer. Numerous studies show how individualization of learning, by allowing instructors to adjust pace, difficulty, content, sequence, and style to individual students, contributes significantly to performance on aptitude tests [5]. In the ALE, students acquire knowledge on their own through multimedia lessons, simulations, and assessments. Instructors are freed to play those roles as necessary, and they can be supplemented by virtual tutors, one per student. The issue, then, becomes how to use technology as supplement (or even surrogate) for one-on-one instruction.

Available Technologies

A host of technologies are available to create intelligent tutors. Technology options include context-sensitive textual help, content-relevant answers to domain-specific questions (like faq lists), animated characters that pop up when the system detects trouble, videotaped clips of an instructor, and interactive, personal agents.

For interaction skills training, we feel that lifelike agents are more likely lead to competency or mastery of subject matter compared with the other options. We reason that the added realism of having an emotive, responsive avatar will engage the student, while immediate guidance and appropriate feedback (through good student and instructor models) will lead to effective acquisition and greater retention [5,6]. Enabling the student to query an intelligent agent, either during or after an interaction, allows strategic and reflective thinking that together produce stronger learning [15,17]. Further, the interactions within our applications use avatars as interactive partners, because we have found this to be a cost-effective approach [10]; avatars as virtual tutors fit naturally within this design.

AvaTalk® AGENT SOFTWARE

We have performed research in the field of responsive agent technology and developed a Windows-based architecture, called AvaTalk, that enables users to carry on natural conversations with avatars and to see and hear their realistic responses. Among the components that underlie AvaTalk are a Language Processor, a Behavior Engine, and a Visualization Engine (Figure 1). The Language Processor accepts spoken input and maps this input to an underlying semantic representation, and then functions as a speech generator by working in reverse, mapping semantic representations to speech output, facial expressions, and gestures, displayed by the Visualization Engine. The Behavior Engine maps the output of the Language Processor and other environmental stimuli to agent behaviors. These behaviors include decision making and problem solving, performing actions in the virtual world, changes in facial and body expression (via the Visualization Engine), and spoken dialog.

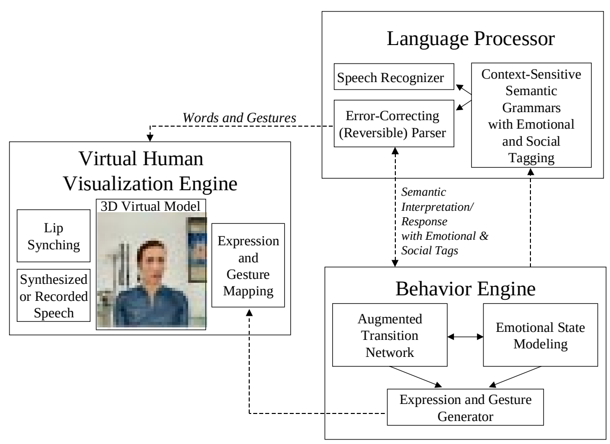

Figure 1: AvaTalk Architecture

Conversation between the user and avatar(s) adds realism and engagement to the training environment. Natural language in our applications uses the AvaTalk Language Processor, which:

- Is speaker-independent.
- Through error-correcting parsing can correctly handle utterances outside the grammar.
- Allows dynamic conversation by changing context as the situation progresses.

- Can resolve pronoun usage and incomplete sentences.
- Computes the likelihood of understanding (a score that can be used to ask for repetition or confirmation).
- Is goal-driven, directing the conversation to satisfy either user- or agent-defined objectives.

Agent behavior is dependent on the AvaTalk Behavior Engine. State variables are maintained for each avatar in the simulation and for the user. One set of variables tracks avatar emotions and personality traits, which are updated throughout the simulation. Another set tracks physical or physiological characteristics of the avatar. Hence, our agents are emotive, symptomatic, idiosyncratic avatars. Another set tracks student progress through training lessons and modules, maintaining a model of student knowledge.

We have created or are creating several effective and engaging training applications using AvaTalk technology. For instance, under Army ACT II funds, we developed the Advanced Maintenance Assistant and Trainer (AMAT), a spoken-dialogue assistant and trainer for the maintenance of line replaceable units in a virtual model of the M1A1 Abrams tank [7]. In AMAT, the soldier conducts a dialog with an intelligent virtual tutor (intelligent because of an integral expert model), who provides verbal cues on how to find appropriate diagnostic information and procedures within technical manuals. AMAT also allows the soldier to speak to the system to manipulate the view in the virtual tank. The virtual tutor in AMAT acts as a coach, mentor, and observer, but not as a demonstrator or trainer, because the soldier is expected to have already acquired basic diagnostic skills.

AMAT is not geared toward interaction skills, but our avatars are capable of exhibiting realistic interactive behavior. We have recently created applications focusing on providing good customer service, interviewing survey respondents, negotiating with mentally disturbed individuals, and eliciting trauma and medical history information from patients. For example, AVATALK-Survey generates a variety of virtual household respondents, with whom the novice interviewer must converse to obtain participation to conduct the survey [2]. An intelligent virtual tutor (whose appearance the student can specify, given available virtual models) is present on the screen and always listening to the student. We claim the agent is intelligent by virtue of its extensive expert model, the integration of an instructor model, and the behavioral model inherent in AvaTalk. The virtual tutor can act as demonstrator by showing the interviewer how to adapt responses to obtain participation from a particular type of respondent, coach by actively providing guidance and feedback, mentor by monitoring student activity and occasionally providing learning support, or simply passive observer. For the coach and mentor roles, the student can control how "intrusive" is the tutor; controls are available for such parameters as level of support (actually a sliding scale rather than discrete choices), need for proactive guidance or reactive feedback, extent of review after one iteration of an interaction has completed, and even personality style. (Table 1 lists sample instructional and tutor variables over which the student may have control.)

Table 1: Sample Control Parameters

Tutor appearance:	Gender Age Ethnicity
Tutor personality:	Humor Politeness Volatility
Tutor role:	Level of support Record/playback the interaction
Application flow:	Timeout Scenario Difficulty Minimum Errors Allowed Max. Misunderstandings Allowed

STUDENT CONTROL

It is important to address the amount of control given to the student. It is often but not always best to give great control to the student. We consider student proficiency, student characteristics, and learning objectives.

Student Proficiency

As discussed, the amount of learning support that an instructor or virtual tutor should provide is related to student proficiency. Training without sufficient practice may cause the student to have difficulty in applying the acquired knowledge and skills. Conversely, coaching and mentoring without sufficient familiarization training may lead to inefficient learning or incorrect practices. We have developed our applications by defining the tutor roles as follows:

- Demonstrator. The tutor demonstrates for the student best practices and good techniques, showing the sequence of steps of a task and what operations need to be done at each step.
- Trainer. The tutor assists the student in progressing through multimedia instruction, providing content-relevant help. The student is largely in control of learning, though frequent assessments of knowledge can help keep learning on track.
- Coach. The tutor plays an active role in prompting or assisting the student through modules and exercises. For instance, the tutor can offer guidance in the form of suggested responses before each conversational turn in a mock interview and feedback after the turn. However, the student actually performs the steps of the task.
- Mentor. The tutor plays a less active role, offering help, remediation, or critiques when necessary or when requested by the student. The tutor is available to answer questions posed by the student, and to interact with the student via dialogs on specific steps of a process. While learning is proceeding, the system is

monitoring the student's actions to be able to provide context-sensitive assistance regarding the current state of the student's efforts. The tutor may intervene if the student makes a critical mistake.

- Observer. The tutor watches and records, noting the student's efforts at task performance but rarely interfering. After the task has been completed, the tutor conducts a dialog with the student about the student's efforts in an "after-action review" style, and/or plays back portions of the interaction to the student so that the student may also observe performance.

The virtual tutor becomes less obtrusive as learning takes place. The system can guide the fading of instructional support, as well as perform some of the fading as it determines (through of a model of the student's knowledge) that learning has occurred.

Student Characteristics

Student characteristics can also affect how much control of the environment the student is given. Some students want direct control over whatever features of the learning environment they can get, other students prefer to be led through it. Student preferences can affect presentation and displays and media use, as well as learning support. We have proposed elsewhere a software program, called a "configurator", that interfaces with the training application [3]. The configurator allows students to enter preferences in learning style and causes the training application to adjust accordingly.

Learning Objectives

Learning objectives (i.e., what is to be learned) can affect control given to the student. The applications designer should carefully weigh alternative approaches that meet learning requirements, a necessity that is frequently overlooked by designers [1]. For instance, objectives that are well-defined, structured, and well-understood, such as acquiring skills at troubleshooting equipment or at inspection, can be met using structured, ordered materials with content-relevant help, provided by trainers. In contrast, objectives that are ill-defined, unstructured, or poorly understood, such as acquiring interaction skills (e.g., customer service, interviewing), can better be met using more free-form instructional materials with context-sensitive help, provided by coaches and mentors.

Further, there should be a train-up [1] of skills, increasing the volatility, ambiguity, uncertainty, and complexity of the learning environment. This "scaffolding" [12,17] can be student as well as application controlled. Types of learning support that applications can provide include direct support (help functions, coaching, mentoring, student modeling), encouragement to reflect on learning that often leads to deeper understanding as well as realization of gaps in knowledge [15], and internal support (such as reducing task complexity or focusing the student's attention). In our applications, we provide train-up of skills by leading the student through demonstration, instructional, assisted practice (with progressively more difficult interaction scenarios), and free-play practice modules. In these modules, the virtual tutor plays the role of demonstrator, trainer, coach, and mentor, respectively. The student has control over time spent in each module (given satisfactory performance on modular assessments) and level of learning support provided in assisted practice and free-play modules.

INSTRUCTOR SUPPORT

The actual instructor, if present and able to monitor the student, can define paths through lessons and modules, direct the student to repeat tasks and procedures, or give directions to the application to filter what is provided to the student.

An intelligent virtual tutor does not necessarily supplant the instructor, but instead acts as a synchronous assistant to an often asynchronous instructor, filling the gap while the instructor is working with other students or performing other duties or remote (as in the case of distributed learning) or otherwise unavailable. The goal is to use technological capabilities to achieve a cost-effective solution when a student needs learning support.

For instance, as demonstrator and trainer, the virtual tutor can provide the strategic, domain-specific knowledge of an instructor. As coach and mentor, the virtual tutor can assist the instructor by dynamically determining an appropriate next lesson or module for the student. In these cases, the virtual tutor acts as the student's agent in implementing the instructor's requirements.

These roles involve two related efforts. First, the virtual tutor must have intelligence to select an appropriate next step or sequence of steps for the student based on the student's background and history of performance. Good expert and instructor models provide the virtual tutor with such intelligence. Second, the tutor may need to adjust simulation parameters based on perceived student strengths and weaknesses (according to its student model) to provide the most valuable learning experience possible for the next simulation. Some of these parameters will be domain-specific, involving changes to the virtual environment, conversational topics, and avatar personalities. Thus, in a military application the tutor may alter tactical elements (e.g., enemy forces and organization) or environmental values (e.g., weather or availability of supplies), whereas in a survey participation application the tutor may alter respondent attitudes (e.g., animosity toward or confusion about survey procedures) or environmental specifics (e.g., presence or absence of children, telephones ringing). Others of these parameters will be domain-independent, such as behavioral or physiological models underlying virtual actors in the simulation.

VALIDATION OF BEST PRACTICES

Our applications aim to make use of the best practices that have been learned by both commercial and military applications of dialog-based coaching systems [2,8]. By "best practices" we mean the knowledge, techniques, tactics, and procedures used by experts in the field, encoded and embedded into the interaction skills training application. Best practices are captured in focus groups, through knowledge engineering, and using cognitive task analysis.

We have found no studies to date of applications using intelligent virtual tutoring as we have described to train best practices for interaction skills. (We are embarking on the development and formal evaluation of one such application, specifically for negotiation by police officers with mentally disturbed individuals.) Informal evaluation of our existing applications leads us to believe our approach to learning support is reasonable. What may be a very practical validation of virtual tutors is obtaining student perceptions of the virtual tutor's instructional value. We can then delve deeper to analyze patterns of use matched against hypothesized patterns of use. For instance, we hypothesize that the students will start with the virtual tutor as demonstrator but will eventually shift it into a coach and then mentor. Similarly, we can assess how many and to what extent students manipulate control parameters, such as level of support, use of after-action reviews, and avatar personality style; the degree of freedom that we provide to students may be greater than they require or desire. The ultimate validation of learning support, of course, is to perform experimental analysis comparing an application using our virtual tutors to another without, evaluating student performance after learning is complete. Given earlier findings of the cost-effectiveness of ALE training applications [8], we are confident that the addition of an adaptive, intelligent virtual tutor will prove constructive.

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