INTELLIGENT EMBEDDED TRAINERS: A NEXT STEP FOR COMPUTER BASED TRAINING

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ABSTRACT

Acquiring the cognitive skills necessary to perform effectively as a member of a tactical decision-making team is neither a smooth nor a consistent endeavor. In order to extend training technology into a more dynamic domain we have created a system that utilizes expert defined problem solving skills and strategies, and compares them to those used by the trainee. Trainee models are inferred on the bases of monitored trainee behaviors and the use of probe techniques (such as verbal reports or questioning). Concurrence and divergence between the trainee and expert models, assessed as a function of outcome (was the answer correct and was it gained using a process similar to that of an expert), serves as the basis for feedback and skill building. Such systems could be embedded within the operational context to meet "train like you fight, fight like you train" requirements. This new generation of training systems is referred to as Intelligent Embedded Trainers (IET).

One ongoing program directed by the Naval Air Warfare Center Training Systems Division is to develop a standard, modular architecture for the development of IET systems. Critical aspects of the architecture include the use of a proven process model of human decision making and flexible knowledge engineering/artificial intelligence techniques in combination with structured training objectives, cognitive feedback techniques, performance assessment and tracking methods. The objectives of this paper are to describe the architecture used, outline the functional modes for development and operation of IET systems, and to demonstrate how the architecture addresses shipboard electronic warfare training.

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INTRODUCTION

Acquiring the cognitive skills necessary to perform effectively as a member of a tactical decision-making team is neither a smooth nor consistent endeavor, especially when the manner in which the US Navy conducts training is in transition. The Navy is rapidly moving to reduce its use of shore-based training facilities by increasing its employment of onboard training. To enable the next generation of sailors to acquire and maintain the cognitive skills they need, we must capitalize on advances in computer science and training technology for the Navy's deployed trainers.

Before we begin to look at what technology has to offer, we need to consider how learning takes place away from the schoolhouse. In most instances we learn by trial-and-error--usually participating in a great number of trials and committing numerous errors. How skillful we ultimately become depends in part on how well we can figure out what we are doing wrong and how to correct it. An alternate method is to find someone to serve as a mentor--someone with years of experience who can demonstrate the task, explain the steps along the way, watch us as we perform the task, and identify what we are doing wrong.

In order to assist the Navy in the delivery of high quality onboard training, how do we capitalize on the benefits of the informal training setting provided by a mentoring relationship and computer science? The approach we focused on was to combine intelligent simulation and training technology. Simulation technology was used to present the trainee with a realistic environment while intelligent systems technology provided the coaching and performance evaluation (cf., Lesgold, Eggan, Katz, & Rao, 1992).

Since current generation computer-based training (CBT) technology focuses on developing basic skills such as multiplication tables, electronic troubleshooting, and weapon capabilities, we were required to create our own training environment. In order to extend CBT technology into a more dynamic domain, specifically electronic warfare, we created a system that utilizes expert-defined problem solving skills and strategies and compares them to those used by the trainee. The trainee's understanding is inferred on the basis of monitored behaviors and the use of probe techniques. Convergence and divergence between the trainee's approach to solving the problem and the expert's approach serves as the basis for feedback and skill building. We refer to this training environment as Intelligent Embedded Training (IET).

One ongoing program directed by the Naval Air Warfare Center Training Systems Division is to develop a standard, modular architecture for the development of IET systems. Critical aspects of the architecture include the use of a proven process model of human decision making and flexible knowledge engineering/artificial intelligence techniques in combination with structured training objectives, cognitive feedback techniques, performance assessment, and tracking methods. The objectives of this paper are to describe the architecture used, outline the functional modes for development and operation of IET systems, and to demonstrate how the architecture addresses shipboard electronic warfare training.

THE KOALAS ARCHITECTURE

The heart of the IET concept is a process control architecture known as the Knowledgeable Observation Analysis-Linked Advisory System (KOALAS) (Barrett & Donnell, 1991). The KOALAS architecture provides support for human induction, incorporates an explicit model of the human operator's tactical situation assessment, and provides a context for the appropriate use of sensor fusion systems in the initialization and maintenance of that situation assessment.

In the KOALAS model, the sensor, decision formation, and action assignment processes are defined to be deductive in nature. The interpretation process, however, entails induction on the sensor data to generate the operative hypothesis for subsequent decision making and action. The most important issue in the design of human-mediated equipment control is the definition of the human operator's role in the sensing, interpretation, decision making, and action processes of the control system being designed. Since sensing, decision making, and action processes in the KOALAS taxonomy are defined to be deductive, these processes can be largely (or wholly) automated; it is in these areas that machine intelligence offers the greatest payoff in the control of multi-channel systems. The crucial human role in the system is in the interpretation process, a function that can be assisted, guided, or trained, but not automated (Willis, Becker, & Harris, 1992). This is the focus of training for IET systems.

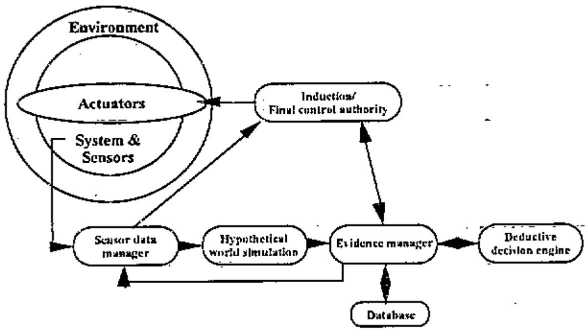

Figure 1. KOALAS process architecture

As illustrated in Figure 1, the KOALAS architecture incorporates an internal object-oriented simulation, called the Hypothetical World Simulation (HWS). In an IET application, the HWS is comprised of several major components: (1) a model of the world based on observed data (deductively generated and representative of ground truth); (2) a model of the subject matter expert's view of the world in terms of situation awareness, decision model, and actions (captured via artificial intelligence techniques); (3) rules for training opportunities such that cognitive skills can be exercised and appropriate measures of trainee behavior can be captured; (4) a model of the trainee including past performance and current competency levels. The function of the Evidence Manager and the Deductive Decision Engine in the architecture is to serve as the agents for comparison of trainee and expert models in order to provide feedback to the trainee, and to collect data on the trainee's responses and feed those back into the operating models in the HWS. Models which initially populate the HWS such as the subject matter expert, trainee history, and training objectives are stored in the Database along with specific information relating to the training application that the IET was developed to address (e.g. domain specific information such as radar signatures, platform and weapon types). The Induction box controls the dialogue and acquisition of information from the trainee. In the present demonstration, the HWS has been populated based on data from one subject matter expert. However, the KOALAS architecture can accommodate implementation of multiple subject matter expert models.

The IET demonstration that was produced was based on the model of human decision making presented in Figure 2. As can be seen in this figure, information in the environment impinges on a sensory system. Once processed by that sensor the information is sent for interpretation. The process of attaching meaning and developing a general model which accounts for the sensed data involves logical induction.

Several key distinctions reside in this model and were considered with regard to training in a dynamic environment. First, this model

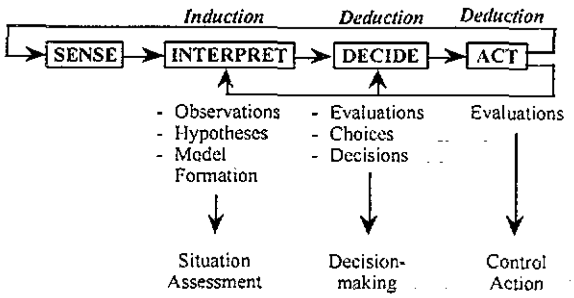

Figure 2. Human operator decision process model

presents a way of capturing where situation awareness occurs in the decision making process and it distinguishes between decision-making processes that are inductive versus those which are deductive. The degree to which a trainee masters the skill sets that allow efficient allocation of resources to those aspects of decision-making may be significant in distinguishing between novice and expert. It is toward that end that the development of IET systems are directed. To accomplish this it is necessary to incorporate the process model into the architecture of the IET. The IET is then built to incorporate techniques which can capture these aspects of subject matter experts and through the process of monitoring trainee behavior comparisons between trainee and subject matter experts are made and appropriate feedback is offered. Training efficacy is measured not solely in terms of "correctness of a decision" (e.g. correct product of a multiplication problem), but also in terms of the processes that the trainee uses to arrive at a decision. To accomplish this, IET utilizes a variety of artificial intelligence and other techniques.

THE EW APPLICATION

Electronic warfare is characterized by serious consequences, time critical identification, no clear right answer, deception, and incorrect and/or incomplete information. Effective task performance in this environment hinges on competent situation assessment requiring interpretation of sensor data to detect, classify, and identify threat systems and platforms, and to assess the threat's capabilities against ownship and/or other friendly forces. Yet, interpreting the sensor data is only half of the problem. Determining whether a particular airborne object is friend or foe may, under some conditions, depend solely upon the unknown pilot's intentions. And intentions, by their very nature, cannot be detected by sensors. Threat intentions, are, however, extremely important in the context of situation assessment and for selecting appropriate tactical action. It is to this task environment that we are looking to demonstrate intelligent embedded training.

The Electronic Warfare Intelligent Embedded Training (EWIET) environment is our proof-of-concept demonstration. EWIET runs on a 486 processor with an Orchid Pro Designer II graphics card and CD ROM and is written in C utilizing CLIPS for real-time artificial intelligence. EWIET emulated the graphical display of the SLQ-32 device, used by the EW community for ship self defense. The display of the device was fully simulated, so that the display changes as the trainee interacts with the device. How the trainee interfaces with the device however was modified due to the differences between a 486 PC keyboard and the SLQ-32's Fixed Action Buttons. As part of our demonstration we elected to incorporate a Navy-developed training scenario rather than develop our own. The scenario we used was designed by representatives of the Aegis Training community for use onboard Aegis equipped cruisers and destroyers. Within the context of this scenario, the trainees are required to identify the emitters which appear on their screen.

The KOALAS structure was embedded in the training system presented in Figure 3. The system functions such that prior to a training session, the system loads from the data base into the hypothetical model expert models comprising both deductive actions (in this case expert search patterns through different information sources) and inductive components (i.e., the general view of the tactical situation). This model once loaded runs in parallel to the training scenario being played such that it remains current. The system monitors the activities of the trainee, recording activities that are both consistent with and divergent from those expected based on the expert model.

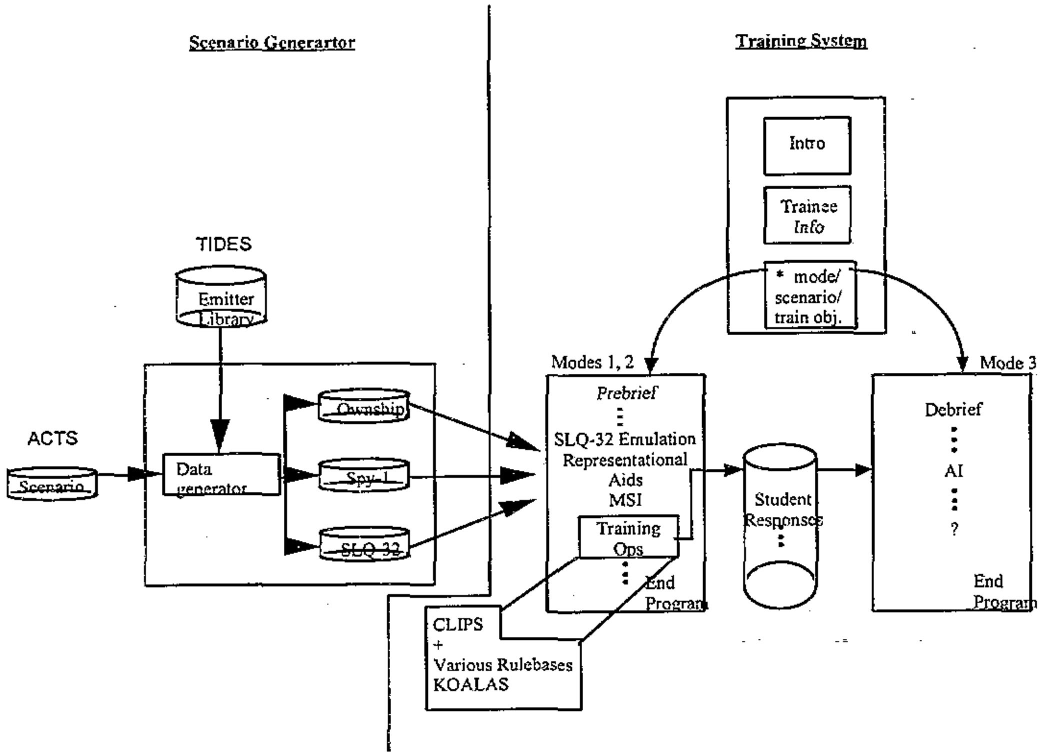

Figure 3. Electronic warfare operator training system design architecture overview

Three operating modes were developed to *support acquisition, evaluation,* and performance feedback. The first mode is a real-time free run mode. Using this mode uninterrupted trainee performance can be monitored and later evaluated and fed back to the trainee. The real-time mode affords an opportunity for the IET to be used non-intrusively within the context of ongoing operations. This capability is particularly important for embedded systems in which there is little time for the system to be *dedicated solely to training and where the* particular system is only one component of a larger group of systems.

While the real-time mode is useful for gathering information about deductive activities, inductive process are usually hidden from observable activity and can at best only be inferred from such activity. Thus, an interactive training mode (Mode 2) in which several techniques to isolate trainee performance and gather information specific to inductive processes, in this case situation assessment, was created. The interactive training mode utilizes probe techniques or interruption analysis to gather information related to inductive process. Using this technique, the training scenario is halted and the trainee is asked to perform activities or answer questions relative to specific training opportunities. Another novel aspect of the IET is the use of expert defined rule bases as part of the KOALAS hypothetical model used to evaluate the scenario in real-time for training *opportunities.* The specific rule base used during any given training session is determined as a function of the trainee's choice of predefined training objectives at set up time. This implementation provides for a very modular implementation which maximizes one's ability to utilize different artificial intelligence techniques to match training objectives and to conserve processing resources by only activating rules germane to the current training session. Moreover, this *implementation also allows training to be* tailored to individual needs and for all aspects of the training to be independent of the scenario used. From the stand point of the EWIET, this allows us the flexibility to use already established fleet training scenarios, incorporate new scenarios as they become available without changing the functionality or utility of the trainer, and to run in real-time (or live) exercises.

Once a rule set for detecting training opportunities is activated, the scenario stops to allow for training when the predefined conditions occur. At this point, the IET monitors observable trainee activities (keyboard inputs, etc.) until such time as the trainee keys that he has completed the task. Following correct emitter identification, a situation assessment battery patterned after the Situation Awareness Global Assessment Technique (Endsley, 1988) appears on the screen. These situation assessment questions specifically focus on gaining information about the trainee's current cognitive model and his inductive processes. Once the battery has been completed, cognitive feedback focused on presenting information to the trainee on the correctness of his response, what were the salient pieces of information for emitter identification and how to access that information, and what actions should/could have been taken. After feedback is given the trainee returns to the training scenario and proceeds until the next predefined training opportunity occurs.

Upon completion of the training scenario, trainees have access to a third system mode: Training Debrief. This mode focuses on giving the trainee a composite "report card" of his performance during the training session, direction for remedial activity, and information about how his performance differed from that of the expert. After the composite feedback, detailed feedback related to each of the training opportunities is available for trainee perusal. In order to compensate for potentially substantial time lags between when a trainee might complete the training session and when he views the debrief, facilities are provided for the trainee to view all critical displays and information as they appeared during the training session for each of the individual training opportunities.

Central to the use of such systems is the ability to clearly define training objectives. While this is not unique to training in general, it represents one of the key areas of stability from which an IET is developed. It guides the development of knowledge bases, the way knowledge engineering must be conducted, the choice of expert system used to train (rule based, CASE based reasoning, etc.), performance feedback, and accommodation of individual differences. The modular design of IET systems allows rapid incorporation of additional training objectives into the system as well as the associated additions to the artificial intelligence and feedback utilities. This flexibility provides for a variety of diverse training objectives to be accomplished within a single training system. Moreover, with many applications being performed on rapidly reconfigurable or generic computer workstations, it is likely that a single advanced IET system will be able to perform training on many jobs.

SUMMARY/CONCLUSIONS

This paper has described a process architecture known as KOALAS which has the potential to provide a unique environment for training complex cognitive skills. In a sense, where traditional CBT helps to develop "book smart" students, IET systems using KOALAS focus on transitioning "book smarts" into "street smarts." However significant challenges to the production of an IET exist. Most notable is the development of a standard or generic architecture which will the allow the system to fold around an existing operational system and be able to incorporate a variety of training techniques. The current concept demonstration has been useful in defining many of the basic functions and core aspects of IET systems but it has yet to undergo rigid testing and evaluation. The next step for the EWIET will be to evaluate the concept in an operational context.

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