Apprenticeship or Tutorial: Models for Interaction with an Intelligent Instructional System

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ABSTRACT

Conventional intelligent tutoring systems are based on the individual tutorial as a model of instructor-student interaction and use a model of the student's understanding as a principal component guiding instruction. Apprenticeship provides quite a different model of interaction in which a model of the student is not essential. Instead, the instructor, interested in making use of the student's work, provides demonstrations and feedback in terms of the product toward which they are both working. Recent advances in the cognitive science of instruction provide insights into the interactive processes by which instructors appropriate the work of apprentices. An intelligent instructional system that instantiates apprenticeship interaction illustrates an alternative to tutorial-based systems that make use of a student model.

Conventional intelligent tutoring systems are built around a model of the student's partial understanding of the expert knowledge which is used to direct instruction (Sleeman & Brown, 1982; Wenger, 1987). The model of instructional interaction on which this approach is based is the *individual tutorial* in which knowledge or skills are transmitted from the tutor to the student. There are many other ways of organizing instruction, for example, collaborative learning or apprenticeships, which could provide models for intelligent instructional systems with characteristics very different from student model-based systems. In addition, the use of these systems in the context of human instructor-student interaction releases extensive human resources (instructor and students) for monitoring progress and directing next steps making some tutoring system features unnecessary. Tracking an individual student's cognitive change may be one of the features which can be dispensed with when advanced technologies are put into use in actual instructional contexts.

This paper examines the properties of intelligent instructional systems developed recently at BBN for use in training contexts. The goal of these projects was to apply known artificial intelligence techniques to training. The results of the work, however, provide cases that illustrate a different theoretical approach to instructional interactions. The instructional format supported by the systems more closely resembles an apprenticeship than an individual tutorial. That is, students work at simulated problems resembling those they will confront in the field while the system gives them feedback and expert demonstrations. The systems do not create a model of the student. They present a model of expert performance through direct modeling as well as by showing how the student actions fit into a framework that the expert uses to evaluate them. It is assumed that students, supported by human instructors, can carry out the interpretive work required to form the expert concept based on the information provided by the system.

A THEORY OF APPRENTICESHIP LEARNING

Cognitive science has traditionally taken the view that the mind of the individual is the appropriate unit of analysis (Gardner, 1985). The individual tutorial is a natural extension of this view of human cognition since the tutor is in the role of the cognitive scientist, diagnosing the individual misconceptions and presenting just the right stimuli to move the individual to a new understanding. Work on intelligent tutoring systems has shared this traditional view in its attempt to simulate the individual's tutor as well as the tutor's model of the individual. A less traditional approach to human cognition, however, may lead to new ways of using artificial intelligence in instructional interactions.

Recent work in the cognitive science of instruction has suggested that a unit of analysis larger than the individual person may be of value in understanding how cognitive change occurs (Hutchins, in press; Lave, 1988; Newman, Griffin & Cole, 1989; Resnick, 1987). The cognitive processes are seen as entirely intertwined with the social organization of instruction. Recent interest in apprenticeship learning (Lave, in preparation; Collins, Brown & Newman, in press) follows from this reformulation since apprenticeships are a part of the organization of work. This fact leads to important constraints (e.g., the sequence of apprentice tasks has to allow for useful work to get done) and provides essential motivations (e.g., the apprentice sees the components of the task in the context of creating a product) which makes apprenticeship a potentially powerful method of instruction. The student-instructor interactions in this context do not resemble Socratic dialogues. The instructor, wanting to be able to make use of what the student is doing, provides demonstrations and feedback in terms of the product toward which they are both working.

Vygotsky's (1978, 1986) developmental psychology provides important insights into instructional interactions relevant to this approach. Vygotsky introduced the concept of a zone of proximal development in which children can work at problems that are beyond their competence as individuals. With "scaffolding" provided by others, children can solve problems interactively while they are in the process of learning how to solve them themselves. Observations of instructional interactions in which a teacher is helping a student or group of students indicate that teachers often do not have, or apparently need, an understanding of exactly how the students are approaching the task. Newman et al. (1989) describe teaching and tutorial sessions in which the teacher appropriates the students' actions into her own way of understanding the task. The teacher has to find some way for the students to play at least a minimal role in the accomplishment of the task and give feedback in terms of the expert understanding of the task: what the goal is, what is relevant, why his move was not optimal and so on. In instructional interactions, both the student and teacher are necessarily somewhat ignorant of each other's mental state. All the student has to do is produce some move that in some way contributes (or can be understood as an attempt to contribute) to the task. The teacher does not have to know exactly what the student thinks he or she is doing as long as she can appropriate what the student does into the joint accomplishment of the task. Seeing how his or her action is appropriated provides the student with an analysis of task as the teacher understands it. Thus the basis for appropriation is the notion that the meaning of an action can be changed retrospectively by the actions of others that follow it (Fox, 1987; Newman & Bruce, 1986).

The concept of appropriation provides a model for a range of interactions between two parties that have different interpretations of the initial situation. An apprenticeship, for example, involves a novice and expert where the expert makes use of the novice's work even at the earliest stages of training when the novice has little understanding of the overall process. An "intelligent" tool can also appropriate the actions of an inexperienced student. For example, a system that provides a trace of the student's algebra problem-solving activities in effect takes the students actions and displays them in a framework that the student may not initially understand (Collins & Brown, 1987). By seeing how his or her actions are displayed, the student can come to understand, for example, that problem-solving is a process of successive attempts and backtracking.

Our design for intelligent instructional systems is based on the notion that students can come to understand the expert approach to the problem by observing examples of expert problem-solving and by seeing how their actions are interpreted within the framework of the expert understanding. This instructional format, which resembles an apprenticeship, depends on the interpretive work of the student in seeing what the system made of his or her actions and on the supportive role of the human instructor (Newman, in press). A theoretical approach focusing on the characteristics of instructional interactions among the student, instructor and computer points to practical uses for relatively simple artificial intelligence.

APPLICATION OF APPRENTICESHIP TO INSTRUCTIONAL SYSTEMS

Three instructional systems implemented on Symbolics AI workstations illustrate these properties. TRIO (Ritter & Feurzeig, 1988) trains F-14 navigators to carry out air intercepts. MACH-III (Kurland & Tenney, 1988; Kurland, 1989) trains mechanics to troubleshoot a complex radar system. INCOFT (Intelligent Conduct of Fire Trainer) trains surface-to-air missile operators in the identification of aircraft (Newman, Grignetti, Gross & Massey, in press). A description of INCOFT illustrates how features of apprenticeships are instantiated in intelligent feedback and articulate expertise of the knowledge-based simulation.

The Missile Operator's Task

INCOFT is designed to train soldiers to perform a complex real-time task of monitoring the operation of an automated missile system in which errors can have tragic consequences. In modern air defense surface-to-air missile systems, radar information is processed and presented to the operators in highly abstract form. The system itself can assign identities to aircraft as friendly or hostile based on flight patterns and transmitted signals. The operator must understand what is happening during the few minutes that a track takes to traverse the radar's area of coverage and be prepared to override the system in cases where local exceptions to the tactics built into the system are required and where a higher echelon calls in information not available to the local computer.

The missile system for which INCOFT trains operators uses a point system for determining identities of aircraft picked up on its radar. The airspace surrounding the missile site and any assets it is defending is divided into volumes. Aircraft lose a certain number of points for each volume they penetrate. Friendly aircraft presumably know the exact location of these volumes as well as of safe passage corridors which cut through them. Flying so that they are aligned with the corridor, for example, is worth positive points as a friendly indicator. Depending on the specific tactical situation, there are also speed and altitude limits which cause points to be added or subtracted. Finally, there are codes which friendly aircraft can transmit that supply additional evidence of friendly status. For each of hundreds of tracks that the radar can follow, the missile system computer can assign an identity as a friend, assumed friend, unknown, or hostile depending on the predefined thresholds.

The task of manual identification is used in training operators. The assumption is that if an operator can do what the computer does, then he or she must understand how the computer works and be able to monitor its operation. The task is to learn the algorithm used by the computer and be able to reproduce it. Given the complex set of criteria and the mental arithmetic this learning task is not trivial. Interviews with students after several hours of conventional instruction indicated that they often did not understand the criteria or utilize the algorithm (Newman, 1989). Tracks which had a positive indicator were declared friendly before sufficient points were accumulated, and tracks with a single negative indicator were declared hostile while the PATRIOT computer would have still considered them unknown according to the given point values and thresholds. Students do not see the task as understanding an algorithm but rather as determining the identity of the aircraft picked up on their radar. An initial step in training, therefore, is to communicate the expert view that there is an algorithm on which these decisions must be based. INCOFT simulates the operator's console, presents scenarios, and provides speech synthesized feedback on the student's actions as well as demonstrations of how the automatic system would have handled the situation. The feedback and demonstrations appropriate and reflect back the student's actions within a framework represented both graphically and in the form of tables that displays the expert's perspective.

Replay of the Exercise

As in conventional intelligent tutoring systems, INCOFT compares the student performance to an expert performance, in this case the missile system's computer. The student is presented with a scenario of between 2 and 13 minutes in which he or she must manually identify a number of tracks. When the exercise is complete, the scenario, exactly as carried out by the student, is replayed in "fast forward", pausing for each student action. Each action is compared to the expert action and commented upon, right or wrong. Where possible, INCOFT provides an analysis of incorrect actions, and of actions that happened to be correct but for which the operator made a procedural error or failed to gather all the necessary data. For example, if the difference between the expert identification and the student identification can be accounted for by one feature or by a piece of information the student failed to gather, then that is pointed out. In all cases, the verbal feedback is accompanied by a graphic representation of the point values and thresholds involved in the arithmetic calculation.

Summary Table

When the replay is complete, a table is displayed listing the actions the missile system would have taken for each track and comparing the student actions. In addition to summarizing the replay feedback, the table displays the time lag between the missile system identification action and the student's action and relates this to the time available for making an identification action before some disaster occurs. The table also provides a summary score of percentage of correct identifications and average time to make the identification.

Expert Demonstrations

The table also serves as a menu for selecting demonstrations of the identification process for any target on which an error was made or for which the process was not understood. Unlike the replay, the expert demonstration shows the scenario as the missile system would process it in automatic mode. The action is shown in "fast forward" up to the time that there is a change in the point total for the track being demonstrated. INCOFT explains each change in terms of volume penetration, corridor alignment, exceeding speed thresholds and so on. A scale indicating the accumulated points and the thresholds for the identifications is also displayed.

FORMATIVE RESEARCH RESULTS

Formative research with students and instructors in the current program of instruction guided the design of scenarios and feedback. It also provided initial information on the potential effectiveness of INCOFT in contrast to conventional simulator-based training. This research was not intended as a summative evaluation of the effectiveness of the system but does point to areas of strength. Students who had completed the relevant portion of the course were interviewed during and after operating a scenario. We also observed two instructors use INCOFT in actual instruction with students who were learning the material for the first time.

INCOFT's Representation of the Task

Students found the replay to be a great improvement over the conventional simulator and over-the-shoulder instruction since the usual student-instructor ratio makes it impossible to obtain feedback on most actions. But beyond simply providing detailed feedback and analysis, a powerful feature of INCOFT's articulate expert became evident in the students' responses to the single track expert demos of the identification process. Students had never before seen a scenario decomposed into separate tracks. Many students remarked on being able to see the precise point at which, for example, a track dealigned with a corridor and was declared hostile. While following any single track is just a matter of straightforward adding and subtracting, the missile system is able to do that for hundreds of tracks simultaneously. A novice human operator faced with, for example, 15 tracks, will have to look at each track, one time, in some sequence and make identifications. This snapshot approach does not take in the continuous history of a single track, yet it is the patterns of motion and activity that reveal a track's identity and intention. Interestingly, interviews with experienced air defense operators who were being reassigned from different systems, indicated that it is the perception of these patterns for particular tracks that seems to mark expertise in air defense operation. By decomposing what the missile system's computer does simultaneously, INCOFT demonstrates part of human expertise in this task.

By presenting the student's task in terms of its own framework, INCOFT utilizes features of apprenticeship in its style of student-machine interaction. The system essentially shows the student how the missile system would deal with the same cases and what aspects of the simulated situation are relevant to it. Operating a simulation is not productive work so, unlike an apprentice's master, the system does not literally make use of the student's work. The feedback, however, shares features with an apprenticeship in that it relates the student's output to the expert performance rather than to the student's internal states. For example, the replay feedback presents the aircraft identifications in terms of a graphically represented arithmetic calculation and the summary table presents the student's decision-making time in relation to the urgency of the situation as an expert would understand it. In this sense, the output is appropriated by the system's interpretive framework providing a reflection for the student in the expert's terms.

The Instructors' Role in the Apprenticeship

It is assumed that human instructors are part of the training context and assist the student in interpreting the feedback and in suggesting additional practice. For example, the instructor can suggest to the student that he or she see a particular expert demonstration. A field test of INCOFT in actual instruction--supervised by instructors rather than researchers--demonstrates the reasonableness of putting this power at the disposal of real instructors and the students rather than attempting to build the entire presentation into an automatic tutor. The summary table provides an opportunity for students to ask questions of the instructors and for instructors to give meta-analyses to the students. INCOFT does not process the data further or make decisions about what the student ought to do next. These decisions are handed over to the people involved.

The following example is taken from a session in which INCOFT was being used in instruction with students who were learning the task for the first time. The instructor is a highly experienced teacher but working with INCOFT for the first time. In this segment, the student has finished a relatively complex scenario and is looking at the summary table.

S: What's the 84 mean? [referring to the summary score at the bottom of the table]

T: That's your average time, average time that you did things, 84 seconds. A minute and a half almost.

S: And it should have all been done in 30 seconds?

T: Well, remember now, 30 seconds is operator override time, and that's maximum operator override time and what we're saying there is that you have that little time to make a decision on critical things that need to be done. If you've got a target, that is if you'd put into- which tab do you have override time?

S: Uh, tab, I got it wrote down in my notes.

T: Tab zero one. And what ever you have down in your operator override time that's the amount of time you have to do something before the system automatically engages the target. Now what this says, what this says to me is that you definitely need to improve and work on your decision making ability and capability, cause 84 seconds average time in order to make a decision is a long time. If you get an aircraft going 800 meters a second,

S: Uh huh.

T: he can go a loong way in a minute and a half, a long way.

S: Okay, I want to try this one again.

This is a complex interaction in which the student displays a misconception about a 30 second time limit introduced in another context and the instructor uses the student question as an occasion to review the concept and the location in the database of the relevant parameter. The instructor returns to the initial topic and presents a graphic case for the need for the student to act more quickly.

Two kinds of instructor-student interaction are evident in this transcript. The instructor conducted a brief *tutorial* on operator override time after having recognized that the student mistook the "average time you did things" for this feature of the system which has to do specifically with time available to override the computer in automatic engagement. Clearly, the instructor recognized the misconception and engaged in an aside to try to clarify the distinction before returning to his main topic.

The other kind of instructor-student interaction evident in the transcript is an amplification of the system's appropriation of the student's actions. The system reflected back to the student the number 84 which is a way of seeing the student's actions peculiar to the expert system which is capable of comparing each student action with the "expert" treatment of the track and coming up with an average time lag. The instructor reformulated the 84 seconds as "a minute and a half almost" and later made his evaluation explicit in terms of a real world concern for PATRIOT operators. This interaction is very different from the tutorial in that it is not based on an understanding of the student in his own right but on an evaluation of the students actions in terms of how it fits into an expert performance. This is more than just feedback on the "correctness" of the performance because it is introducing and motivating considerations that become evident to the student only after he sees how the system (including the instructor) appropriates his actions. The instructor and machine work together in the appropriation: INCOFT provides the student and instructor with detailed feedback on which to base this interaction but it is the instructor, not the machine, who handles the more complex misconceptions and places the task in a motivational context.

CONCLUSION

Instructional interactions in which a tutor is attentive to the student's understanding of the task can be a valuable form of instruction but is only one of many forms in which intelligent technology can be employed. While perhaps an interesting theoretical problem, creating a machine to model human tutoring is very difficult as a practical concern. Our work on INCOFT demonstrates some simplifications of the conventional tutoring system model that make the concept practically useful in instruction. Apprenticeship provides a model of instructor-student interaction that guides our design of feedback. In an apprenticeship, the instructor is interested in appropriating the student actions into productive work. Feedback shows the student whether his or her actions are productive in the framework of the task as understood by the instructor. INCOFT does not attempt to mimic a tutorial interaction. It also does not attempt to carry the entire weight of instruction. By putting various decompositions or representations of the processes in the hands of students and human instructors, we might expect useful instructional interactions to ensue between the people involved.

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