

Next-Generation Semi-Automated Forces (SAFs): A Guidance Model

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ABSTRACT

One challenge in answering the Department of Defense's call to improve the capabilities of integrated training environments is populating training scenarios with the appropriate quality and quantity of realistic entities (friendly, adversarial, and neutral). Employing entities in Live, Virtual, and Constructive (LVC) training environments is commonly accomplished using combinations of live role players and constructive entities (i.e., Semi-Automated Forces [SAFs]). This currently requires qualified personnel to role-play in complex tactical scenarios, which creates fiscal challenges (e.g., increase in manpower and material costs). A less costly solution is to increase the use of SAFs and decrease human role-player requirements; however, current SAFs possess a limited range of behaviors, lack individual differences, and require a high amount of instructor/operator interaction (e.g., pre-scripting, monitoring, scenario control). For these reasons, SAFs are only as adaptive and interactive as the instructor/operator's capabilities (i.e., workload, willingness, attention). Additionally, no standardized requirements exist for the next generation of SAFs due to a lack of common direction and goals. This lack of requirements and standards yields SAFs that ultimately lack the realism to provide effective training without excessive intervention. This paper outlines challenges of current SAF technologies, introduces a guidance model for standardizing SAF development and assessment (Human Behaving SAFs, [HBSs]) for developers and entity authors, and identifies areas of ongoing science and technology development. Ultimately, if followed, this HBS guidance model will produce future SAFs capable of enhancing the efficiency and effectiveness of LVC training, thus reducing workload associated with SAF management, and alleviating fiscal concerns.

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INTRODUCTION

Economic pressures cause the Department of Defense to face the challenge of reducing costs associated with live training. Improving the capabilities for integrated (i.e., live and synthetic) training environments will support enhanced effectiveness and efficiency of training while minimizing the use of live aircraft. These integrated training environments – often termed Live, Virtual, and Constructive (LVC) training – can range from large-scale distributed training (e.g., Joint Fleet Synthetic Training) to local small unit training (e.g., United States Marine Corps Infantry Immersion Training). While effective, there are numerous challenges (e.g., interoperability between assets, fidelity, and cost) that inhibit the maximum potential of integrated LVC environments. This paper focuses on the challenge to populate training scenarios with the appropriate quantity and quality of realistic entities (friendly, adversarial, and neutral) by proposing a model to guide the development and assessment of such entities. Employing entities in these environments is commonly accomplished using combinations of human role-players and Semi-Automated Force (SAF) software. However, identifying qualified human role-players is difficult and manpower and material costs substantially increase (Abbott, Basilico, Glickman, & Whetzel, 2010). Although less costly, SAFs currently possess a limited range of behaviors and must be pre-scripted, monitored, and controlled by instructors/operators. Due to their pre-scripted nature and need for considerable instructor/operator intervention, SAFs are only as adaptive and interactive as the instructor/operator's flexibility and available attention permit. To illustrate, recent interviews with the F/A-18 community indicate instructors/operators frequently intervene during SAF scripted scenarios to ensure the trainee meets their training objectives within the allotted time as SAFs do not dynamically react, thus substantially increasing workload during complex training scenarios (F/A-18 Operator Team, personal communication, November 7, 2012).

Consequently, there is a need for more effective approaches to creating realistic SAFs that will reduce instructor/operator intervention and increase training efficiency and effectiveness. Furthermore, a need exists to develop a model that guides SAF behavior generation. The lack of a guidance model results in the utilization of varying development techniques that are ineffective and lack interoperable behavioral capabilities thus increasing the probability for runtime issues. This paper presents the challenges with current SAF programs and proposes a guidance model for developing and assessing SAFs to provide standardization [i.e., Human Behaving Semi-Automated Force (HBS) Model]. The HBS model will yield SAFs capable of enhancing LVC training, reducing workload associated with SAF management, and reducing total ownership cost. This enhancement is feasible, as the model would aid in the development of realistic SAFs who require little instructor/operator intervention, as they would behave appropriately and effectively within the training event.

CHALLENGES OF CURRENT TECHNOLOGY

The challenges associated with current SAF technology in training environments include the decreased realism associated with “smart SAFs” and the workload associated with pre-scripting and runtime modifications. Details of these challenges are outlined below.

SAFs can use Finite State Machines to generate linear behaviors from rules defined by domain knowledge (i.e., subject matter experts and manuals) (Henninger, Gonzalez, Gerber, Georgiopoulou, & DeMara, 2000). This method

results in a set of independent behaviors programmed one after another to achieve a sense of continuity for non-complex behaviors. This lack of behavior continuity can cause SAFs to appear unrealistic, creating detrimental effects to the students' training experience, and providing limited training utility in LVC environments (Abbott et al., 2010; Jensen, Ludwig, Proctor, Patrick, & Wong, 2008). For example, behaviors may appear to be choppy and incongruent, as one behavior may not systematically lead to the next. In an attempt to facilitate more realistic combat behaviors, many mission variations must be pre-scripted by Subject Matter Experts (SMEs) (e.g., instructor/operators, education specialists) (Cox & Fu, 2005). However, the high volume of training throughput for such exercises, burdens instructional personnel with scripting multiple vignettes for a large number of entities in a short period. Time constraints and limited availability of instructional personnel often lead to high workload demands that result in scenarios designed with little variability and limited flexibility to meet requirements. Consequently, multiple communities (e.g., F/A-18, P-8) have expressed the need for flexibility within scenarios and more time instructing versus generating scenarios (or adjusting SAFs) during training. Instructor/operators have also reported that the lack of SAF fidelity (e.g., SAFs losing speed when conducting multiple maneuvers) results in the need for intervention and increased monitoring.

Another challenge with using traditional SAFs is their inability to incorporate individual differences and human imperfections into their behaviors. Consequently, SAFs are often seen as machine-like or "too smart" when compared to humans conducting the same task. For example, SAFs maintain exact distances apart from one another while flying in formation, while humans flying the same formation will vary in distance due to individual differences (e.g., skill, workload). This machine like behavior occurs because SAFs typically lack human performance data (i.e., recorded behaviors during live and/or simulated events) to model human variability. This is problematic for LVC environments as trainees may easily distinguish between live and constructive entities. Another cue for trainees is the inability to communicate with SAFs, as many commonly used SAFs (e.g., NGTS, JSAF, OneSAF) lack the capability of two-way voice communication. Two-way communication (i.e., radio and phone) is a necessity in the operational environment (Furness & Tyler, 2001). Thus, the inability to provide this capability in an LVC training environment with SAFs can negatively affect the degree of immersion experienced by the trainees. For example, trainees may feel as though they are interacting with an irrelevant gaming environment rather than a high stakes-training scenario and may lose motivation (Gelenbe, Hussain, & Kaptan, 2005). A commonly used mitigation technique has been the use of instructors to role-play these communications. However, this too becomes problematic for two reasons. First, a single instructor may have to role-play several SAFs, making it easy for trainees to distinguish live entities from constructive entities, as voices do not vary. Next, the added requirement to role-play multiple SAFs increases instructor workload demands and may inhibit the ability to provide quality instruction, as their attention shifts from instructing to role-playing. Multiple communities have expressed concern regarding the reduced quality of instruction as the role of evaluator and role-player has begun to overshadow the role of instructor.

The above challenges contribute to SAF technologies' lack of simulation fidelity and of training quality. Previous research efforts have focused on developing more realistic SAFs that incorporate environmental and human performance data to adapt behavior in real-time (e.g., Abbott et al., 2010; Best, 2009; Jones, Strensrud, & Taylor, 2009). However, there is still a lack of theory-based architectures to support software development standards. The incorporation of human decision making theories into the SAF development architecture will provide a more comprehensive approach that accounts for environmental impacts (i.e., cues) to SAF behavior and not simply isolated SAF behaviors.

PROPOSED SOLUTION

This effort proposes to increase SAF realism by constructing a model that not only includes the use of behavior models, but also includes human behavior theories to essentially model SAF behavior from human behavior. While there are many models of human cognition that can be adapted to aid the creation of more realistically behaving SAFs (e.g., Anderson, Bothell, Byrne, Douglass, Lebiere, & Qin, 2004; Del Vecchio, Holsopple, Moskal, & Sudit, 2008; Klein, 1989), Endsley's (1995) model of Situation Awareness (SA) in dynamic decision making was deemed most appropriate. This model was selected because it provides a more comprehensive framework of the processes associated with human performance and decision making relative to other models (Endsley, Holder, Leidbrecht, Garland, Wampler, & Matthews, 2000) as it accounts for not only the perception of the environment (or cues) but also the basis behind such perception. Understanding the cues driving behavior can lend insight into decision making processes. Additionally, previous researchers have suggested implementing a perceptual front end utilizing

different techniques (i.e., cognitive mapping, learning and recognition, visual attention for virtual humans etc.) to interface between human behavior models and environmental cues in order to increase situation awareness (Herrero & de Antonio, 2010). This technique allows SAFs to actively search (or sense) the environment to gather the necessary cues to remain situationally aware and make decisions. Moreover, the Endsley model is the most clearly defined model, one of the most widely accepted models, and it pertains to many different domains (Salmon, Stanton, Walker, & Green, 2006). According to Endsley (1995), a human develops SA from cues in the environment that provide a sense of “what’s going on” around them. Based on the awareness and interpretation of these cues, a person must decide what to do, then carry out the most appropriate actions within the environment. The resulting actions change the state of the environment and resulting cues. These new cues provide feedback to the individual to update or confirm his/her mental model of what is going on around him/her.

The authors propose an HBS model to aid in SAF behavior development and assessment, not a new technology for generating SAFs. Figure 1 illustrates the HBS guidance model derived from the model of SA in dynamic decision making (Endsley, 1995). The adaptation involves leveraging the human elements of SA, Decision Making, and Individual Differences to identify key capabilities for consideration in the next generation of SAFs. This guidance model utilizes a number of component technologies to provide more realistic and dynamic SAF capabilities. The goal of this model is to reduce workload for authoring and controlling behaviors while increasing the fidelity and effectiveness of the overall training experience.

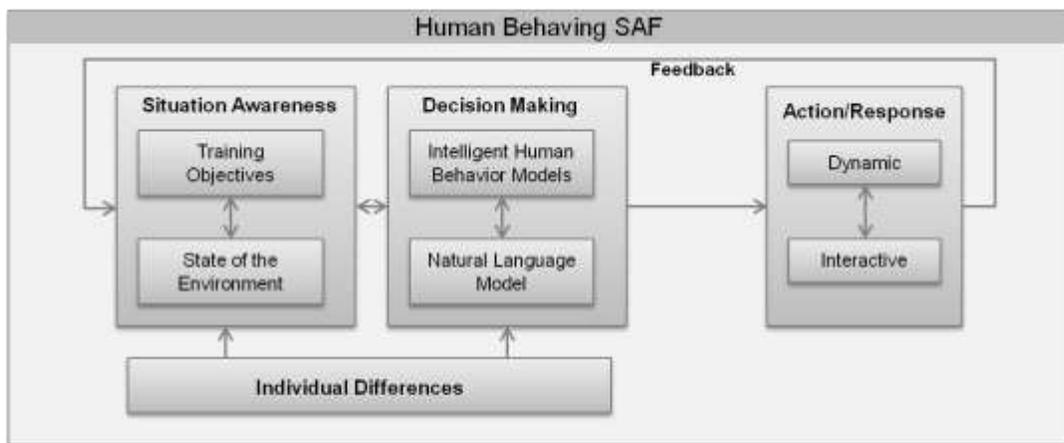


Figure 1. Human Behaving Semi-Automated Force (HBS) Guidance Model (adapted from Endsley, 1995)

Situation Awareness

SA¹ is a critical component of the HBS model as it enables constructive forces to display more realistic, adaptive, and variable behaviors (e.g., individual differences). This is because SA plays a large role in the cognitive aspect of decision making. The objective of considering SA is to provide the ability to make accurate inferences using multiple vague cues (e.g., imprecise, uncertain, partial) (Frias-Martinez, Magoulas, Chen, & Macredie, 2005; Tenenbaum, Griffiths, & Kemp, 2006). The inclusion of vague cues within the model is critical because currently SAFs use overt cues in order to perform. Live forces are able to make decisions and behave using small, but influential, vague cues. Thus, in order for SAFs to behave more like their live counterparts, they must model this perception and response capacity. Utilizing soft computing methods (e.g., genetic programming, neural networks, and Bayesian networks) alone or in combination may improve the SAFs capability to accept such imperfect environmental data. This can be illustrated through the example of a SAF accounting for minute (possibly vague) fluctuations executed by submarines during tactical missions such as small deviations in degrees of depth. Current SAF programs are not able to detect and react to such cues; however, the HBS model calls for SAFs capable of using multiple environmental cues to perceive, comprehend, and anticipate future events within the environment. Projections from the SA layer are then used as input to the Decision Making component to more accurately model complex cognitive processes (Schaffer, Whitley, & Eshelman, 1992).

¹ The Endsley (1995) model depicts SA as being comprised of three serial processes: perception, comprehension, and projection.

It is important to note that environmental inputs, which influence SA in the HBS guidance model, also include the trainees' actions. This provides SAFs with an awareness of trainee performance that current SAFs lack. In general, trainee awareness ensures that training objectives are met by providing the appropriate level of difficulty per the trainees' needs (Gelenbe et al., 2005). While this concept is similar to the concept of overall awareness of the environment described above, the focus is not necessarily on improving realism but rather ensuring trainees meet training objectives and receive the most from their training experience. Specifically, the HBS guidance model accounts for trainees having disparate levels of mastery within a training continuum by tailoring behaviors toward a trainee's needs. In order to prevent over-stimulating a novice, or under-stimulating more advanced trainees, algorithm research demonstrates the capability to tailor SAF behavior toward the trainees' needs (Herrero & de Antonio, 2010). Such a tailoring capability would have a profound impact on integrated training by providing the following benefits: 1) it ensures that training objectives are met expeditiously and improves mission readiness, and 2) it helps to reduce training costs by allowing the same simulated forces to be used for both novices and more advanced trainees. For example, the need in the F/A-18 community to tailor the SAF's heading, speed, altitude, and sensor capability to a trainee's skill level can be accomplished with the same simulated force for both novices and advanced trainees (F/A-18 Operator Team, personal communication, November 7, 2012).

Decision Making

SAFs today lack decision making capabilities limiting their range of behaviors and ability to realistically react. The HBS suggests including decision making models to allow the SAF to interpret incoming information using soft-computing technology. More specifically, based on projections from SA and the influence of individual differences (discussed below), future SAF technologies must consider enhancing decision making by including human capabilities such as speech (i.e., Natural Language model) and using Intelligent Human Behavior Models (IHBM) (e.g., cognitive architectures, machine-learning algorithms) to build a repository of human behaviors (Giordano, Reynolds, & Brogan, 2004). This increases the tactical realism of entities by providing more robust behavior variations and allows for the automatic adaptation of behavior in real-time based on SA inputs. These dynamic behaviors add an element of unpredictability to training scenarios that traditional SAF models do not (Cox & Fu, 2005). While IHBM help enhance the realism of traditional SAFs, they remain distinguishable from a human unless they respond to the environmental cues. Therefore, the HBS proposes incorporation of a SA layer (e.g., IHBM) to incorporate environmental and performance factors to adapt the way SAFs carry out behaviors.

The Decision Making component also suggests utilizing a Natural Language capability in order to provide the highest communication fidelity in a virtual environment possible (Guinn & Montoya, 2009). In order to fully support natural language (e.g., anticipating, receiving, interpreting, and executing), the Decision Making layer contains two components: 1) Dialogue System for information management, and 2) Speech Recognition System to support comprehension of communications (Allen et al., 2001). The Decision Making layer dictates what behaviors and speech the SAF program carries out. For this reason, integration between Natural Language and IHBM is necessary to ensure speech and behavior outputs are aligned. While the inclusion of a communication capability is preferred, implementation of IHBM alone can aid decision making well beyond the capabilities of current SAF models.

Individual Differences

In order to remove the machine-like perfection of SAF behaviors, the HBS guidance model also suggests incorporating performance-mediating factors into the SA layer in order to create individual differences between SAFs. Individual goals, objectives, experience, and training play a large role in instructor/operator performance (Stytz & Banks, 2003) making individual difference factors a critical piece of the HBS guidance model. Soft computing methods can integrate multiple levels of human performance data to elicit behaviors that are less than computationally perfect and, therefore, more realistic (Henninger et al., 2000). To do this, several different computational modeling techniques are used to develop intelligent machines such as neural networks and Bayesian networks. The intelligent machines are validated by comparing the behaviors to actual human SME behavior.

These differences then feed into both the situational awareness and decision making layers. Human cognition plays a role in both layers and refers to the attributes and abilities of the SAFs in the simulation. The SAFs must contain the capability to 'understand' the goals and objectives of the training scenario (e.g., underlying machine learning

algorithms) in order to behave accordingly. These goals and objectives, like their human counterparts' performance, support the ability of SAFs to anticipate actions thus further increasing realism.

With this, SAFs should be developed with the flexibility and range of behaviors based on individual differences. For instance, a SAF within a dynamic, complex training environment needs to have a wider range of capabilities than those SAFs in introductory courses. For example, within the P-8A community, introductory courses will focus on familiarization skills with the technology requiring minimal behavior variations from SAFs. Specifically, a novice trainee is required to accurately manage sonobuoys with loud emissions. More advanced courses will include other skills such as tracking or localization of quiet emissions (P-8A Instructor Team, personal communication, 2012). More examples of general capabilities include calculating distance, speed, time to complete routes, environment stressors etc. More specific influential features include training level, stress of battle, fatigue, time pressure and danger (Stytz & Banks, 2003).

Action/Response

Currently, SAFs execute actions and behaviors within the training environment, but do not necessarily interact within the environment. The SAFs lack the individual differences stated above that are needed to interact and execute appropriate behaviors. The HBS model provides a guideline to ensure SAFs are interacting with the environment to increase the training experience. Specifically, HBS includes an Action/Response portion, which consists of dynamically behaving and interacting within the environment. This can be accomplished by including both a SAF program (e.g., JSAF, NGTS) and possibly a Speech Synthesis System (i.e., Text to Speech System). The Speech Synthesis System attempts to replicate realistic communication that occurs in live training scenarios. To do this, it contains a text-to-speech capability that returns text-based commands as audible speech (Allen et al., 1996) to the environment and trainees. These applications possess a bi-directional relationship, as the SAF's actions and speech must be congruent to be realistic. As such, the SAF performs behaviors that are specified by the Decision Making component using machine learning algorithms and/or cognitive architectures while concurrently converting the text-based commands provided by the dialogue system to computer generated speech (Allen et al., 2001). SAF Action is then carried out in the simulated environment by the training communities' SAF program of choice. Once the SAF acts upon the environment, the environmental and trainee responses provide feedback, such as reactive behaviors, to allow the SAF to enhance/update its SA and adapt the performance within the environment (i.e., SA, Decision Making, SAF Action). While a Speech Synthesis System is the only way to truly achieve realistic SAF action that is indistinguishable from humans, communication is not the only behavior available to increase realism of existing SAFs. Other behaviors, such as anticipatory actions derived from IHBM and soft computing methods can accomplish a comparable fidelity. Further maturation of speech technology is needed to make this capability a requirement for the HBS model.

PROPOSED IMPLEMENTATION

The HBS model is to guide and standardize the development and assessment of SAFs in training environments, not to provide a prototype for generating SAFs. It is believed that current technologies (e.g., machine learning algorithms, cognitive architectures, soft computing methods, etc.), when integrated, may be sufficient to create realistic SAFs; however, there is a lack of guidance and standards to hold all SAF programs to an adequate level of fidelity that would allow SAFs to be used with little instructor/operator intervention or role-playing. At the time of this paper and to the knowledge of the authors, little research has been conducted on such standards. The model has not yet been implemented however; the proposal is well supported by experience and literature.

This guidance model can be used by existing SAF programs to identify gaps in current SAF implementation or during generation (e.g., missing an SA component). Moreover, the model can provide insight as to how multiple methods can be integrated to provide environmental cues to the SAF. Ensuring each component of the model is present within the SAF can help minimize issues of fidelity and realism as the model aims to incorporate realistic human behaviors into SAF design.

HBS GUIDANCE MODEL SUMMARY

The HBS model presented here is meant to provide design guidance utilizing Endsley's (1995) model of SA and human behavior. This model has been adapted to meet the needs of simulated forces while maintaining the core factors of human behavior and decision making that will provide a more adaptive and tactically plausible capability.

To summarize, the SA layer is used to search for persistent and dynamic environmental cues to ensure the Decision Making component is provided with the correct signals to appropriately choose behaviors from the IHBM behavior repository. Once the appropriate actions are selected from the IHBM behavior repository, the SAF program (e.g., JSAF) carries out the appropriate behaviors in the training environment. Behaviors and speech operate congruently using a bi-directional communication in which the dialogue system and IHBM task the SAF program with both the appropriate behaviors and speech. Lastly, the environment (i.e., LVC environment including trainee behavior) gives feedback to the HBS to provide further SA. By providing an integrated solution, the HBS model provides guidance to create dynamic SAF capability with increased realism.

LIMITATIONS OF THE HBS MODEL

Although the technologies suggested by the HBS model are largely available, there are several limitations inherent to each of its subcomponents that must be considered when designing an entity using the HBS model. These challenges can be divided into 3 categories: 1) the computational speed and processing power needed for real time performance, 2) initial cost, and 3) the realism and integration of component technology.

First, SAFs developed utilizing the HBS guidance model will require a significant amount of data processing at high processing speeds for immediate, accurate system responses. The rate of such responses is important as the SAF response time should not be distinguishable from a human's (Turing, 1950), acting neither faster nor slower than natural human response time. This poses a challenge because many of the soft computing (e.g., genetic algorithms), can be slow by nature because they work over iterations, or the lifecycle of the SAF. The final product, however, can often lead to more refined, accurate, and genetically diverse solutions than faster methods (e.g., neural networks) (Endsley, 2000). A reduction in processing time, however, is often achieved through increased processing power. According to Henninger et al. (2000), the computing time of a network-based model can take up to two-thirds more processing power than the conventional SAF. To counter this limitation, recent advances have made models capable of harnessing the power of Graphics Processing Unit (GPU) super-computing, which can dramatically reduce computing time (Banzhaf, Harding, Langdon, & Wilson, 2009). However, reducing time while increasing machine power leads to the second challenge of initial cost.

Increased research and development for the HBS model is required to identify the best method, or combination of methods, to collect the initial human behavior data, populate the architecture, and test the model. Once the initial research is completed, engineering costs will also increase as the engineers work to implement the model. However, once the development is complete, long-term costs will be reduced, as there is a limited need for additional SME scripting and role-playing.

Finally, the SAFs developed using the guidance model will yield behaviors that can only be as realistic as the underpinning component technologies. Each of the component technologies has specific challenges unique to its requirements. For example, while IHBM techniques can produce more realistic behaviors than traditional SAF programs, they are subject to data requirements and constraints of the employed architectures. Cognitive architectures, for example, rely on SMEs to describe the task and develop a model of behaviors (Garcia & Griffith, 2005). Learning algorithms may elicit unpredictable behaviors if the appropriate number of plausible tactical variations (up to 1500) are not modeled (Best, 2009). Further, imprecise, or flawed sub-component integration efforts can yield implausible and unrealistic behavioral variability (e.g., flying through mountains, tanks floating on water). Each of the SAFs developed using this model must have subcomponents that are flexible enough to allow ad hoc changes, yet rigid enough to be dependable in training environments. This modular approach poses a difficult challenge for specific subcomponent technologies such as the speech system, which must be speaker-independent and should not be constrained by a predefined vocabulary list.

CONCLUSION

LVC training environments provide a robust alternative to live and simulated training by increasing fidelity while decreasing the total ownership costs associated with live training. Total ownership costs include operational equipment, instructor/operator labor, and trainee instruction over time. However, to meet its full potential, there is a need for constructive forces that demonstrate human-like responses, such as behavior and communication ability, without added costs and requiring little instructor/operator intervention. As proposed, the HBS model seeks to guide the integration of advanced technologies capable of dynamic behaviors, increased awareness, and speech-based communication to increase training efficacy. While the component technologies embedded in the HBS model may not be fully mature (i.e., trainee awareness, speech), they make correct strides in the movement to create more realistic simulated forces. When the components suggested by the HBS model are integrated appropriately, they can greatly reduce manpower requirements, instructor/operator workload, and overall training costs. Scientific and technological exploration in these areas is ongoing, suggesting that these benefits will further improve as the technologies mature. The authors would also like to note that by utilizing the HBS guidance model the possibility still exists of creating entities that are “too smart” as previously explained. Future research should focus on creating SAFs that are tunable or scalable while maintaining high fidelity.

As stated in the model, the addition of a reliable, natural language capability would increase behavior realism by modeling communication that occurs in live training events and yield SAFs that act more human-like. Currently, this capability is difficult to achieve due to the timing required with using synthetic generated language. However, other unique developments in the field could also provide similar realism. Generating behaviors from real human performance (i.e., recordings of live flight or simulated training events) allows the entity to be dynamic to the surrounding environment (Abbott, 2010). This learn by demonstration concept involves software agents learning to behave like the human counterparts through specific applications.

Currently, the Office of Naval Research (ONR) Capable Manpower Future Naval Capability funds several efforts investigating the fidelity of SAFs. These technologies strive to reduce scenario authoring and runtime workload, reduce costs, and increase training effectiveness. A major component is the development of “dynamic SAFs” where behavior is dependent upon student abilities (i.e., experience level). Findings from this research can be used to further refine the HBS model by providing empirical research based examples of component technology integration. Additionally, this research and others (e.g., Unmanned Aerial Systems Interface, Selection, and Training Technologies (UASISTT)) can provide insights into emerging technologies to aid the issues previously discussed.

Other research has focused on providing instructors with a single point of control for multiple databases during training (e.g., Tactical Environment Role-Player Station [TERS]). This allows instructors to plan, monitor, and control the tactical environment, manage the network, perform sophisticated performance assessments through automated data capture, and support data link role playing from a single GUI. Furthermore, this effort includes research on a scenario advisor tool to aid instructors in tailoring a training event to the needs of the trainee by automatically providing recommendations regarding difficulty level. This research would aid the situational awareness layer of the HBS model, as this is where the environment, training objectives, and needs of the trainee exist.

Next steps in the development of more realistic SAFs include the actual implementation and test of SAFs utilizing the HBS model. Empirical validation of the guidance model is crucial to ensure a practical approach is feasible. Additionally, this validation will lend itself to further refinement of the model that includes specific guidance for combining multiple techniques and technologies to produce realistic entities.

Authors’ Note. The views expressed herein are those of the authors and do not necessarily reflect the official position of the organizations with which they are affiliated. Joseph Reni supported this paper while he was a NAWCTSD employee. He now currently works at Design Interactive, Inc.

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