LEARNING SITUATIONAL AWARENESS BY OBSERVING EXPERT ACTIONS

Taha A. Sidani
Avelino J. Gonzalez
University of Central Florida
Electrical and Computer Engineering Dept.
Orlando, FL 32816
taha@oak.ists.engr.ucf.edu
ajg@conflict.engr.ucf.edu

Abstract

The aim of many research projects in the field of artificial intelligence entail the incorporation of human-like intelligent behavior in the computer. The represented level of intelligence is highly dependent upon the amount of knowledge possessed by experts in the field and the efficiency and effectiveness of transferring this expertise from man to machine. This knowledge acquisition process is difficult and time consuming. Furthermore, most of the current knowledge acquisition techniques focus on gathering information about a domain which is static in nature. They capture explicit static information which does not vary over time and is easy to mold into a symbolic representation. Most real-life situations, however, involve dynamically changing information and require a non-symbolic form of representation. Current knowledge acquisition techniques are not well suited for the extraction of implicit expert knowledge while handling a situation in a dynamic environment.

This research describes a general methodology for learning implicit situational knowledge by observing the expert while reacting to a real-time simulation. The paper outlines the IASKNOT system methodology which gathers, represents, and learns expert knowledge by examining the expert's simulated surroundings while simultaneously monitoring the expert's actions for a given situation. It utilizes recent advances in the areas of neural networks and artificial intelligence. The method demonstrates the ability to train on basic skills and to generalize learned actions to handle more complex situations not previously encountered. It was implemented and tested for handling specific situations in the driving domain.

1 INTRODUCTION

Knowledge about a domain is typically predetermined and acquired through one of two methodologies: use of a knowledge engineer, or use of automated knowledge acquisition techniques. The primary objective of the two methodologies is to capture the expertise (expert knowledge) and efficiently represent it in the computer for later use.

The most commonly used knowledge acquisition approach is to employ a competent knowledge engineer as an intermediate between the expert and the system (Boose and Gaines, 1989). The knowledge engineer facilitates the transfer of human expertise to the computer. This involves interviewing the expert and preprocessing the information before deciding on the best representation scheme to use to represent this expertise. It is a time consuming process. The query process is repeated until the amount and the form of the knowledge is satisfactory for the current domain. However, there are major drawbacks with this methodology that limits its effective representation. They include non-articulate experts, limited domain knowledge possessed by the knowledge engineer, and bias (Gonzalez and Dankel 1993; McGraw 1989).

Automated knowledge acquisition, on the other hand, improves the knowledge acquisition process. It attempts to automate the knowledge engineering (query) process by allowing the expert to interact directly with the computer. It provides the expert with the needed tools and environment for entering information into the system. It allows for a direct link between the expert and the system and attempts to query the expert on various concepts related to the overall domain. The elicited expert knowledge is mapped into an internal representation that the computer can comprehend. The automated methods provides an enhancement to the knowledge engineering techniques, yet most still acquire knowledge by asking the expert for information on how to handle different situations. Relying on querying the expert for knowledge limits the represented information to that which is "explicit".

2 EXPLICIT VERSUS IMPLICIT KNOWLEDGE

Experts utilize different types of knowledge for handling each situation. Slatter (1990) emphasize the importance of differentiating between the types of expertise, explicit and implicit , which is applied by experts while dealing with real-life situations (Slatter, 1990). Explicit knowledge can be described as knowledge that can be verbalized and thus represented symbolically.

as the rules of thumb, theories, and facts. It is easy for the expert to articulate this type of knowledge which makes it relatively easy to elicit and model. Implicit knowledge involves tacit knowledge that is intuitive and judgmental in nature. It is considered non-articulated experience-based knowledge used by experts to perform a task or solve a problem in an intuitive manner. The actual representations used by experts to model this knowledge are complex and poorly understood; consequently, it is very difficult to define, acquire and represent. Experts build an internal feeling about the criticality of a situation and learn to apply proper actions without conscious effort. For instance, turning onto a two way street or passing another vehicle represent common every day situations which necessitate the use of implicit expertise, see figure # 1 below.

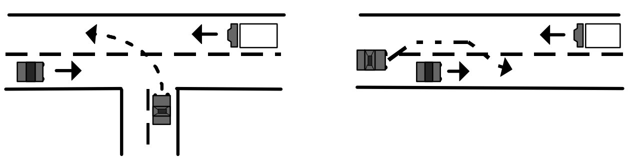

Figure # 1: Examples of the use of implicit expertise

When asked to turn left on a two way street the driver uses his/her own judgment to decide when it is safe to cross. The driver assesses the situation and evaluates the threats imposed by the other vehicles. The presence and absence of vehicles on the two lane road is taken into consideration. More importantly, the driver does not calculate the speed of the oncoming vehicles but rather, he/she relies on their intuitive judgment about the dynamics of the vehicles involved as well as their own capabilities. Using previous experiences, the expert driver learns to map situations to actions. If asked to describe the decision process that was used to handle the situation, most experts would not be able to properly articulate their reasoning process. A common reply would be: “it felt like the right thing to do at the time.”

Experts possess a sense of awareness to their environment and base their actions on implicit feelings about the current situation. Relying on the experience gained by encountering a vast number of previous problem situation, an expert typically deals with new situations intuitively by matching the new situation with prototype situations stored in memory rather than applying rules that deal with the situation (Dreyfus and Dreyfus, 1992). In many instances, it would be much easier for experts to demonstrate their actions rather than attempt to verbalize them. The traditional knowledge engineering approaches totally avoid representing the expert's implicit knowledge. Some techniques have been applied toward skill acquisition (Lee and Shimoji, 1991). Most, however, are too restricted and are unsuitable for the formulation of domain knowledge.

3 SITUATIONAL AWARENESS

Humans rely greatly on learning by watching others handle new or difficult situations. It is common practice to observe others in action and “implicitly” learn from them strictly through observation. Mimicking this learning process in the computer requires the use of simulation to model real-life situations. A computer that learns by observing the expert must have a sense of awareness about the current situation. It must be capable of sensing the presence and absence of dynamic objects in the simulation, defining and hypothesizing about the current situation, predicting future situations, and monitoring and learning how the expert would remedy that situation.

The field of psychology and military research in Command and Control (C^2) have provided much needed insight in explaining the human aspect of situational awareness and the implementation of situation and threat assessment on a computer, respectively. The psychological research in SA views it as a cognitive process that involves the integration, extraction and comprehension of environmental stimuli and the projection of future events (Garland et al., 1991). Although the military research in C^2 does not utilize the same terminology for SA, their research in multi-sensor data fusion clarifies some of the elements needed to implement machine SA (Andriole, 1991). Walts and Llinas (1990) break down SA to three levels. Level one involves *data processing* activities which include the detection, data association, state estimation, and attribute classification. Level two and three, known as *Situation Assessment* and *Threat Assessment* (STA) respectively, represent a comprehensive analysis of the findings in level one. They emphasize information processing activities rather than data processing. Common functions include *Alignment*, *Association*, and *Correlation* (Waltz and Llinas 1990).

While research has been conducted on components of Situational Awareness (SA) like knowledge acquisition, representation and memory, representing SA in a computer is a difficult task that has not yet been entirely accomplished. SA involves acquiring implicit expert knowledge that cannot easily be represented using explicit rules. The variations in the environmental stimuli that distinguish various situations cannot efficiently be used to represent situational knowledge without having to generate an enormous number of explicit rules. The study of Artificial Intelligence (AI) and Artificial Neural Networks (ANN) provide researchers with the tools to learn, represent and reason about knowledge. Ideally, a learning paradigm should exist which allows implicit situational knowledge to be acquired by "observing" the expert carry out a task in a simulation-based environment.

4 GENERAL SYSTEM DESCRIPTION

A framework was developed to capture the expert implicit situational knowledge via observation. IASKNOT, Implicit Acquisition of Situational Knowledge fOr Training, is a system which applies current research in AI, ANN and simulation to enable the acquisition of implicit knowledge. It gathers, represents, and learns expert knowledge by examining the expert's simulated surroundings while simultaneously monitoring the expert's actions for a given situation, see figure # 2 below.

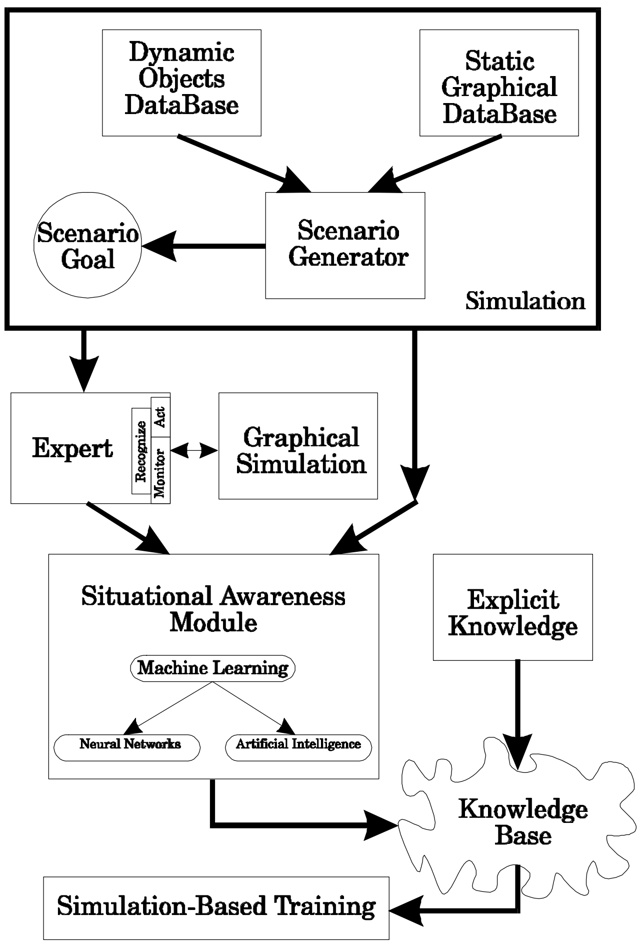

Figure # 2: IASKNOT information processing

It formulates a knowledge base which incorporates a model of the expert's intuitive, judgmental responses to various situations. The approach uses a simulated environment to generate various situations (scenarios generation); allows the expert to react to the current situation (take action); observes the actions; and reasons about the implicit knowledge in the situation that caused the action. This requires the following functions:

1) sensing the presence and absence of dynamic objects in the simulation.
2) defining and hypothesizing about the current situation,
3) predicting future situations, and
4) monitoring and learning how the expert remedies the situation.

A static and dynamic object databases are used to generate a realistic dynamic situation that requires an expert to apply his/her implicit expertise. Each scenario identifies an underlying goal (i.e., drive to the next intersection) that must be met by the expert. A *Situational Awareness Module* (SAM) monitors the expert actions as well as the changes in the environment. It handles all of the complex reasoning required to associate the expert actions to the current state of the environment. The main purpose of this module is two-fold: clarifying the current state, and learning the implicit expert actions and skills necessary to remedy the situation. Its knowledge base is augmented with easily accessible explicit knowledge provided by a knowledge engineer or other sources of inputs such as books (e.g., driver's education book). The explicit knowledge is used to help the system generalize learned actions to handle more complex situations not previously encountered.

5 SYSTEM MODES OF OPERATION

The IASKNOT system is composed of three modes of operations: *Data-Collection*, *NN-Training*, *System Testing*. Several events within the simulation are identified as "critical training events". These events constitute a limited section of the overall domain expertise. During the *Data-Collection* mode, the system presents the expert with the generated scenario. The expert utilizes the given controls, also known as "control variables", to manipulate the current state in response to the current situation. SAM collects the dynamically changing information describing the current situation as well as data learned from monitoring the expert behavior. A *Data Sampler* component identifies critical points in time and selects the appropriate sampling rates to reduce the collected data without loosing important information about objects and time relationships. The pre-processed data is used to train specific neural networks (i.e., recurrent networks) to learn to mimic the expert behavior. The customization, setup, and creation of the applicable ANS are some of the functions that are performed in the *NN-Training* mode.

A knowledge base composed of several Neural Network Knowledge Units (NNKU) is then compiled. Individual NNKU are developed and trained to handle specific events (i.e., speed signs events, traffic light event, etc.). Furthermore, a hierarchical structure is constructed that ties the relationships between various objects and events. The methodology applies Object-Oriented techniques to model this structure. The

System-Testing mode used by SAM relies on applying the learned skills encapsulated in NNKU along with its explicit knowledge to handle the situation at hand. The *Resolver* component used in testing compares the outputs of each NNKU and checks for noticeable inconsistencies in the suggested actions provided by current active NNKUs. Each active NNKU is concerned in reacting to its own inputs. The Resolver inspects the overall picture and attempts to resolve the conflict by examining the available explicit knowledge (i.e., facts and rules) associated with the involved objects and events. This module is responsible for evaluating the overall holistic picture which describes the current situation.

6 SYSTEM IMPLEMENTATION

The defined framework follows a generic approach that can be applied to most models of dynamic environments. The automobile driving domain was selected as the application domain for testing the effectiveness of the IASKNOT methodology. The primary interest in using this simulation is to provide a realistic environment where the actions of the expert driver can be monitored while dealing with various scenarios. Several factors played a role in the selection of this domain. These include the following:

1) embedded richness of its implicit expertise
2) familiarity of the domain to others
3) availability of experts
4) variability of objects and situations
5) ease of interpretation of the results

The developed system was implemented on a PC compatible machine using object-oriented techniques. Visual C++ for windows was used to code the user interface as well as the required neural network algorithms. CLIPS, an expert system shell, was used for representing some of the expert reasoning processes that enable the generalization of learned knowledge. The resulting knowledge base incorporates both numeric and symbolic forms of knowledge. It forms a representation of expert knowledge modeled via rules, facts, objects and encapsulated in separate NNKUs. The encapsulation of implicit knowledge makes the resulting knowledge base better suited for simulation-based training.

7 SYSTEM TESTING

The overall testing approach involved one expert driver who is familiar with using the system controls. The expert is given ample practice time to adjust to the perception that is provided by the simulation. Expert actions are assumed to be the correct actions while in data-collection mode. The driver was presented with fifteen sessions of every training situation. The lower and upper bounds for expert actions were determined. Additionally, the mean action was calculated and used to train the system to handle the specific event.

Three criterias were used to evaluate the system: learning, generalization, and coping capabilities. The first tests how well the system learned to mimic the expert given the same conditions as those used for training. It mainly measures the accuracy of the system actions. The second criteria, generalization, tests how well the system can adapt what it learned to some variation of the training events. The coping capabilities test the extension of learned implicit knowledge to new and compound situations. A compound situation is a complex situation comprised of more than one training event at a time. An example of such an instance can be illustrated by having a situation which is not previously seen by the system. The scenario might involve both a traffic light training and a pedestrian crossing event occurring at the same time. The test evaluates how well the system can apply and generalize its NNKUs to handle conflicts between events.

The data was evaluated using correlation tests, mean absolute differences, and standard deviation of errors. These measures examine how well the system outputs follow the expert outputs, determine its closeness, and determine the deviation on average from the mean. The results of the tests showed that the correlation were very high and the absolute differences were low for system learning, generalization, and coping. Table # 1 describe an example test results for learning to handle a red-green traffic event which changes state at 42 seconds.

Table # 1.

Test results for traffic at 42 sec

	Stopping Distance	Braking	Accelera-tion
Correlation Tests	0.9997	0.9876	0.9921
Avg. Abs. Diff.	0.7981	1.399	1.145

The high positive correlation values, close to 1, indicate that the system learned to mimic what the expert does. This means that when the expert increased braking pressure the NN also increased braking. The table shows the average absolute difference between the expert and the system. The stopping distance for the stopping distance was 0.7981 pixels with SD of 0.7883. Considering that the resolution used in the simulation was 1/2 mile for 145 pixels or 18.21 feet per pixel, a mean absolute difference of 14.5 (equals 0.7981 pixels) for stopping distance is actually 0.55% error. It is evident that the actions learned by the system fall well within the expert's upper and lower bounds. As a matter of fact, the system actions almost overwrite the mean expert actions, see figure # 3.

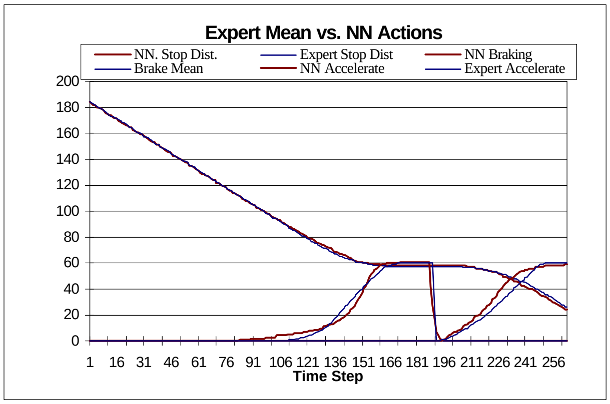

Figure # 3. Expert mean and system actions for a traffic light at 42 seconds.

8. CONCLUSION

The described research represents a methodology for the acquisition of expert implicit situational knowledge by "observing" the expert behavior while interacting with the simulation. It focuses on acquiring the expertise by allowing the expert to demonstrate his/her know-how rather than by the traditional query session methodology. The benefits of such an approach eliminate many of the problems encountered with the traditional knowledge engineering methods and permits learning new implicit knowledge which can not be described in symbolic forms. The ideas formulated by SAM can be applied to different types of simulations.

References

Boose, J. H., and Gaines, B. R. 1989. Knowledge acquisition for: Knowledge-based systems: Notes on the state-of-the-art. *Machine Learning,* 4, pp. 377-394.

Dreyfus, H., and Dreyfus, S. 1992. *What Artificial Experts Can and Cannot Do.* AI & Soc., Springer-Verlag, 6: 18-26.

Garland, D. J., Phillips, J. N., Tilden, D. S., and Wise, J. A. 1991. *Theoretical Underpinnings of Situational Awareness: Towards an Objective Measure Final Report* (Report No. CAAR-15498-91-1) Daytona Beach, FL: Embry-Riddle Aeronautical University, Center for Aviation/Aerospace Research.

Gonzalez, A., and Dankel II, D. 1993. *ENGINEERING OF KNOWLEDGE-BASED SYSTEMS: Theory and Practice,* Prentice Hall.

Horne, W. G. 1993. *Recurrent Neural Networks: A Functional Approach.* Ph.D. dissertation, University of New Mexico.

Lee, S., and Shimoji, S. 1991. Machine acquisition of skills by neural networks. In *International Joint Conference on Neural Networks,* II, pp. 781-788, IEEE.

McGraw, K. L., 1989. *Knowledge Acquisition: Principles and Guidelines.* Prentice Hall, Englewood Cliffs, N.J.

Sidani, T. A. 1994. *LEARNING SITUATIONAL KNOWLEDGE THROUGH OBSERVATION OF EXPERT PERFORMANCE IN A SIMULATION-BASED ENVIRONMENT.* Ph.D. dissertation, University of Central Florida.

Slatter, P. E. 1990. Models of expertise in knowledge engineering. In: Hojjat Adeli (Ed.), *Knowledge Engineering: Volume I Fundamentals.* McGraw Hill, Inc, pp. 130-156.

Waltz, E., and Llinas, J. 1990. *Multisensor Data Fusion*, Artech House, Inc, Boston.