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TUTORING ELECTRONIC TROUBLESHOOTING IN A SIMULATED MAINTENANCE WORK ENVIRONMENT

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ABSTRACT

Expert performances on authentic technical problems such as electronic fault isolation are being captured in "real time" to provide the basis for a new generation of Air Force training systems. Experts (and novices) in dozens of maintenance jobs in electronic and electro-mechanical domains are being studied with a hybrid knowledge engineering-cognitive task analysis methodology. A primary goal is to establish what humans really need to know and how they use their knowledge when they problem solve in complex workcenters that are saturated with "smart" machines. The cornerstone of the method is an expert problem solving dyad. One expert poses a problem and simulates equipment responses to a second expert who attempts to isolate the fault conceived by the first expert. Engineering expert knowledge in this fashion situates skill in the actual problem context and thus highlights the conditionalized character of expert knowledge. This is in contrast to representation techniques that yield decontextualized (and perhaps nonessential) declarative knowledge through interrogation of a single expert. A series of intelligent tutoring systems--or intelligent maintenance simulators--is being developed based on expert and novice problem solving data of this type. The training systems rest on the same problem-based cornerstone. A graded series of authentic troubleshooting problems provides the curriculum, and adaptive instructional treatments foster active learning in trainees who engage in extensive fault isolation practice and thus in conditionalizing what they know. A proof of concept training study involving human tutoring was conducted as a precursor to the computer tutors to assess this integrated, problem-based approach to task analysis and instruction. Statistically significant improvements in apprentice technicians' troubleshooting efficiency were achieved after approximately six hours of training.

INTRODUCTION

Both military and industrial work environments have grown steadily in complexity in recent decades as technologies, particularly electronics related, have advanced at staggering rates. Today's workers find themselves in contexts where interacting with complex machines is the rule. And yet, the nature of intelligent performance in such machine interactions is not well understood. In addition, beliefs that cognitive demands on humans have diminished with the proliferation of so-called smart machines have diverted attention away from the human capabilities that are important for a high-tech workforce. Yet, it now seems clear that for the foreseeable future, machine diagnostic capabilities have definite limits. These limits in turn place a premium on the human expertise that is needed to pick up where the machines leave off. For example, the hit rate for some built-in diagnostics for the B1B is only 65 percent. Even with today's widely used maintenance aiding machines (many having expert system features), the ratio of maintenance hours to flying hours for the F-15 aircraft is 50:1 (Atkinson & Hiatt, 1985). In more general terms it has been estimated that as much as 90 percent of the life-cycle cost of a defense hardware system is the cost of maintaining it.

A large-scale research program is underway at the Air Force Human Resources Laboratory in direct response to this problem. The goals are to develop methods for representing human expertise on complex technical tasks so that training systems capable of meeting the demands of high-tech workcenters can be realized.

THE ENGINEERING OF CONDITIONALIZED KNOWLEDGE

The knowledge engineering approach in the Air Force Basic Job Skills (BJS) Research Program involves "real-time" problem solving, multiple stages and types of knowledge engineering inquiry, and a number of formats for knowledge representation. A framework has been adapted from knowledge engineering work in medical diagnosis to represent the mental events of troubleshooting as conditionalized knowledge (Clancey, 1985). In this framework, actions of the problem solver are recorded as discrete operations or procedures, e.g., tracing

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schematics or measuring voltage. In addition, reasons or precursors for the actions are expressed as the goals or intents of the problem solver, and the interpretations of outcomes resulting from the actions are recorded as well. Finally, block diagram-like sketches of the equipment parts that are affected by the outcomes and actions are generated by the technician to illustrate the series of steps. Sequences of mental events such as these are called PARI structures (Precursor [to Action] - Action - Result - Interpretation). An example of PARI data for a single action node is shown in Table I.

Notice in this PARI example that the Action element is a familiar troubleshooting procedure, namely, taking a voltage measurement with a multimeter. The representational formalism of the PARI framework does more than reveal that a technician needs to know how to take a voltage measurement, however. What is also captured are the conditions that surround such a measurement operation, including the reasons behind the action (..."to see if the signal is good up to test package cable") and the interpretation of an expected voltage level (..."tells me...that part of stimulus path [upstream] is good"). In effect, the vital strategic processes of troubleshooting are made explicit with this representation scheme. The plan that produced the measurement operation becomes known. The technician's plan is to constrain the problem space by eliminating either the stimulus or measurement (return) portion of the signal path. It is precisely this kind of strategic skill that too often goes "untaught" in electronics training, in much the same way that strategic knowledge is frequently ignored in the teaching of mathematics (Greeno, 1978). When problem solving performances are captured in real time, it becomes possible to engineer strategic knowledge for input to instructional systems along with the more standard declarative knowledge. In this manner a skill such as taking a voltage reading is represented in terms of its ties to the conditions of use, just as it occurs in real world expert performances.

Representing skill components in this form offers considerable power to instruction, given that conditionalized knowledge is a recognized hallmark of expertise. Conversely, novices often display fragmented, unprincipled behavior that suggests weakness in the proceduralizing (or conditionalizing) of their skill components. In the present example, novices may know how to use a multimeter to take a voltage reading but often do not produce that action under the appropriate conditions. If produced, they often have difficulty interpreting the results of the action.

KNOWLEDGE ENGINEERING RESULTS

Approximately 15 technical experts and 200 less-than-expert technicians in four related AF electronics specialties have participated to date in knowledge engineering studies similar to those described above as part of the Basic Job Skills Research Program. On the basis of these studies, a meaningful superstructure for organizing troubleshooting performance data has been developed. It consists of three components, one of which is strategic knowledge as previewed above. The three interacting components are (1) system knowledge or the equipment device models experts use in problem solving (e.g., system knowledge regarding the stimulus or measurement functionalities of the equipment); (2) troubleshooting procedures or operations performed on the system; and (3) strategic knowledge, which includes (a) strategic decision factors that involve fault probabilities and efficiency estimates and (b) a top-level plan or strategy that is responsible for the orchestration of skill components in task execution. The orchestration occurs as the Strategy component, which sits on top of the Procedures and System Knowledge components, deploys pieces of knowledge and procedural subroutines as needed and as driven by the decision factors (Figure 1).

The System Knowledge component of the architecture deserves special attention for several reasons. First, it provides the dominant organizing principle for this cognitive skills architecture. It is the foundation to which the companion Procedures component in Figure 1 is attached. According to this view, a measurement or swapping operation is attached to a device model representation, since the purpose of the operation is viewed as adjusting the technician's present model of the device with new knowledge of faulty components. This "attachment" is part of the conditionalized character of expert knowledge. System Knowledge also feeds the strategic decision factors that underlie the Strategy component, since these factors involve system fault probabilities and efficiency estimates associated with operations on the system, e.g., it is judged time efficient by experts to run self diagnostics on some pieces of equipment but not others. Finally, System Knowledge influences the goal structure of the Strategy component in the sense that certain areas of the equipment are targeted before others (again due to fault probabilities and efficiency considerations).

The second reason why System Knowledge merits special attention here is because the curriculum content for the intelligent tutor described in the next section is directly influenced by the different system perspectives of expert troubleshooters. In the course of the knowledge engineering studies conducted to date in the BJS project, it has become clear that experts' decision making during troubleshooting is partially driven by system schemas. The schemas represent a set of system-related questions that experts entertain at various stages in the fault isolation process (Collins, 1987). They include the following:

-Is the system fail a glitch, an intermittent fail, or a hard fail?
-In which large functional area of the equipment--i.e., Line Replaceable Unit (LRU),

Test Package, or Test Station--is the fault located?
-Is the problem a power-related fail?
-Is the problem a stimulus or measurement problem?
-Is the problem a signal or data flow problem?
-Do the symptoms indicate the fault is in a device or in the connections between devices?

These questions can be viewed as the major parses the expert makes of the fault isolation space in which he/she works. Three of these parses have provided the framework for the troubleshooting problems that comprise the instructional content for the avionics intelligent tutor to be described next.

A SIMULATED MAINTENANCE WORK ENVIRONMENT

An intelligent maintenance practice environment for F15 integrated avionics technicians has been developed by researchers at the University of Pittsburgh's Learning R&D Center in collaboration with AF technical experts (Lesgold, 1987). The tutor is based on results from cognitive analyses of expert and novice AF technicians using the knowledge engineering methods referenced above. The analyses have provided three general types of input to the intelligent tutoring system: detailed characterizations of expert performance which are the targets for instruction (expressed in terms of the cognitive skills architecture of Figure 1); a framework for the design of the troubleshooting curriculum based on three parses experts make of the problem space in this domain; and guidelines for the instructional treatment based on expert-novice differences as well as on present impediments to apprenticeship learning in the workplace.

Expert Parses

Two central system schemas that experts activate as they navigate and parse problem spaces in this domain have provided the design framework for the maintenance tutor's problem set. These schemas represent two system perspectives experts' invoke, depending upon the conditions of the problem. The first concerns the major functionalities of the equipment, namely, stimulus and measurement functions. Recall that in the example reported in Table I the expert both explains his action and interprets the system's response to the action in terms of the stimulus portion of the equipment. More specifically, the procedure (action) used allows him/her to achieve the goal of verifying that a major functional area of the equipment is operating properly.

The stimulus-measurement functionalities of this equipment are illustrated in Figure 2. This is an abstracted characterization of the system's signal path. As shown, the signal originates in the stimulus drawer of an avionics test station, travels through the station's switching drawer (S/C) which performs signal switching functions, and through an interface test package to an aircraft line replaceable unit (LRU) which is being tested for a malfunction. It returns through the interface package to a measurement source in the test station.

Problems in the tutor curriculum represent faults at varying levels of difficulty in the stimulus and measurement routing of the equipment. Trainees will have modeled for them how an expert uses this perspective to isolate various faults. They will then have extensive opportunities to solve problems--with the assistance of a hint-giving coach--so that system functionality knowledge is tied to problem solving conditions. This kind of learning environment is in contrast to instruction where system knowledge would be taught as declarative facts detached from the conditions of use, or where measurement procedures would be taught in isolation from the system and the fault isolation context.

Results of our knowledge engineering work plus input from the dominant theory of skill acquisition in psychology today (Anderson, 1982) have shaped this instructional approach. First, our results have indicated that a principal form of the conditionalized knowledge of experts in this domain is the coupling of conceptual system knowledge (e.g., the stimulus-measurement functionality) with procedural and strategic components. This results in experts' investigating their equipment with specific intents and particularized procedures. In other words their system knowledge is not detached and inert, but rather is tightly interwoven with problem solving actions that are produced by strategic plans in response to certain malfunction conditions. Presently, in the Air Force this form of conditionalized knowledge results only after many years of experience, as would be predicted by Anderson's theory. A principal goal of the BJS maintenance tutor is to speed up that conditionalizing process.

The second system perspective or schema used to shape the tutor's problem set is signal flow vs data flow. Experts also view the equipment (and thus represent faults) in terms of these two interrelated system properties. In short, this schema involves knowledge that both an electronic signal and instructions (control data) to the equipment for handling the signal move through the system. Faults can occur with respect to either property. Accordingly, signal flow and control data flow problems are incorporated in the tutor at varying levels of difficulty.

Finally, a third schema, namely, the macro level functional representation of the equipment (LRU vs Test Package vs Test Station) has guided problem development. This schema is integrally tied to experts' strategic planning knowledge in the sense that they typically plan their moves through the problem space so that they systematically rule out the LRU before moving their focus to either the Test Package or Test Station. Trainees will make decisions within the tutor environment to pursue either an LRU Plan, a Test Package Plan, or a Test Station Plan.

In summary, the development of the Air Force avionics tutor illustrates that knowledge engineering can usefully feed instructional design as well as provide the more standard type of input, i.e., the expert knowledge base. Further, dynamic, problem-based knowledge engineering allows for the representation of conditionalized knowledge so that the most critical stage of skill acquisition can be targeted by instruction. That is the stage at which knowledge becomes tied to conditions of use. The avionics maintenance tutoring system based on this approach will be discussed in more detail in the next section.

An AI Instructional Application.

The BJS tutoring system that has resulted from the expert dyad approach to knowledge engineering is an interesting AI application in the sense that it embodies minimally deep intelligence. It avoids complete qualitative physics of the work environment as well as a complete computer representation of expertise (Lesgold, 1987). In short, there is neither a fully articulate expert nor a runnable equipment simulation. Later tutors in the BJS series will have these features; however, this initial system is of special interest in its own right. Its development is much less resource intensive than that of deep intelligence tutors, and it has received an enthusiastic reception from technical experts at the three operational sites where it will soon be tested. If the evaluation results reveal troubleshooting performance gains in accordance with the predictions of field personnel, this form of intelligent tutoring system represents a quite feasible prototype that can immediately generalize to other troubleshooting domains.

A rigorous evaluation study will accompany the intervention in order to formally assess its effectiveness. A controlled experiment will permit the determination of how much on-the-job experience is replaced by the 30 to 50 hours of tutor instruction. In addition, performance of individual technicians and the shop-level productivity of the three F15 workcenters will be tracked longitudinally to ascertain the long-term impact of the instruction.

As a precursor to this series of BJS intelligent tutoring systems, a training study involving a human tutor (versus a computer coach) was conducted in a related F15 integrated avionics domain. One goal was to test the concept of basing instruction on representations of conditionalized expert knowledge. The treatment involved the posing of authentic troubleshooting problems similar to those generated in a BJS knowledge engineering study as described above. The expert-like skills targeted for enhancement were particular instantiations of the cognitive skills architecture (Figure 1). The system knowledge of interest was the abstracted signal path shown in Figure 2, plus several layers of elaborated system knowledge. The procedures of interest were three methods for investigating the equipment that ranged from rudimentary to advanced:

(1) swapping equipment components
(2) using self-diagnostics to test system integrity
(3) measuring device and circuit functionality.

Increasingly complex system and strategic knowledge are associated with increasingly sophisticated methods.

During three to five hours of individual instruction over a period of three days, seven technicians were tutored. They were presented a troubleshooting scenario and then probed regarding what they would do to isolate the fault (Actions), why they would take the particular action (Precursors), and what the outcome (Result) of the action meant to them (Interpretation). In effect, technicians were instructed to generate PARI records (see Table 1) including the associated device model sketches. The human tutor gave feedback to their stated Precursors, Actions, and Interpretations in the form of hints intended to move them toward more expert-like performances.

To evaluate their learning, they were given both an end-of-training problem-based test as well as a delayed posttest after the weekend. The tests were authentic troubleshooting scenarios belonging to the same class and difficulty of problems on which they had been tutored. Their progress was scored both in terms of the sufficiency of their operations--that is, whether they sufficiently investigated all suspect pieces of the equipment--and the efficiency of their moves--that is, whether they efficiently conserved time and equipment resources.

Results showed statistically significant improvements in both areas, with particularly dramatic gains in efficiency. Mean scores are plotted in Figure 3. The group's Sufficiency in examining all suspect parts of the equipment improved from a pretest mean value of 84 (range = 60 to 95) to a posttest mean of 100. The dalayed posttest mean was also 100, indicating the improvement was retained over the weekend. The group's Efficiency in fault isolation improved over twofold. The mean pretest value was 37 (range = 24 to 52); the initial posttest mean was 92 (range = 81 to 100); and the delayed posttest mean was 93 (range = 81 to 97).

Pedagogically, this human tutor training study was based on the same instructional principles that underpin the computer-based avionics tutor. Technicians were afforded extensive practice in fault-isolation; they were required to articulate and focus on their reasons and their interpretations of various troubleshooting moves; they were aided by a human tutor who, principally through Socratic dialogue, challenged them to reflect on what they did in terms of expert standards of thoroughness and efficiency. The technicians later attributed the gains they made to the opportunities they had to practice fault isolation procedures intensively and to solve problems independently. They reported that recording and reflecting on their actions and reasons was helpful and that they profitted from the hints and consistent feedback. This successful study is viewed as empirical support for the effectiveness of skill acquisition treatments that focus on the conditionalizing of knowledge in intelligent learning environments. External support in the form of the PARI records and the human tutor's feedback appeared to play a central role in learning. Finally, the instruction was realizable because of the knowledge engineering input that revealed the processes by which experts conditionalize what they know.

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Table 1: PARI DATA

Precursor: Want to see if the stimulus signal is good up to test package cable

Action: Measure signal at J14-28 with multimeter

Result: 28 volts

Interpretation: This is expected reading; this tells me that the stimulus is getting from the test station through the cable, so that part of the stimulus path is good

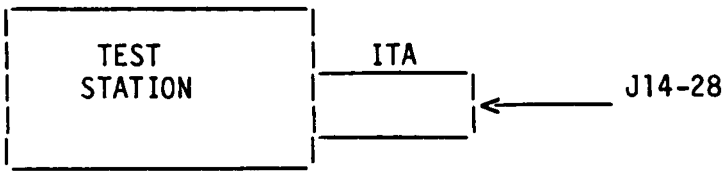

Figure 1.

Cognitive Skills Architecture

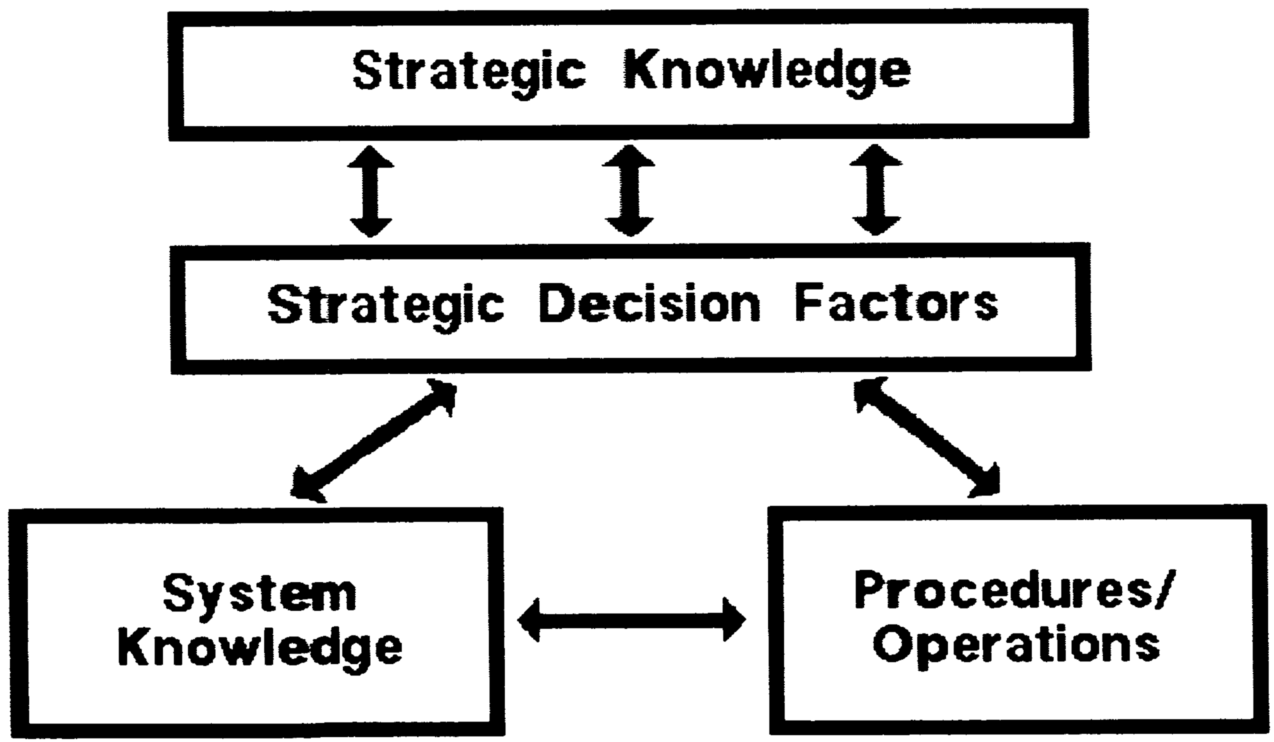

Figure 2.

Avionics Equipment Configuration (Signal Path)

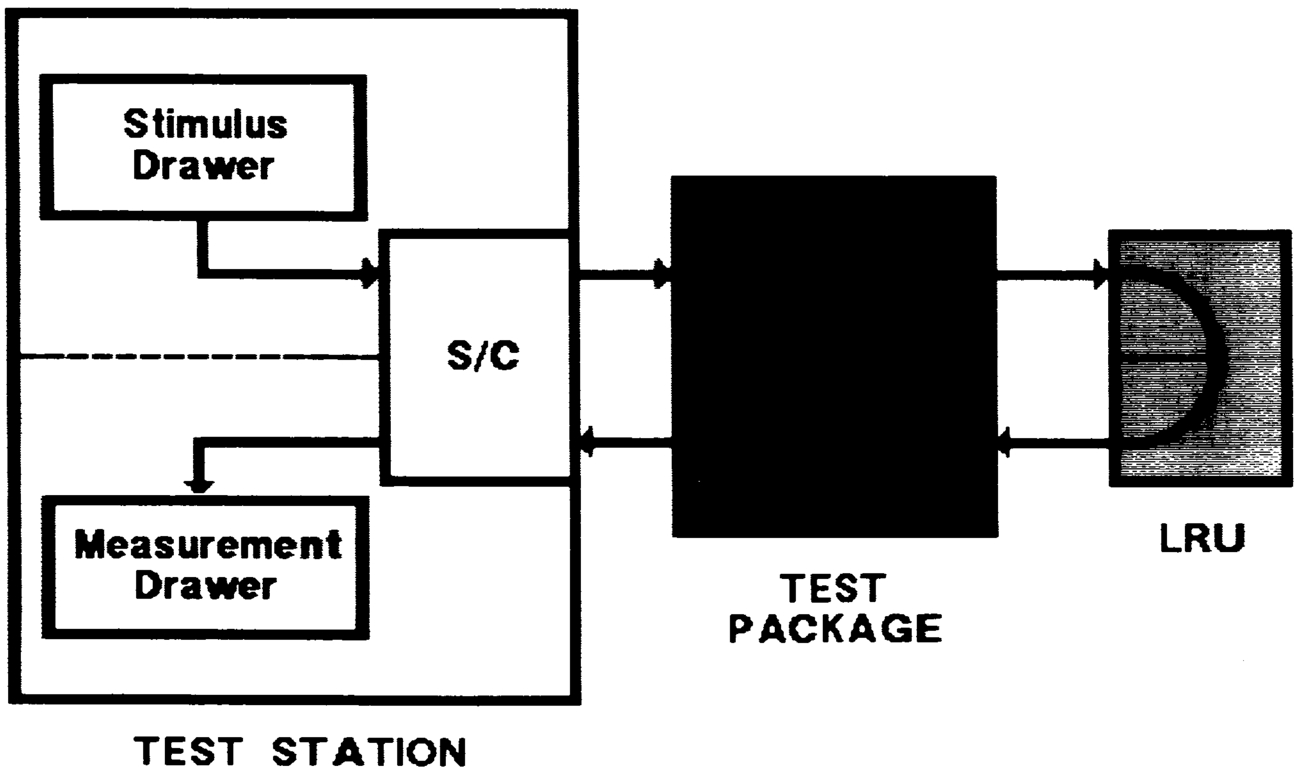

Figure 3.

BJS
Proof of Concept
Training Study