Vehicle Model Generation and Optimization for Embedded Simulation

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ABSTRACT: *The development and use of Inter-Vehicle Embedded Simulation Technology (INVEST) offers several distinct advantages for 21st Century training environments. Benefits of embedded simulations include the ability to perform "in-situ" exercises on actual equipment, more direct provision of support for the wide array of equipment in the field, and a greater opportunity to develop new training exercises using much shorter lead times than previously possible with stand-alone training systems. Nonetheless, the INVEST program also presents several challenging, yet surmountable obstacles to interconnecting the real and virtual layers within their actual environments. These challenges include 1) how to more efficiently and effectively create, refine and maintain vehicle models, and 2) how to optimize the operation of these models within the INVEST environment, so as to best utilize the computing resources available on board the vehicle and the available communication bandwidth. Addressing these technology challenges remains a prerequisite to the feasibility of realistic INVEST simulations involving ground combat vehicles. In this paper, we describe a multifaceted investigation aimed at addressing these tasks.*

1. Introduction and Problem Definition

The U.S. Army has realized significant benefits through the use of linked simulators to enable federate-level exercises on stand-alone trainers. A successful transition to INVEST simulations, however, will require new techniques for the incremental development and distributed processing of massive quantities of vehicle models. In particular, each entity that participates in the simulation will require either construction or adaptation of a unique instance of its vehicle model in order to properly simulate its interaction with the other entities in the exercise.

Proper model development can be difficult as well as expensive, as models must cover numerous situations. To represent all situations explicitly, and to gather them manually is a truly significant undertaking. One realistic approach to overcoming this model generation bottleneck is to create and refine vehicle models through automated observation of the behavior of the entity in question while being controlled by a human. An automated model generation approach addresses both the challenges of developing the necessary quantity of models and the requirement for production on relatively short notice.

Furthermore, once each vehicle model is developed and deployed, it must be continuously correlated with the actual behavior of the physical entity throughout the duration of the training exercise. Thus, one of the primary technical difficulties is the need to convey and assimilate the large amount of positional, operational, and status information exchanged between players. Clearly, it is necessary to make this data available within a timeframe suitable for real-time interaction, yet utilize as little as only 2400 bits per second peak bandwidth which is available per player, as in the Army's currently available Range Data Measurement System (RDMS). Thus, the challenge is to take advantage of the distributed processing resources available in the INVEST environment to compensate for the decreased communication resources.

We address the aforementioned problems with an integrated approach to vehicle model generation and optimization. This paper will describe in detail the concepts and tasks involved in developing the automated vehicle models through observation of an expert's performance in a simulated environment. Once the automated vehicle models have been developed, we will introduce appropriate model monitoring and correction procedures to ensure that the vehicle models faithfully reproduce the vehicles' behavior. Lastly, we will take into consideration the available computational and communication resources on board the vehicle in order to optimize the model to best take advantage of these existing resources. At the completion of our work we expect to have accomplished the following:

- Develop a vehicle model framework for INVEST,
- Demonstrate the feasibility of automated model development techniques,
- Determine the computation/communication requirements in INVEST environments for the developed models.

2. Technical Objectives

Our main objectives in this investigation are:

- Model definition, generation and refinement, and
- Model processing optimization

These objectives are discussed in greater detail in the sections below:

2.1 Model Definition, Generation, and Refinement

Behavior modeling has been extensively researched in the past several years, mostly as part of the Computer Generated Forces (CGF) effort sponsored 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. They model reactive behavior through if-then-else constructs in a conventional programming language. While successful in many ways, the knowledge engineering effort involved in developing these models is quite extensive. Such existing models may be usable as the models to be employed in the proposed project. However, it is likely that it will not be highly applicable due to the great variability in the behaviors to be represented. Therefore, a difficult and long model development (or modification) process would ensue. One way to overcome this model generation bottleneck is to develop and implement a way to automatically or 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

We believe that the explicit a-priori knowledge can be best acquired through a question and answer session between an expert decision-maker and an automated knowledge acquisition tool. We believe that the tactical knowledge, on the other hand, 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.

2.1.1 Model Definition

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 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) [1]. This approach equates the situation being faced by the decision-maker to a context that carries with it a set of predetermined procedures typical of that entity's expected or required 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 upon 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 hierarchies 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 represent the high-level maneuvers and actions that the vehicle expects to execute 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 and 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 [1], as well as for automobile driving [2] [3]. This concept has generated some interest from other researchers as indicated in the published technical literature [4] [5] [6].

2.1.2 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 system developers 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 an 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 was shown by Henninger [2] [7] in her work to design and develop an automated knowledge acquisition system that gathers exactly this type of knowledge. We therefore propose that this method be used to automatically obtain the explicit knowledge known a-priori by the vehicle. Henninger's work can be used as the basis for this phase of the research.

2.1.3 Learning Through Observation

The transition from one context to another, a key element of context-based behavior representation, however, cannot be easily obtained through a question and answer session. Such transitions are the essence of tactical knowledge. 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 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 campus [8]. 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 [9] [10] 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).

Sidani's 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 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 will be investigated as part of this investigation 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 certainly be a need for a certain amount of a-priori knowledge before the observation process can become effective.

2.2 Model Processing Optimization Task

The transition to real-time simulation and model deployment in an INVEST environment presents three challenges when compared to simulation in a Distributed Interactive Simulation (DIS) environment. First, an INVEST simulation potentially involves more entities than those used in DIS. Second, the communication bandwidth available in an INVEST environment is several orders of magnitude less than that of DIS. Third, INVEST communication latencies are longer than those which occur in DIS. Specifically, a realistic INVEST exercise may require coordination of roughly an order of magnitude more entities than are currently feasible in real-time with state-of-the-art DIS systems, but the INVEST simulation must do so utilizing a communication bandwidth which is a fraction of what is available for DIS. For instance, a 10Mb/sec Ethernet link or 100Mb/sec channel per DIS simulator will necessarily be reduced to a collection of low bandwidth links with an effective throughput of only thousands of bits per second each. Moreover, the communication latency will be increased due to the distances and signal processing requirements of data transmission in the field, as opposed to DIS simulators directly connected to ports or routers on a Local Area Network (LAN).

Utilization of dead-reckoning models of entity behavior has already proven to be useful in reducing communication in LAN-based DIS exercises [11]. The proposed task is to extend the processing and communication abilities of the dead-reckoning technique to include the use of the adaptive models generated for the INVEST environment. A promising approach is to employ pairs of *concurrent models* that reduce inter-entity communication requirements by predicating certain aspects of the behavior remote entities [12]. As in the typical first-order linear dead-reckoning techniques, the entity's update requirements are reduced because certain behaviors can be anticipated in advance by the model. For instance, the required information about the current position of a remote vehicle can be inferred from its previously known position and velocity vector. This utilizes local computation to model remote behavior rather than requiring updates to be continually transmitted by the remote entities.

The concurrent model approach examines extending these to other types of entity behaviors. In particular, a high fidelity model of the vehicle is executed on the remote subject vehicle, which is then tuned in a closed-loop fashion. Simultaneously, a replica or clone of this vehicle model is executed on the local platform. Periodically, the necessary adjustments to the replica model are transmitted from the remote vehicle to allow the two models to again become coherent. Thus, whenever the remote and local models remain coherent, updates need not be transmitted from the remote model.

Since excess communication capacity is minimal in an INVEST environment, the tradeoff between communication bandwidth and computational resources using concurrent models is extremely critical. To make even linear interpolations functional will require optimal use of the available communication bandwidth. Furthermore, the vehicle platform must have a sufficient amount of surplus computational cycles to model all of the remote entities within its current field of view or influence. Thus, the fundamental issues are to identify and optimize the processing and communication tradeoffs in the particular models developed for the ground vehicles.

3. Work Plan

In order to achieve the objectives set out above, the following tasks are or will be in progress:

<u>Task #1: Requirements Generation</u> **-** This task encompasses the collection and/or generation of the required elements to permit project startup. This includes the determination of the computing environment, the infrastructure to be used for the observation (ModSAF), as well as the scenario to be used in the testbed.

Task #2: Model Framework Development - One of the most significant contributions to be made by this investigation will be the development of an efficient cognitive modeling framework that will optimize the computational and communication resources available within the INVEST program. Furthermore, the modeling framework developed should allow for ease of model development, as will be described in Task #3 below. This task will develop that framework.

Task #3: Develop Observational Procedures for Model Generation - The second most important contribution expected from this project 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 project and the one with the greatest technical risk.

Task #4: Develop on-line Model Monitoring Procedures - It is important to know when a model, placed in service and executing its mission in a training simulation exercise, no longer accurately predicts the behavior of its corresponding manned vehicle. Furthermore, a model developed using this framework cannot become static after initial development. It must be continually refined and improved to maintain its representational accuracy. A model that gradually degrades (due to possibly, change in doctrine, or a general improvement in task performance by the experts) will slowly disintegrate into a situation that calls for increasingly more communication activity until the capacity is exceeded. Monitoring of the model during its on-line use provides us with several opportunities for functional and performance optimization. The main goals of this task are to continuously monitor model behavior and compare it to observed human performance in order to: 1) minimize the time that the model is not in use, 2) improve the model when compared to expert performance.

Task #5: Testbed Development - This task will have as its main objective the construction of a vehicle model integration testbed for INVEST. The Model Integration Testbed (MINT) will be used to develop and optimize the vehicle models developed for the INVEST program.

Task #6: Processing Optimization - The processing optimization task will identify and resolve the processing bottlenecks in the implemented vehicle models using the MINT testbed. The overall goal is to determine the processing and communication requirement needs per entity and the number of entities possible within the fidelity requirements of the INVEST environment.

4. Anticipated Benefits

The anticipated benefits of the proposed integrated approach to vehicle model generation and optimization include:

- Development of a vehicle model framework for use in INVEST - We cannot underestimate the advantages of successfully completing the task of developing a framework for automated generation of a model for a manned vehicle in the battlefield. In doing so, we will have provided a methodology for efficiently and successfully emulates human behavior in a complex environment affected by a variety of forces. This framework will be instrumental in assisting the Army in developing and maintaining vehicle models for the INVEST program.

- Demonstrate feasibility of automated model development techniques - If our effort of modeling the behavior of a manned vehicle in the battlefield is successful, we would have accomplished this goal by using powerful AI technologies, such as context-based reasoning, template-based reasoning, neural networks and fuzzy logic. Since the ideas that lie behind the successful use of these technologies are generic, we could utilize our approach to solve problems of similar nature. For example, although our effort will focus on modeling the behavior of a few manned vehicles in the battlefield, we expect to be able to extend our experiences to virtually any battlefield vehicle whose behavior needs to be emulated. Furthermore, the techniques developed to observe the expert's behavior could also be used to observe and evaluate a trainee's performance. This can be used as part of the after-action review.

- Determine Computation / Communication requirements in INVEST vehicles - During the process of designing an appropriate model of the behavior of a manned vehicle in the battlefield, we will conduct an investigation of the computation and communication requirements needed to do so. Since, as we have mentioned above, our approach in designing such models will be as generic as possible, we will be able to make a good estimate of the total communication/computation requirements of the manned vehicles that participate in a realistic military exercise. Hence, we will be able to assess the feasibility of our approach in INVEST environments for realistic military scenarios.

- Construct and optimize a model testbed for INVEST - The Model Integration Testbed (MINT) for INVEST will be developed around entity attribute management concepts. The protocols developed, implemented, and optimized within the MINT testbed will add new functionality to the services layer, in addition to optimizing the vehicle models themselves. These new services will provide protocol support for low-bandwidth interconnected distributed simulations. Furthermore, the MINT testbed routines will be parameterized so that the impact of new communication and processing technology can be readily evaluated in realistic scenarios. By simply updating the bandwidth, latency, and throughput parameters used, the benefit of new technologies under consideration for INVEST can be evaluated directly for any number of simulation scenarios, without incurring the expense to procure, install, and debug the new equipment in the field.

5. Summary

The on-going investigation promises to develop an innovative means of generating, refining, and maintaining vehicle models for use in the invest project. This will provide an efficient and effective way to create, validate, and maintain vehicle models easily. Furthermore, the project will also optimize this model in order to best utilize the computing resources available in the INVEST vehicle, and the communication bandwidth allocated to the training exercise.

Although our effort will focus on modeling the behavior of a few types of manned vehicles in the battlefield, we expect to be able to extend our experiences to virtually any vehicle whose behavior needs to be emulated.

The most direct means of optimizing the distributed processing activities within the constraints of the INVEST environment are to consider the bandwidth, latency, and throughput requirements throughout the model development process. Bandwidth optimization can be achieved through a statistical analysis of the type of messages (positional, operational, status) that need to be communicated to preserve the situational context. Next, a technique for hiding latency is then employed by caching parameters and updates to the models during idle periods of the communication channels. This serves to pre-fetch some of the needed data so that at least part of the context-shift information does not have to be transmitted in real-time. When these optimizations are in-place, then throughput enhancement can be achieved through data dependence analysis, which identifies those tasks in the model that can be performed concurrently. A static analysis of these tasks at compile-time best determines their initial allocation to the processor(s) available within the vehicle.

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