Chapter 6 – THE APPLICATION OF INTELLIGENT AGENTS IN EMBEDDED VIRTUAL SIMULATIONS (EVS)

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1.0 INTRODUCTION

During the NATO HFM research workshop, a special session was dedicated to learning techniques. The discussion following the presentation was guided by the following questions:

- What are the factors enabling/limiting learning in EVS?
- When is the optimal time to provide feedback in EVS? On error, on trainee request, other?
- How much human involvement is required to support learning in EVS, and how much can be delegated to intelligent agents?
- How is feedback provided to trainees during embedded training?

A significant part of the discussion on learning technologies centered on intelligent agents for embedded training and how they might support the constraints (e.g., lack of availability of a human tutor) inferred by the questions above. Also discussed was how they differ from conventional technology-based training environments.

So why might intelligent agents be important to embedded training? In September 2010, IBM asserted that '66 [percent] of new products have some kind of intelligence built in'. Less than a year later, 66 percent is likely a low estimate of new products that take advantage of Artificial Intelligence (AI) techniques. The need for artificial intelligence for the masses highlights the expectation for user-friendly products with 'on demand' support. This expectation translates well to training applications where human interaction and support (e.g., tutors) are either limited, not available, or impractical (e.g., embedded virtual simulations). IBM's statement also parallels a need for new equipment training in the military, where expectations are growing for products that use AI to 'teach' the user about their capabilities and how to exploit them.

Intelligent agents take many forms, but the NATO group explored three primary classes of intelligent agents for EVS applications: learning agents, Non-Player Characters (NPCs) and process managers.

Learning agents are functional elements of computer-based tutors and support the trainee's learning process. Agent functions might include the development/maintenance of trainee and expert models, the prediction of the trainee's cognitive state (e.g., affect or motivation), assessment of trainee performance and the optimization of instructional strategies (e.g., hints, questions or pumps) employed by intelligent tutors.

NPCs represent real people or weapon systems, including their behaviors and cognitive states (e.g., decision-making capabilities). NPCs can be fully automated representations of friends, adversaries, or neutral characters.

Process management agents could be used to automate laborious processes including: the development of training content; management of interfaces and network loading; and the collection and analysis of data during a distributed EVS training exercise.

Intelligent-agent capabilities, including the evaluation of the trainee's 'readiness to learn', agent feedback delivery and frequency, the degree of automation, learning enablers, and the limitations of agent technologies, are reviewed, along with examples of successful implementations of intelligent technologies within a sample of NATO countries. Recommendations for future embedded training capabilities driven by intelligent technologies are also discussed.

2.0 INTELLIGENT LEARNING AGENTS

As noted above, learning agents are autonomous functional elements of computer-based tutors that observe and act upon an environment and direct their activity towards achieving goals (Russell & Norvig, 2003). In computer-based tutors, learning agents observe and act upon information about the trainee and his/her performance relative to an ideal trainee model, also known as an expert model.

Learning agents might use behavioral and physiological sensors, past performance and other competency measures, demographic information, human observations and/or self-reported data to assess the trainee's current 'readiness to learn', predict their future performance or cognitive state. Learning agents might also use trainee data to build expert models or to determine optimal instructional strategies used by intelligent tutors. Instructional strategies include, but are not limited to: pace of instruction, challenge level of instruction, frequency of direction and support, questions and pumps. Examples and frameworks for learning agents were presented and discussed during the 2009 workshop.

Sottilare (2009 & 2010) asserted that the lack of human tutors within operational platforms limits the understanding of each trainee's cognitive state (e.g., emotional state) and the completeness of the trainee model within computer-based tutoring systems. Tutor technology is not sufficiently mature to provide accurate, portable, affordable, passive, and effective sensing and interpretation of the trainee's cognitive state and limits the adaptability and effectiveness of the instruction in today's embedded training systems and other computer-based tutor-dependent environments.

Jensen, Mosley, Sanders and Sims (2009) reviewed two case studies of embedded training prototypes developed for the U.S. Army that employ structured training methods to optimize learning without direct instructor involvement. These prototypes include a man-wearable trainer for dismounted operations, and a robotic vehicle control station trainer.

3.0 INTELLIGENT AGENTS AS NPCS

Heuvelink, van den Bosch, van Doesburg, and Harbers (2009) utilized intelligent agents as non-player characters in a stand-alone low-cost desktop simulation used by a single trainee who played the role of the Officer of the Watch (OW) in shipboard fire fighting training scenarios. The Chief of the Watch (CW), Machinery Control Room Operator (MCRO), Confinement Team Leader (CTL), and the Attack Team Leader (ATL) are all agent-based characters. This allows individuals to train in realistic and complex environments in the absence of other human team members.

Bell & Short (2009) advocated the utility of speech-interactive synthetic teammates for training, mission planning and rehearsal. They identified the following issues with human role-players: many training exercises use trainees as training aids; human role-players introduced unwanted variability into the training; sometimes instructors were also trainees and this complicated performance assessment; and costs for human role-players were recurring (e.g., compensation and transport). Non-player characters were seen as a viable option to overcome these issues. As an example, they created a set of CAS scenarios, focusing on dialogue between the pilot and a Joint Terminal Attack Controller (JTAC), which was played by an intelligent agent.

4.0 INTELLIGENT PROCESS AGENTS

As noted above, process management agents could be used to automate laborious processes associated with training. There is potential for intelligent agents to supplant painstaking cognitive task analyses used to develop expert models for computer-based tutoring systems (Williams, 1993). Advances in sensor technology (e.g., unobtrusive physiological and behavioral sensors) and machine learning techniques make it possible to produce more expansive and accurate expert models automatically, but additional research is needed to standardize processes and improve the accuracy of these models.

5.0 DISCUSSION

Morrison & Orlansky (1997) noted that 'provision of individualized instruction by embedded tutors, requiring little or no supervision' as a common positive feature of embedded training systems evaluated at that time. This is based on the assessment of trainee performance as part of a simplified trainee model. The systems noted in this study did not consider physiological sensors, past performance or other inputs to assess the trainee's cognitive and affective states, and therefore were limited in optimizing instructional strategies (e.g., feedback or scenario adaptation). This limitation could be seen as a negative attribute of these systems and should be considered in the design of new EVS.

An analysis of EVS requirements by the HFM-165 RTG highlighted significant technical challenges in the development and deployment of EVS within operational platforms. Among those challenges were communication and interaction with the trainee to support real-time feedback as well as an after-action review of their performance during embedded training exercises. This involves more than just movement of information to and from the trainee, but also includes intelligent observation. In live simulations, performance data is collected via sensors on an instrumented range and/or by human observers, but the use cases identified by the RTG included deployed scenarios in un-instrumented areas and without specialized observer personnel.

The RTG evaluated technology-based solutions and more specifically intelligent agents and their potential to: overcome the EVS lack of knowledge about the trainee state; and answer some of the guiding questions posed below:

- How should information (e.g., feedback, instructional content, etc.) be provided to the trainee in EVS?
- When (and how often) should feedback be provided in EVS and is it different than in conventional training simulations?
- What level of human involvement is needed in EVS? Can it be a fully automated or semi-automated process?
- What are learning enablers and limitations in EVS?

The following provides discussion of the application of intelligent agents to EVS in aircraft. Examples of embedded training in the aviation domain are primarily onboard fighters. The predominant type of intelligent agents in aviation EVS applications is NPCs.

The literature on EVS in the aviation domain is generally mute on the use of intelligent process agents. Process management functions, such as starting and stopping the EVS, data logging, data analysis and safeguarding functions (which take care of e.g., automatically terminating the EVS when flight safety requires) are generally not implemented as intelligent agents. A brief description of the architecture that is used for such functions can be found in Krijn and Wedzinga (2004), which deal with an early implementation of EVS for the F-16 aircraft. The latter implementation is of the 'single-ship' type, which means that aircraft equipped with such EVS have no dedicated EVS-communication link with other live aircraft. As a consequence, these aircraft can only engage in an EVS scenario in which they are the only live asset, i.e., they can only act as a single ship, not in a team.

This is a significant restriction because nearly all tactics training of fighter aircraft is done in formations of at least two aircraft. Lemmers (2009) and Keuning (2009) describe a multi-ship implementation of EVS for F-16 aircraft. Bills, Flachsbart, Kern and Olson (2009) describe a multi-ship implementation of EVS under development for the F-35 aircraft. The current review of the literature in the airborne domain doesn't mention the application of aforementioned 'learning agents' either. No documents in the public domain were found that revealed operational user requirements relating to specific functions in EVS that support the trainees' learning process, let alone the implementation of these functions in the form of intelligent agents.

Hence, the description of the use of intelligent agents for EVS in aircraft must currently be limited to the use of Non-Player Characters. Current efforts seem to focus on the development of adversary NPCs (Harrison, et al., 2010). One obvious reason is that the inclusion of synthetic adversaries in EVS is highly relevant to tactical training of fighter pilots and is cost-effective in the sense that fewer live-assets in the adversary are needed. Also, synthetic adversaries do not need to be equipped with complex communication architecture as would be the case with other relevant NPCs in a supportive or friendly role. After all, there is usually no communication through voice or datalink between fighter pilots and their advisories. Communication between, for example, a live flight lead and a synthetic wing man would be difficult to capture in an EVS architecture and would require a high quality and robust implementation for the cockpit environment, even in the least ambitious scenarios, as was discussed by Roessingh and Verhaaf (2009). Intelligent synthetic team mates in fighter formations will probably first be applied for ground-based virtual simulations, before being applied in EVS.

EVS for fighter aircraft applications is a relatively recent development, with the first concepts emerging in the late nineties of the last century. The first implementations concerned two types of NPCs: adversary aircraft and adversary ground threats in the form of Surface-to-Air-Missiles (SAMs). The adversary aircraft NPCs reduce the need to train against live mock enemies, or 'red air' in jargon. The SAM NPCs reduce the need to train at specifically instrumented flying ranges. Both types of NPCs are considered to contribute to substantial cost savings, as is further detailed by Bills et al (2009).

The first generation of adversary aircraft NPCs is further characterized by a virtual range from the EVS equipped 'ownship' which is beyond the visual range of the pilot. Those NPCs will never enter the visual range of the pilot during an EVS scenario. Hence, the training application of those adversary aircraft NPCs is limited to Beyond Visual Range (BVR) scenarios. According to Roessingh, van Sijll and Johnson (2003) this is mainly for technological reasons: to realistically visualize virtual adversary aircraft in the cockpit environment, when these aircraft come Within Visual Range, is technologically complex. As a result, the behaviour of these NPCs will only be observed directly via cockpit displays of on-board sensors (radar, radar warning receiver, possibly infra-red sensors). Hence, the behavior that these NPCs need to demonstrate only needs to be intelligent insofar observable via cockpit displays in the EVS equipped aircraft.

However, even intelligent behaviour BVR is far from trivial. Real enemies are, at least to some extent, unpredictable. They seek to maneuver themselves into a better position as the tactical situation changes. They react to friend and foe. They are adaptable. In other words, they are smart. The smart element in the behavior of these virtual opponents involves a number of factors. For instance, they should be able to detect and identify targets to attack, but should also be capable of defending themselves against enemy action. And just as the individual characters of people may vary, the variety in individual pilots and their personal style and preferences should also play a role. The eventual objective of NPCs into EVS is to create training scenarios where the threat is realistic, both in the air (adversarial aircraft) and on the ground (SAMs). This requires advanced cognitive modeling and the modeling of domain expertise. To reach the level of proficient behavior, NPCs could be 'trained', using machine learning algorithms, to instill the expertise that meets the requirements of the scenarios and the live participants. Harrison et al. (2010) propose genetic programming to train NPCs for EVS. However, the maturity level of machine learning applications for EVS has not been demonstrated as yet.

6.0 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Five critical areas were identified for additional intelligent agent research: technology (tools and methods) to assess of the trainee's learning needs and tutor feedback based on those learning needs; methods for automated scenario selection and adaptation based on trainee's competency and learning needs; methods for automated instructional strategy selection; methods to optimizing performance and retention; and automated data collection and assessment for after-action reviews.

Based on the RTG's research, discussions and workshop outputs, the following conclusions are offered relative to trainee feedback in EVS, the application of intelligent agents in EVS, their limitations and recommendations for future research.

Feedback (e.g., direction, support) should be presented when the trainee's actual performance varies sufficiently from their expected performance. The measurement of expected performance is largely based on experience and previously demonstrated competency in the domain being trained. The determination of current performance is critical to adapting training. Given the isolation of the trainee in an EVS from human observers, performance assessment will be largely left to computer-based techniques.

Feedback frequency should be driven by the trainee's competency, their levels of engagement, and their motivation. Accuracy, interference, calibration, and human variability will likely complicate the assessment of engagement and motivation through sensor technologies. Feedback should also be task dependent in that tasks involving high risk and consequence might involve more frequent feedback. Feedback should be triggered by trainee mistakes and trainee requests for help or clarification.

Intelligent agents may enable training: in situations where human tutors and human role players, such as mock-enemies, are either unavailable or not practical/cost effective; by reducing support costs via automated tutors, scenario directors, coaches, Non-Player Characters and simulation process management agents; by increasing availability of training through EVS as training goes with the Warfighter to the theater of operation. As they exist today, intelligent agents have limited adaptability and ability to motivate trainees, limited interfaces/interaction within virtual simulations and limited capability to perceive and understand a trainee's cognitive and affective states. This limits the ability of computer-based tutoring systems within EVS (or other training environments) to optimally select instructional content and strategies.

NPCs are viable as tutors, directors and coaches within EVS and other simulation environments, but additional research is needed to develop their interaction design (e.g., natural language understanding and generation) and cognitive modeling.

Elements of trainee models within computer-based tutoring systems may include demographics, input from behavioral and physiological sensors, self-reported and observed data and/or historical performance data. Physiological sensors are limited by human variation and electromagnetic interference (EM). EM is a concern in ground vehicles and naval platforms where EVS is likely to be deployed. Additional research is needed to assess what the essential elements of trainee models are and how they can be used to determine the trainee's cognitive state and optimal instruction in EVS.

In air applications, most notably EVS for fighter aircraft such as F-16 and F-35, NPCs are more often employed as adversarial NPCs (either ground threats, SAMs, or air threats, adversary aircraft). Currently application is limited to BVR scenarios, in which adversarial intelligent agent behaviors are observable via on-board sensor displays (e.g., radars) only.

Some research challenges include display of Within Visual Range (WVR) behaviors, cognitive modeling of entities (e.g., weapons platforms), tactics modeling of entities and multi-agent collaboration/interaction. Machine-learning approaches (e.g., decision trees, Bayesian networks, genetic algorithms) are growing tools of choice.

Intelligent learning agents show promise in spanning the gap between human and computer-based tutoring capabilities in one-to-one tutoring domains, but additional research and development is needed to make agents practical for use in fully autonomous training environments such as EVS.

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