COGNITIVE TASK ANALYSIS FOR DEVELOPMENT OF AN INTELLIGENT TUTORING SYSTEM

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ABSTRACT

Training programs are increasingly relying on high level Artificial Intelligence modules to provide computerized feedback to trainees. The work reported here consisted of the use of cognitive task analysis methods developed at the University of Idaho to perform knowledge acquisition for a proof of concept training module targeted toward the defensive counter air mission. The specific subtask analyzed was "the use of fire control radar for search and sort" at the beginning of an Air-to-Air intercept performed by F-15 and F-16 pilots. The cognitive task methodology was conceptual graph analysis, a method that uses conceptual graphs to structure interviews and observational data gathering. The analysis consisted of three steps: (1) Development of conceptual graphs from existing documentation; (2) Expansion of the graphs through interviews structured with question probes; and (3) Expansion and completion of the graphs through performance observation and inductive analysis. After the conceptual graph analysis was completed, additional decision heuristics were used to identify the type of expert system architecture(s) most suitable for the task. These architectures include a rule-based system with explanation capability, classifiers with some type of explanation capability, and case-based reasoning with analytical ability

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INTRODUCTION

Expert systems are increasingly being used in computer-based training programs as a way to efficiently capture the expertise of instructors and other personnel, and provide that expertise to students. In most cases, a computer-based tutorial is first developed and then a standard rule-based expert system is embedded as a module within the system to provide task-related information and performance feedback at appropriate points.

While expert system technology can provide useful tutorial mechanisms, it has been noted that traditional rule-based expert systems have certain drawbacks. One of the most critical is the fact that they often have inadequate explanation capabilities (e.g., Gordon, 1992). Because of this and other limitations (e.g., "brittleness" and the difficulty of obtaining rules from experts), new types of expert systems are under development that have a broader range of capability. These includes systems such as neural networks, fuzzy logic systems, and deep model-based systems (Gordon, 1991). These new systems may be more appropriate for certain types of training programs than more traditional rule-based systems.

In summary, training systems that must capture some element of cognitive expertise can rely on expert systems as a mechanism, but there are certain issues involved in their implementation. One is the question of which expert system technology is appropriate for a given project. Gordon (1991) recently published a heuristic for determining which of the expert system technologies would be most appropriate for a given task, depending on certain characteristics of the task and user. While this heuristic was developed for the use of expert systems as a general class of tools, we hypothesized that it might be equally applicable for determining the appropriate expert system technologies for a given training application.

Among other types of information, the decision heuristic for identifying the appropriate type(s) of expert system requires identification of the types of knowledge primarily used in the task. This means that a cognitive task analysis must be performed before implementing the heuristic. Since some type of task analysis should be conducted to acquire the knowledge base for a training program anyway, this step does not constitute an additional requirement.

PROGRAM OBJECTIVES

The project described in this paper is a multiyear proof of concept endeavor. For the first year, there were three objectives. The first was to identify a task that is primarily cognitive for which part-task training could be implemented. The second was to perform an in-depth cognitive task analysis using the conceptual graph analysis methodology recently developed at the University of Idaho (Gordon & Gill, 1992; Gordon, Schmierer, & Gill, in press). The third was to use the results of the cognitive task analysis as input to the expert system decision heuristic. This would allow us to evaluate the usefulness of the heuristic for choosing expert system technologies within the specific context of a computer-based training program.

The three tasks corresponding to these objectives will be described below. However, before describing the work performed for the project, we will provide a brief overview of the basic cognitive task analysis method, conceptual graph analysis (CGA).

CONCEPTUAL GRAPH ANALYSIS

The CGA method consists of using several knowledge acquisition techniques to develop a knowledge base in the form of one or more conceptual graph structures (Gordon et al., in press). The knowledge acquisition techniques vary, but usually consist of the following steps, done in the order listed, although one may iterate through steps 2 and 3 several times:

1. Document analysis
2. Structured interviews; question probes
3. Observation and inductive analysis.

Before describing each of these methods, we will briefly review the knowledge representation syntax upon which the method rests.

Knowledge Representative Via Conceptual Graph Structures

Conceptual graph structures are a type of concept graph or network based on a highly specific graph syntax. They are most easily described as a combination of semantic networks, propositional networks, and goal hierarchies (e.g., see Gordon & Gill, 1992; Graesser & Gordon, 1991).

Conceptual graphs consist of nodes linked by labeled, directional arcs. Figure 1 shows an example of a small, incomplete graph for

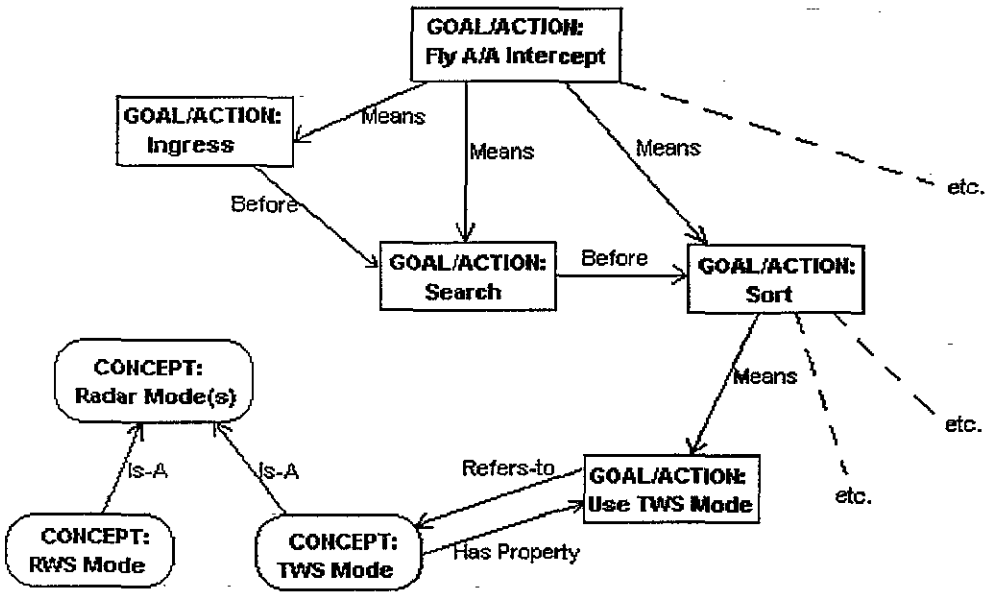

Figure 1. Small and incomplete conceptual graph structure with concepts and goal/actions relevant to sorting task.

information relevant to the F-16 radar sorting task used in this study.

Each node in a graph contains two types of information; the specific content of the node (e.g., TWS Mode) and the category or type of information contained in the node (e.g., Concept, State, Event, Goal/Action, etc.). The categorization of the information in nodes preserves information about the types of knowledge and relationships, helps organize the *information into substructures*, and provides support for the question probe method (described shortly).

Unlike other graph methods such as concept mapping, conceptual graph structures are based on a specific and well-defined set of arcs that relate the nodes. The most frequently used arcs are listed in Table 1; organized by the type of substructure in which one typically finds them. That is, a body of knowledge may consist of many types of knowledge, such as functional system components, goal hierarchies containing information about how to use the system, etc. These different types of knowledge tend to cluster into subgraphs, but the subgraphs are also interrelated with one another, as shown in Figure 1.[1]

It can be seen that conceptual graph structures can be used to represent a variety of types of knowledge, including semantic knowledge, knowledge of structural systems such as an automobile or jet aircraft, knowledge of causal systems such as how various factors interrelate in systems such as an engine, *the human body, the physical* environment, etc., and knowledge of complex procedures such as using controls and displays for controlling a vehicle.

In addition to general or "semantic" types of knowledge, conceptual graphs can be used to represent more specific information. Examples might be specific instances of categories such as doctors we have known or cars we have owned. Each instance is associated with its more general term via a Has Instance arc (or conversely, by an Is-Instance-of arc). Episodes we have experienced are likewise associated with relevant nodes in the network. Similarly, visual or auditory information is assumed to be associated with parts of the network. In representing this type of information, we generally include labels for the information in

[1]Readers are referred to Gordon & Gill, 1992, or Gordon, Schmierer & Gill, in press, for a more in-depth presentation of this material. In addition, a tutorial on conceptual graph structures is available from M. DeVries and D. Sorensen at University of Idaho.

Table 1. Conceptual graph substructures and arcs commonly used within the substructures.

TAXONOMIC STRUCTURES: Specify the relationships between superordinate and subordinate concepts (e.g., Apple Is-A Fruit).

Is-A
Has Property
Has Instance
Has Part
Refers-to
And/Or

SPATIAL STRUCTURES: Contain knowledge delineating the spatial layout of regions and objects in regions.

Above/Below
Left-of/Right-of
Behind, etc.

CAUSAL NETWORKS: Contain knowledge about causally driven state and event chains.

Has Consequence
Manner
Before/During/After
And/Or

GOAL HIERARCHIES: Specify goals, cognitive activities, and behavior procedures for accomplishing goals.

Reason/Means
Initiates
Before/During/After
Manner
Has Consequence
And/Or

the actual network itself (e.g., "image of Dr. Smith").

The specific information as well as visual and auditory nodes is important because sometimes people rely on direct associative learning to perform a task. For example, I might associate a range of images with the concept of "too dark" for toast. There is no specific conceptual or semantic rule for too dark, just a set of instances. If I make judgments in the future by comparing new instances with old instances, this "expertise" can be captured directly within the network by using instances rather than by trying to derive more general rules.

In summary, conceptual graph structures are used to represent a variety of types of knowledge. We can say that they capture verbalizable, declarative knowledge via the four types of subgraphs listed in Table 1. They also capture the more difficult to verbalize procedural knowledge by representing specific associations between stimulus sets and responses (e.g., the toast example).

Methods for Performing the Conceptual Graph Analysis

The task analysis method termed Conceptual Graph Analysis consists of a complementary set of methods for eliciting, representing, and analyzing a body of knowledge using conceptual graph structures as the representation medium. The methods have been chosen because, used together, they maximize the amount and types of knowledge that will be elicited during the task analysis. They are especially appropriate for use with experts who may be able to verbalize only part of their domain knowledge. The methods are briefly described below (see Gordon et al, in press, for a more detailed presentation).

Document Analysis. The first step in conceptual graph analysis usually consists of *identifying relevant information in documents* and translating the information into conceptual graph form.

In developing conceptual graph structures *from documents, one typically encounters* several problems. Among others, these include three critical ones. First, much of the information written in a prose format contains semantic ambiguities. For example, when one determines to graph the statement;

"hold the valve open and loosen the nut,"

it is unclear whether one performs these tasks at the same time, or one before the other. Readers are unaware of the extent to which ambiguities exist in written material because they use their own knowledge to interpret the material. However, sometimes ambiguities are problematic for the reader. When conceptual graph structures are developed from documents, there are often ambiguities which the researcher cannot resolve alone. These instances are noted and addressed in the next interview phase.

A second problem that will become noticeable during the process of graphing document information is that certain information will be missing. For example, the document might instruct a person to perform some task but not include relevant information regarding how to perform the task, or more frequently, omits necessary information on the conditions under which one should perform the task (when to perform the task).

The problem just described can be thought of one where there are missing nodes in the conceptual graph structures (either single nodes or whole branches). A third related problem is that while there may be a sufficient number of the appropriate nodes, the relationships between them are lacking to some degree. This is a frequent occurrence in science and engineering textbooks. For example, the author will describe a principle, and next describes a problem along with the steps needed to solve it. But the author fails to adequately describe the relationships between the basic principles and the problem steps (i.e., goal hierarchy).

When people have trouble with instruction manuals, it is almost always because either information is ambiguous or it is missing. The expert who wrote the manual was so familiar with the task domain, that they couldn't see these deficiencies. Graphing the information makes it "visually salient" that the information is missing. For example, each goal/action node *should have subordinate nodes* (via Means arcs) and initiating nodes describing the circumstances under which one performs the goal/action.

Structured Interviews. Documents almost never contain all of the information needed to create complete and conceptually coherent conceptual graphs. Therefore, after the graphs have been initialized using document analysis, the next task is to expand and clarify the graphs by consulting the domain experts. This is usually done through structured interviews.

Interviews with one or more SMEs are structured through the use of question probes (Gordon & Gill, 1992). Question probes are questions that elicit knowledge relevant to each node on the conceptual graph structure. Question probes are specific questions that the researcher asks for each node on the graph. Each node type has its own unique set of questions. For example, a Concept node would result in the researcher using questions such as:

What is _____________?

What are the properties or characteristics of _____________?

What are some instances of __________?

Thus, the Concept node of "TWS mode" would result in questions such as:

What is TWS mode?

What are the properties of TWS mode (that is, what happens in TWS mode)?

etc.

For most of our applications, the researcher takes the conceptual graph structure to the interview session (the graphs are actually divided into several subgraphs to make them more manageable). These graphs are used as a visual job aid for the researcher and expert to examine. The question probes are given to the expert, and answers are tape-recorded. The interviews usually go into great detail about all types of information; conceptual knowledge, tasks and how they are performed, the conditions under which one performs subtasks, and so forth. This process usually takes numerous interviews, and the expert frequently looks at the graphs to remind him or herself what has been said previously.

Observation and Inductive Analysis. Most of the information can usually be obtained through interviews structured with question probes. However, experts often perform tasks without really knowing how or why. When they have trouble verbalizing this information, it is then necessary to have them perform the task under a variety of circumstances and record the stimulus conditions and resultant actions.

Therefore, this step consists of asking SMEs to perform the primary task under a wide variety of circumstances. Think aloud verbalization is not required, although they are encouraged to do so if it does not interfere with their performance. Audio tapes or videotapes are made of task performance and the researcher reviews these tapes afterwards. In many cases, the expert and researcher review the tapes together. Through review, rules associating situational cues with specific decisions and behaviors are induced. These rules are validated against other instances of task performance. Occasionally, it is not possible to identify a specific set of rules to account for the expert behavior. In this case, the situational cues and associated actions are represented directly as instances in the graphs.

Rational Analysis. While the previous three methods are the means by which we acquire the information to go into the conceptual graph structures, ideally the analyst will also spend some effort evaluating the conceptual graph structures for clarity, completeness, logical consistency, etc. This has several functions. First, it can place less of a burden on the expert to perform this function. Second, while the expert may have described his or her particular method for accomplishing a goal, a rational analysis of the system components and functional relationships might yield a more efficient or effective method.

Advantages of Conceptual Graph Analysis

Conceptual graph analysis has several advantages over other methodologies. In addition to receiving empirical support (Gordon et al., in press), it has now been used for knowledge acquisition and task analysis in over a dozen different domains (e.g., forest management, using a literature search system, *using* a VCR, *engineering mechanics* and problem solving, teaching cooking skills to cognitively disadvantages learners, etc.).

It can be seen that one advantage is that it is domain-general. Other advantages include:

1. Unlike other syntaxes such as GOMS or concept maps, it can be used to represent and integrate all major types of knowledge including general taxonomic knowledge and goal structures.

2. The graphs provide a standardization of representation, a useful shorthand for interviews, and a visual means to see interrelationships among concepts.

3. The graphs yield and support question probes for structuring interviews.

4. Question probes are a simple to use but powerful method for pressing the questioning *process into incomplete areas of the* knowledge base.

5. The method integrates several complementary means for knowledge acquisition, which results in acquisition of both verbalizable and implicit or procedural knowledge.

METHOD AND RESULTS OF TRAINING ANALYSIS RESEARCH EFFORT

For the project described in this paper, the work was performed in three steps corresponding to the three objectives noted earlier. For each step, we will briefly describe the method and results obtained.

Identify Cognitive Subtask

There were several constraints that needed to be met during the process of identifying the *cognitive subtask to be used in this study.* These were:

- Since the work was largely to be performed at Armstrong Laboratory, Williams Air Force Base, the task had to be one that could be studied at that site.

- The Air Intercept Trainer (AIT) was available for observational data collection (required by conceptual graph analysis). *This system is a relatively high level* computer-based simulator for pilots to practice air intercepts against 1-5 targets. Therefore, the task had to be one that pilots could perform on the AIT.

- The task had to be one such that expert pilots were available either from Williams or Luke AFB to act as subject matter experts (SMEs).

- The subtask itself and knowledge used to perform the task must be unclassified.

- The task must be primarily cognitive.

- The task must be relatively limited in scope and unrelated to other tasks.

The cognitive subtask chosen for the training program consists of using the F-16 radar to "develop the big picture" during an air intercept. In other words, the process of *searching* a *given airspace and developing* a mental model of aircraft activity within that space. Subtasks include searching for targets using the F-16 radar search mode, evaluating the nature of target aircraft activity using additional radar modes, and developing a complete and accurate mental representation of the air space before deciding on a group to target. For this particular project, the task was further constrained such that a pilot is performing these subtasks without help or outside communication.

In standard terminology, this task essentially consists of using the radar for searching and sorting. While not quite accurate, for the sake of expediency, in this paper we will refer to the task as "sorting."

Cognitive Task Analysis

Conceptual graph analysis was used to carry *out the cognitive task analysis.*

<u>Document Analysis</u>. The first step in the analysis consisted of translating existing documentation relative to the subtask into conceptual graph structures. Working at Armstrong Laboratories, a dozen documents were reviewed and all information relevant to the task and its subtasks was translated into conceptual graph structures. The documents included basic conceptual booklets on the fire

control radar system and training manuals for performing air intercepts. Approximately 12 *conceptual subgraphs were first drawn on* drafting velum (to be able to see the big picture), and then converted to one large computer-based network using a special version of "SemNet" (Fisher, Saletti, Patterson, Thornton, Lipson, & Spring, 1990) on a Macintosh personal computer. This program displays all of the nodes and arcs in either graphic or list format. It program also has several search and traversal mechanisms.

The document analysis took approximately 80 man-hours; much of this time consisted of identifying the specific subtasks to be included and carefully combing through the documents to find applicable material. Most of the information obtained from the documentation pertained to the radar system; it's functional components, descriptions of radar modes, etc. While a moderate degree of information was also found for flying intercepts, little was found for how to use the various radar modes for searching and sorting.

Structured Interviews. Interviews were carried out with nine SMEs consisting of F-16 pilots, F-15 pilots, and instructor pilots. For each SME, the (paper-based) graphs were evaluated to determine what information was inconsistent or missing. The SMEs were given question probes based on the graphs (see Gordon & Gill, 1992) to obtain the necessary information.

In the interviews, pilots described their use of the various radar modes for searching and sorting activities. Some pilots focused mostly on strategies for carrying out the intercept, and did not seem to focus substantially on the radar modes. Other pilots discussed radar modes in conjunction with other strategy information, and indicated that various modes are most appropriate only under certain circumstances. All interviews were tape-recorded, and the information was subsequently added to the graphs. One pilot (F-15) *had goal hierarchy information* that was substantially different from the other SMEs; this information was translated into a separate graph.

The graphs were greatly expanded through the structured interview process. The interviewing and graphing processes took somewhere between 120 and 160 man-hours on the part of the researcher. The combined graphs at this point had approximately 1100 links. *While much information was gained, it* was apparent that some of the task was performed using perceptual or "implicit procedural" knowledge not easily verbalized. For this reason, observation with inductive analysis was next performed.

Observation and Inductive Analysis. For this part of the task analysis, two F-16 pilots and one F-15 pilot performed numerous air intercepts on the AIT simulator. In each scenario, they were required to search for targets and determine the number of groups, number of individual targets, and location of all targets. They then decided on one group/plane to intercept, and flew the simulator in for the intercept. Once it became apparent that they either would or would not make the intercept, the scenario was terminated. All scenarios were videotaped and the radar screen was also recorded separately for clarity in the review process. In this way, we were able to determine the *general activity of the pilot as well as his* specific use of the radar at all times.

It was apparent from the performance of the three pilots that the F-15 pilot was the most expert at using the radar and its various modes for searching and sorting. For this reason, the F-15 pilot was asked to participate in follow-up reviews of the tapes and additional structured interviews. During reviews of the tape, the expert gave explanations for cognitive and behavioral activity during the scenarios. These review sessions were tape-recorded.

Based on researchers' analysis of the videotapes as well as the expert reviews of those videotapes, additional information was added to the conceptual graph structure. Most of this was of the goal hierarchy type of information; what to do, for what reasons, and under what circumstances. In creating a traditional expert system, this information becomes the IF-THEN rules of the system.

The observation, retrospective inductive analysis, and expansion of the graphs took approximately 120 hours on the part of the researcher. At this point, the combined graph had approximately 1500 links.

Findings From The Cognitive Task Analysis.

The conceptual graph analysis resulted in a large and useful conceptual graph structure. The use of several SMEs revealed the fact that while all pilots were experts at their job, some were more expert than others at using the radar modes for searching and sorting. In particular, the F-15 pilot was extremely adept at this task, undoubtedly because it is a more central part of that job (Air-to-Air Intercepts) than the F-16 pilot who focuses more frequently on Air-to-Ground missions.

The conceptual graph structures showed that some of the knowledge used for searching and sorting is verbalizable declarative knowledge, while some of it is a more difficult to verbalize implicit/procedural type of knowledge. However, this latter type of knowledge was simple enough in structure that we were able to induce the concepts and interrelationships from behavior, and make it explicit in the graphs.

Table 2. Potential architectures for expert systems used in training programs.

SYMBOLIC/ANALYTIC
- Traditional rule sets
- Rule sets with explanation capabilities
- Fuzzy logic systems
- Static classifiers
- Classifiers with genetic algorithms
- Model-based systems

CONNECTIONIST
- Neural networks
- Neural networks with connection weights for explanation

CASE-BASED
- Case-based reasoning, retrieval
- Case-based reasoning, analytical ability

Front-End Analysis: Determining the Appropriate Expert System Technology

Once the conceptual graphs were complete and the performance data base obtained, it was possible to analyze the task with respect to the underlying cognitive characteristics. Gordon (1991) reviewed several expert system technologies and suggested that certain characteristics of the task along with user needs will determine the most appropriate expert system technology. The technologies are shown in Table 2.

The major task characteristics used in the decision heuristic include:

- Whether it is a stable or unstable stimulus environment (do stimuli and therefore decision rules undergo change over time)
- Whether there is subjective judgment (preference)
- Whether the task knowledge base is narrow or broad and complex
- Whether the task knowledge base is well-defined or ill-defined
- Whether expert performance is rule based, analytical, perceptual, or a combination

Application of the heuristic consists of identifying where the particular domain lies on several dimensions and then using the Table published in Gordon (1991) to identify the appropriate expert system technology.

The task analyzed in this project is characterized by a dynamic environment where information is obtained by the pilot in a sequential manner. The knowledge base is large and complex (many interrelationships), but relatively well-defined. Expert performance is based on analysis, rules, and perceptual performance. In addition, the time to perform the sorting task is extremely short. This last characteristic suggests that two training approaches using expert systems are possible: either feedback from the system as the pilot is performing the sorting task, or feedback after the pilot has performed the sort.

Consider the first case, feedback during task performance. In this case, certain types of system are not likely to be appropriate, for example, a case-based reasoning approach is not likely to be helpful because the time required for the pilot to process the case and make an appropriate conversion is limited.

A rule-based expert system might be used if hardware allowed direct access to situational cues and timely provision of an answer. Other acceptable systems include classifiers with or without genetic algorithms. The major drawback with this approach is that the provision of additional explanatory information would prove disruptive.

More likely, the trainee would perform the task on a simulator, without guidance, and then an expert system would be consulted for feedback. To determine the most appropriate expert system technology, the following analysis was performed:

1. For the task of sorting, the answer cannot be gained from analysis of a complete system model, therefore the "model-based system" approach is not appropriate.

2. The task is characterized as ill-defined, complete, and relatively narrow. The task is performed by a novice-trainee, who presumably would want explanations to accompany "answers." This points to the use of one of the following types of expert system:

- Rule-based with explanation capability
- Classifiers with some type of explanation capability
- Case-based reasoning with analytical ability

Because the task is information or verbal-based as well as perceptual, a neural network alone would probably not be the best choice.

SUMMARY AND CONCLUSIONS

The cognitive task analysis method, conceptual graph analysis, was successfully applied to the defensive counter air mission subtask of "sorting" using the fire control radar system. We were able to identify the goals and actions required to perform the task, the various conditions for alternative methods of performing the task, and the situational cues used to choose among the alternative subgoal hierarchies. Pilots were able to verbalize most of this information in great detail during question probe sessions. However, it was also necessary to observe actual task performance to identify some of the conditions under which pilots used various strategies. For the SME who was used most heavily for the analysis, it was helpful to intersperse performance sessions with follow-up structured interviews. We found that the SME performance was very consistent with rules verbalized via interviews.

The conceptual graph analysis resulted in a knowledge base in network format, with approximately 1500 links. This knowledge base will yield the information required to develop a cognitive part-task trainer with an embedded expert system.

Analysis of the cognitive characteristics of the task, as well as analysis of user needs, was successfully performed, and suggested several appropriate expert system technologies. This is a preliminary indication that the heuristic developed for expert system selection was adaptable to the context of instructional system design. The next step will be to implement the system as an actual training program.

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