Automating the CGF Model Development and Refinement Process by Observing Expert Behavior in a Simulation

Avelino J. Gonzalez, Michael Georgiopoulos, Ronald F. DeMara, Amy Henninger, William Gerber
Electrical and Computer Engineering Department
University of Central Florida
Orlando, FL 32816-2450
ajg@ece.engr.ucf.edu
(407)-823-5027

1. Abstract

Ultimate widespread use of CGF entities in tactical simulations will depend on how easy it will be to develop, refine and maintain models of the behaviors to be represented. However, proper vehicle behavior model development for CGF applications can be difficult as well as expensive. Means to quickly and effectively create models for new vehicles and/or behaviors must be developed to permit CGF models to be widely used in the future. One realistic approach to overcoming this model generation bottleneck is to create and refine vehicle models through *automated observation* of the behavior of an entity being controlled by a human expert in a simulation. This is a learning paradigm quite commonly used by humans. This paper describes an on-going research effort that introduces some new ideas on how to accomplish autonomous model development through observation.

2. Introduction

Behavior modeling has been extensively researched in the past several years, mostly as part of the Computer Generated Forces (CGF) effort sponsored mainly by DoD. Several approaches have been devised and implemented to control simulated enemy as well as friendly forces in a training simulation. ModSAF and CCTT-SAF have been the major efforts undertaken, but several others have been active in the recent past. ModSAF and CCTT-SAF model reactive behavior by representing SME rules through control statements in a conventional programming language. While successful in many ways, the knowledge engineering effort involved in developing these models is quite extensive. Therefore, a difficult and long model development (or modification) process would ensue if their modeling paradigms were to be used in other applications of intelligent simulated entities. One way to overcome this model generation bottleneck is to develop and implement a way to automatically (or at least quasi-automatically) create and refine these models.

The knowledge necessary to build an accurate cognitive model of the decision-maker in a fighting vehicle can be said to be composed of two different elements:

- General a-priori explicit knowledge about the mission, the battle, the enemy and the capability of the decision maker's own vehicle, and

- Tactical knowledge (both explicit and implicit) used to determine the desired course of action as a result of the current situation.

In the long term, we believe that the explicit a-priori knowledge will be best acquired through a question and answer session between the expert decision-maker and an automated knowledge acquisition tool. On the other hand, we believe that the tactical knowledge, as well as possibly the implicit general knowledge, can be best learned through automated observation of an expert decision-maker executing the task(s) on a simulated environment. Our approach will be to minimize the former and develop the means to do the latter. However, before entering in a discussion of these techniques, it is important to describe the modeling infrastructure that we believe can support the techniques to automate the model generation and refinement process.

3. Automated Model Creation

In confronting real-world computing problems, it is frequently advantageous to use several computing techniques synergistically rather than exclusively, resulting in construction of complementary hybrid intelligent systems. With this in mind, we propose to address the current problem using a combination of modeling paradigms. The basic model structure will be founded upon a modeling paradigm referred to as *Context-based Representation* (CxBR) [Gonzalez 95]. This approach equates the situation being faced by the decision-maker to a context which carries with it a set of predetermined procedures that are typical of that entity's expected behavior under those conditions.

Briefly, life for a modeled vehicle under the CxBR paradigm is being under the control of a sequence of contexts, which at any one point in time represent the expected behavior of that vehicle. Which context is in control of the modeled vehicle is dependent on the situation faced. The context in control (the *active context*) not only defines the vehicle's behavior, but also what to expect from the environment. Since only a limited number of things can be expected to happen under any one context, the search space for a situational awareness module is neatly trimmed to only those that are realistic under the presently-active context. Thus, the modeled vehicle goes through a simulation transitioning from one context to another, depending on which ones best address the situation at hand.

Contexts are defined as a hierarchy of increasingly less abstract ones. At the top of the hierarchy is the Mission Context, which defines the mission to be undertaken by the vehicle to be modeled. This broadly defines the objectives, the constraints and the opportunities of which to take advantage during the execution of the mission. It may also define which lower level contexts are applicable to this mission. At the next lower level are the Major Contexts, which form the backbone of the CxBR technique. These contexts contain the high-level maneuvers and actions that are expected to be executed by the vehicle when under the applicable situation. It also defines what criteria indicate that a transition to another major context is necessary because of changes in the situation. At the lowest level of the hierarchy are the sub-contexts. These are low-level operations that may be required as part of the major context, but that may be reusable by another major context. CxBR operates by determining the appropriate major context and making it active. This context will control the behavior of the vehicle by executing behaviors that are required and/or typical for that entity under those circumstances. Furthermore, it will also look for changes in the situation that may warrant a *transition* to another context. If changes in the situation warrant it, the current context will deactivate itself and activate the one selected for transition, thus maintaining appropriate control of the vehicle.

We should briefly mention that successful prototypes based on the CxBR approach have been implemented in the domain of submarine warfare for NAWC-TSD [Gonzalez 95], as well as for automobile driving [Henninger 96; Brown 94]. This concept has received some interest from other researchers as indicated in the published technical literature [Turner 93; 95; Bass 96].

3.1 A-Priori Knowledge Acquisition

Explicit knowledge has traditionally been relatively easy to elicit from experts through interview sessions. However, these sessions have also been long, drawn out processes that have taxed the patience of many a system developer as well as experts. Furthermore, the long times typically taken to carry out this process has always resulted in high development costs. One way to facilitate the acquisition of explicit knowledge has been to develop tools that can interact with an expert and elicit the requisite knowledge from him/her through a question and answer dialogue. This has been a relatively successful field of research, with several systems having emerged from the laboratories.

We believe that the use of CxBR as the base paradigm in our work will further facilitate this process. This is largely due to the highly structured nature of the context-based representation and reasoning approach. A Q&A session with the experts will allow a automated knowledge acquisition tool based on CxBR to define the various contexts applicable to the mission being undertaken. This will include definition of the goals and constraints of the mission, as well as of the various contexts potentially being experienced by decision-maker. The feasibility of this approach to model development for CGF's was shown by Henninger [Henninger 96; 97] in her work to develop an automated knowledge acquisition system to gather exactly this type of knowledge. We therefore believe that this method could be used to automatically gather the explicit knowledge needed to be known a-priori by the vehicle. We will use Henninger's work as the basis for this phase of the research.

3.2 Learning Through Observation

Knowing what transitions to make and when to make them is the essence of tactical behavioral knowledge. These transitions from one context to another are a key element of context-based behavioral representation. However, these cannot be easily obtained through a question and answer session. We believe that this knowledge is best learned through the process of observation.

By observation we refer to the concept of learning about a behavior to be emulated by observing a manned (simulated) vehicle as it performs that behavior in battlefield situations similar to that to be seen by the model. This has the additional advantage of being able to capture the subtle behaviors not clearly articulated by experts in the field.

While learning through observation is a relatively new concept, there is some precedent in the literature. Pomerleau, using a neural network, designed an autonomous vehicle system that was able to drive an automobile throughout the Carnegie-Mellon University campus [Pomerleau 92]. The neural network was trained by observation, and it was able to generalize after its training was completed. In particular, although the neural network was trained to drive the vehicle through a one-lane road under ideal environmental conditions, it was able to perform satisfactorily in two-lane as well as in dirt roads, and under adverse environmental conditions (rain, snow, etc.).

More recently, Sidani [Sidani 94; 95] captured the behavior of an expert automobile driver by observing his/her actions in a simulated task. He built a hybrid system based upon neural networks and symbolic reasoning which learned and then emulated the expert driver's behavior. The system was successful in operating a car in a traffic signal situation as well as in the presence of a pedestrian crossing the street in front of the vehicle. The interesting aspect of this work was that the model was trained in the traffic light and in the pedestrian situations separately. Yet, when combined in a complex situation that it had not seen before, it was able to carry out the correct actions (i.e., stop for the pedestrian crossing in spite of the light being green).

This work provides an excellent starting point for our proposed task of partially developing a model through observation. However, additional work must be done to make this idea a useful reality. First of all, Sidani's prior work identified a-priori all the parameters to be employed in the neural network training. This is often not realistic. On the other hand, to employ all possible parameters in the simulation will make for highly complex and probably untrainable neural networks. A means to determine the applicable variables in the simulation needs to be investigated in order to make the technique useful. Furthermore, the use of neural networks as the main modeling paradigm may not be adequate by itself due to the weaknesses normally associated with neural nets: difficulty to train and review the logic behind its actions. This last issue becomes important when validating the model's performance. Lastly, the domain of ground warfare is many times more complex than that of driving an automobile, and thus will likely require a more complex modeling paradigm than the latter domain. There will likely be a need for a certain amount of a-priori knowledge before the observation process can become effective.

In order to do this, we propose a supervisory system that observes an expert decision-maker in action performing a simulated task within a vehicle. This system will look for "interesting" occurrences in the actions of this vehicle. Such interesting occurrences are likely to be the cause or the result of a context shift. Thus, by correlating these observed context shifts with an interpretation of the context to which the decision-maker is shifting to, the transition criteria between contexts can be learned.

One approach for interpreting to what context the decision-maker is transitioning to is a new technique called *Template-based Interpretation* (TBI). TBI is an experimental technique developed by Drewes and Gonzalez [Drewes 95] to interpret the intent of actions by a human-controlled entity in a training simulation. Templates are expectations of behavior by a human performing a specific task. Observations of an expert's actions in a simulation and applying these observations dynamically to competing partially-filled-in templates will result in the identification of the one most likely to be representative of the intended actions. This technique is similar to case-based reasoning except that the comparisons of attributes will be time-dependent as well as potentially sequenced. Furthermore, a competing template will be declared the successful one when sufficient evidence exists to uniquely identify it as the "winner."

The second approach is to use neuro-fuzzy computing, composed of the integration of neural networks and fuzzy logic. Fuzzy set theory provides a systematic calculus to deal with imprecise and incomplete information linguistically (i.e., the kind of information that humans contend with in their every day lives, including the battlefield environment), and it performs numerical computation by using linguistic labels stipulated by membership functions. Moreover, a selection of "fuzzy-if-then" rules forms the key component of a F*uzzy Inference System* (FIS) that can effectively model human expertise in a specific application. Hence, fuzzy logic should be an integral part of the technology vying to automatically and realistically emulate the behavior of certain military forces in the battlefield. But fuzzy logic alone cannot accomplish the task. One of the requirements of an effective FIS that emulates human behavior should be its capability to adapt to changing environments, and its ability to learn real-time (on-line), both of which are inherent capabilities of a human being. This is where neural network technology comes to the help of fuzzy logic, in the form of intelligent systems that are referred to as *Fuzzy Neural Networks* (FNNs). A fuzzy neural network emulates human behavior by training with an appropriate collection of “fuzzy data” and/or “crisp data”, but it is also adaptive in the sense that it can learn new data (crisp or fuzzy), and forget if necessary, old data, through a retraining process.

A number of interesting approaches to design fuzzy neural networks have been proposed in the literature [Keller, 92(a), 92(b); Ishibuchi 93; Ishibuchi 94; Harashi 93; Chen 96]. Some of these approaches, though, learn the data rules through learning techniques that are slow to converge, and they require extensive retraining when new data are added to the repertoire, or old data are eliminated. A class of fuzzy neural network architectures that do not suffer from this slow convergence problem is the class of ART neural network architectures developed by Carpenter and Grossberg at Boston University. Furthermore, ART architectures have the additional advantage that their output responses to input excitation can be logically explained. Prominent members of this class of architectures are: Fuzzy ART [Carpenter 91a] and Fuzzy ARTMAP [Carpenter 91b]. The theoretical properties of the Fuzzy ART and Fuzzy ARTMAP fuzzy neural networks have been extensively investigated by Huang [Huang 95], and Georgiopoulos [Georgiopoulos 96].

Furthermore, the sub-contexts involved in the CxBR paradigm typically represent low level actions, such as steering, braking and accelerating the vehicle. It is in such actions that the implicit knowledge referred to by Sidani [94] can be typically found. Neural networks may be the best means to represent the implicit nature of such low-level actions. This is re-inforced by work done by Crowe [90] in which he uses neural networks to learn air combat decision-making skills. Our work goes beyond that of Sidani and Crowe by learning how to make high level decisions without the use of neural networks.

4. <u>Learning by Observation – The Process</u>

Creating a CGF model automatically by observing an expert exhibiting a behavior in a simulation is a complicated process. The ideas discussed above are only discussed generally. This section describes the steps and the more detailed issues involved in this difficult undertaking.

4.1 Framework Development

One of the most important aspects of doing learning through observation is the development of a suitable and efficient cognitive modeling framework or infrastructure. This modeling framework should allow for a model that will easily accommodate the learned knowledge. It is anticipated that this framework will be based upon the Context-based Representation paradigm described above. However, to convert a conceptual paradigm into a framework, with defined procedures, reasoning mechanism, and representational syntax, merits significant attention. Several issues involved with the conventional CxBR paradigm may have to be reconsidered as it applies to learning through observation.

Also important is the definition and development of an observational environment that will permit the observation to be done easily and effectively. This environment is the simulation in which the expert exhibits the appropriate behavior to be observed. It must provide easy access to the variables that are being observed. ModSAF is the environment being used for this task.

4.2 Observational Techniques

The second most important issue is the development of techniques that facilitate the development of model instances from the defined framework. Capture of implicit knowledge represents a challenge that can best be overcome through observational techniques. This is one of the most difficult aspects of this undertaking and the one with the greatest technical risk. It is composed of the following issues:

- **Definition and discovery of "interesting occurrences"**: This is very important, as these will serve as indications that the human has shifted contexts. These interesting occurrences represent indication of potential transitions between contexts in the model. They, moreover, represent implicit knowledge, and are best captured through observation.

- **Interpretation of expert's action**: It is important that the system know what tactic the expert is currently carrying out without asking questions of the expert. When an interesting occurrence is detected, it is likely that the context has shifted for the vehicle being modeled. If so, it must be able to determine to what context the vehicle shifted to, so it can learn what the transition was. This is done through Template-based Reasoning, but other techniques will be investigated as well.

- **Development of the observational technique itself**: There are two candidate technologies to accomplish this: 1) Fuzzy neural networks, and 2) similarity and difference-based learning techniques [Winston 92]. Fuzzy neural networks can be used to decide when to transition from one major context to another in our CxBR modeling paradigm. Fuzzy neural networks have the capability to acquire the aforementioned knowledge through training with data collected through observation, or through training with rules obtained from subject matter experts.

5. Summary and Conclusion

A means to quickly and effectively create models new vehicles and/or new behaviors must be developed if CGF models are to be extensively used in military simulations. In this paper we propose a solution to this problem by describing an automated technique that can generate these CGF models in a quick and effective way. This technique is based upon the Context-based reasoning paradigm (CxBR). The success of this model relies upon knowledge acquisition via non-intrusive interaction with an expert, primarily through observation of the behavior of the simulated entity controlled directly by an human expert. The various steps to be carried out in this investigation are carefully outlined.

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7. References

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7. Author’s Biographies

Avelino Gonzalez is a Professor of Computer Engineering in the Electrical and Computer Engineering Department at the University of Central Florida, in Orlando. He has been involved in research on intelligent simulations and computer generated forces since 1987.

Ronald F. DeMara is a faculty member in the Electrical and Computer Engineering Department at the University of Central Florida in Orlando, Florida. Dr. DeMara received a B.S. in Electrical Engineering degree from Lehigh University in 1987, an M.S. in Electrical Engineering from the University of Maryland, College Park in 1989, and a Ph.D. in Computer Engineering from the University of Southern California, Los Angeles in 1992. His research interests include parallel processing, computer architecture, and performance of distributed simulation environments.

Michael Georgiopoulos has a Diploma in EE from the National Technical University of Athens (1981), a M.S. in EE from the University of Connecticut Storrs (1983) and a Ph.D. in EE from the University of Connecticut, Storrs, CT (1986). He is currently an Associate Professor at the Dept. of Electrical and Computer Engineering of the University of Central Florida. His research interests lie in the areas of neural networks, fuzzy logic and genetic algorithms and the applications of these technologies in cognitive modeling, signal processing and Electromagnetics. He has published over a hundred papers in scientific journals and conferences. He is a member of IEEE and the International Neural Network Society.

Amy Henninger has earned B.S. degrees in Psychology, Industrial Engineering, and Mathematics from Southern Illinois University, an M.S.E. in Engineering Management from Florida Institute of Technology, and an M.S. in Computer Engineering from University of Central Florida. Currently, Ms. Henninger is a doctoral student in computer engineering at UCF and a Consortium of Universities Research Fellow at STRICOM, where she works on the Commander Support System project.

William J. Gerber is a Ph.D. student in Computer Engineering at the University of Central Florida. He is currently working as a Consortium of Universities Research Fellow at STRICOM and a Graduate Research Assistant at UCF. A retired Air Force lieutenant colonel and command pilot, he has held several technology and engineering management assignments while on active duty, including ones with the Strategic Defense Initiative Organization, the Navstar Global Positioning System Joint Program Office, and various Air Staff offices.