Modeling Environmental Impacts on Cognitive Performance for Artificially Intelligent Entities

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ABSTRACT

The Marine Corps utilizes virtual simulations as a training tool for ground combat operations. Currently, the artificial intelligence of the entities within these simulations do not exhibit appropriate performance degradation due to environmental conditions such as heat and humidity. These gaps impact training fidelity and can adversely impact transfer of training. To address these gaps, this paper reviews existing approaches to modeling the influence of environmental factors, specifically heat and humidity, on human performance in vigilance and attention tasks. We also explore existing environmental modeling and path finding behaviors within relevant military simulations in order to refine the scope of the problem. We present a novel agent behavior model which incorporates a modified A* search pathfinding algorithm based on empirical evidence of human information processing under the specified environmental conditions. Next, an implementation of the agent behavior model is presented in a military relevant virtual game environment. We then outline a quantitative approach to testing the agent behavior model within the virtual environment. Results show that our human information processing-based agent behavior model demonstrates plausible agent performance degradation in hot, humid temperature environments when compared to paths around the danger area in mild temperature environments. We also present a technique for demonstrating to adjacent agents the environmental temperature condition currently felt by agents in the environment. Doing so will allow for trainees to recognize a potential source of negative performance from members of their unit, and allow for better training on how to operate in spite of these challenges. The results of this research provide an approach for implementing an agent behavior model that accounts for environmental impacts on cognitive performance. We recommend future work to validate the model in a human subjects experiment to facilitate improving the realism of simulation training.

ABOUT THE AUTHORS

Captain Pierce C. Guthrie is an active duty United States Marine with the primary military occupational specialty (MOS) of Infantry Officer. Following graduation from the Naval Postgraduate School's Modeling, Virtual Environments, and Simulation Institute in 2017 with a master of science, he received the additional MOS of Modeling and Simulation Officer. He is currently assigned to the Marine Corps Training and Education Command's Training and Education Capabilities Division.

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Perry McDowell attended nuclear power training after commissioning as a naval officer. He served in USS VIRGINIA (CGN-38) as M-division officer, R-division officer, and DCA from 1990-1993. He later served as operations officer in USS ELROD (FFG-55) from 1996-1997 and reactors control assistant and main propulsion assistant in USS ENTERPRISE (CVN-65) from 1997-2000.

In 1995, Perry earned a master of science degree in computer science at the Naval Postgraduate School, where he was awarded the Grace Murray Hopper Award as outstanding computer science student. Upon leaving the Navy in 2000, he returned to NPS and joined the faculty. Although he has served as a principle investigator for a wide variety of projects in the MOVES Institute, from 2003 – 2012 he worked primarily as the Executive Director for the Delta3D open source game engine. From 2012 to the present, he has taught courses in simulation for training and conducted research in the areas of training effectiveness and the creation of systems to improve warfighter performance.

Michael Guerrero is a game industry transplant who has spent the last 11 years lending his talents to the design and implementation of serious games. He has published and presented innovative character animation techniques at I/ITSEC and won the best paper award at AIIDE. In addition, he has contributed to publications in the PSI Handbook of Virtual Environments for Training and Education and a chapter in Design and Development of Training Games: Practical Guidelines from a Multi-Disciplinary Perspective (Cambridge University Press, 2013). Michael holds a B.S in Computer Science from the University of California, Santa Barbara and an M.S. in Interactive Technology from Southern Methodist University (SMU). He is currently employed as a software engineer and teacher for the MOVES (Modeling, Virtual Environment, and Simulations) Institute in Monterey, CA.

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INTRODUCTION

The use of first-person-shooter (FPS) virtual simulations for training has become commonplace within the U.S. Marine Corps and U.S. Army. Limitations in training system availability can limit simulation-based training events to a unit's key leadership, resulting in the need to represent these subordinate unit members with computer-generated forces (CGF) powered by artificial intelligence (AI). In order to enhance the user experience and breed "buy in" to this training technique, the CGF within the simulation must behave realistically. An observation made in an Office of Naval Research (ONR) presentation on an AI virtual simulation training suite highlighted this need for realism, declaring that "unacceptable role player AI within existing simulations and game environments prevent widespread adoption" of those simulations for training use (Stensrud & Hamel, 2015).

Many of the operating environments that the military currently operates in have high levels of heat and humidity, which can adversely impact the physical and cognitive performance of Marines and Soldiers who operate in such conditions. Partially addressing these realities, important advances in the physical CGF models within FPS simulations have been made in recent years that account for certain physical performance decrements. Specifically, the U.S. Army's Virtual Battle Space 3 (VBS 3) simulation has made significant strides in the realism of the physical models utilized for FPS simulations (Lopez, 2014). VBS 3 allows Soldier avatars to model the physique and physical performance of the actual Soldier by accounting for the Soldier's "height, weight, Army Physical Fitness Test scores and even their weapons qualifications scores" (Lopez, 2014, para. 2). These inputs create more realistic looking avatars, and generate decremented marksmanship performance and fatigue of the Soldier's avatar based on the avatar's physical actions in the simulation (Curthoys, 2014).

In spite of the advances in physical models, a gap exists in modeling the effects of the physical environment on the cognitive skills internal to the agents represented within the simulation. VBS 3's advanced portrayal of Soldier avatars, to include modeling the impacts of fatigue and physical fitness test performance, provides a step in the right direction. As a U.S. Army Training and Doctrine Command analyst points out about these improved features, "Small unit leaders" receive the "capability to understand the performance of their squad" (Lopez, 2014, para. 5). This provides a step in the right direction. We see a similar opportunity for improvement concerning the current gap in FPS training simulations where Marines do not receive an adequate representation of the decremented decision-making capabilities of their fellow Marines as a result of the hot, humid operational environment. This creates the possibility of introducing negative training. Essentially, Marines and Soldiers would greatly benefit from training where they could learn to recognize "when a given individual is showing appreciable changes in performance and cognition" (Lowe et al., 2007, p. S98).

To address this gap and promote a better training experience for Marines and Soldiers, we present a novel approach to modeling the impact of environmental heat and humidity on the pathfinding performance of an agent within an FPS simulation. We describe how environmental temperature could negatively affect the performance of a ground combatant's information processing capabilities, specifically with respect to two aspects of human information processing—attention and vigilance. A meta-analysis of heat studies and an information processing model from the literature form the basis of this interaction. We then utilize this relationship to quantify and illustrate an agent's decremented pathfinding performance in navigating around an improvised explosive device (IED) danger area in hot, humid temperature conditions when compared to paths around the danger area in mild temperature conditions.

MODEL FOUNDATIONS

We now include an outline of the human information processing model and heat meta-analysis from the literature that underpin our model. We also discuss the A* search approach to pathfinding that we modified within our model.

Human Information Processing

Wickens, Hollands, Banbury, and Parasuraman (2013) provide a simplified construct for modeling how humans process information from the environment and then translate this information into action called the Human Information Processing (HIP) Stage Model (Figure 1).

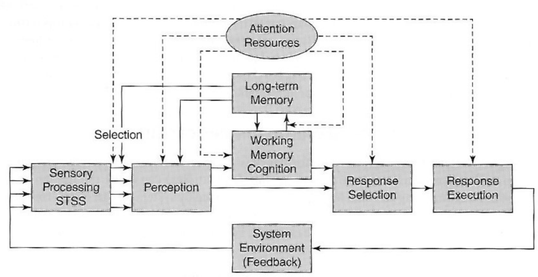

Figure 1. Human Information Processing Stage Model.
Source: Wickens et al. (2013).

The HIP Stage Model divides into multiple components that consist of: sensing the environment, synthesizing the information from those senses into perception of the environment, combining the information that one perceives with working and long-term memory to give sensory information meaning and incorporate continuously incoming information, synthesizing all of the relevant inputs up to that point, and finally making and executing a decision (Wickens et al., 2013). Attention and vigilance—the "ability to sustain…attention over extended periods of time" (Chun, Golomb, & Turk-Browne, p. 76)—play important roles within this model. Wickens et al. (2013) describe how sustained attention correlates strongly with vigilance, divided attention describes paying attention between multiple information sources, and focused attention describes honing in on key pieces of information and ignoring distraction.

We make use of Wickens et al.'s (2013) description of attention as an information "*filter*," and attention as a source of "*fuel*" for governing the HIP Stage Model (p. 5). The information filter role means that attention serves as a selection mechanism that allows individuals to key in on important information (believed to be more important by the human processor, i.e., having "higher perceived value"), while discarding other elements of information (p. 248). The information fuel role focuses on the draining of attentional resources, resulting in negative affect on the performance of multi-tasking (Wickens et al., 2013). In theory, the authors describe how drained attention could lead to mistakes made in later portions of the model for other "concurrent" tasks, such as making a decision (p. 5). Our model provides a representation of these observations of information processing.

Environmental Factors

A meta-analysis performed by Hancock, Ross and Szalma (2007) completing an extensive statistical analysis of fifty-seven studies derived from a large body of literature measuring the impacts of environmental heat and cold on human performance informed our model. One of the key takeaways from this work centers on its finding that "performance under thermal stressors proved on average to be approximately one third of a standard deviation or about 11% worse than performance at a comparative thermoneutral temperature" (Hancock, Ross, & Szalma, 2007, p. 857).

Hancock et al.'s (2007) meta-analysis argues for a 85ºF Effective Temperature (ET) (pointed out as equivalent to 87.4ºF WBGT) "threshold" as the point of demarcation for analysis due to the fact that the body begins to store heat without any resistance, and the body's core temperature begins to rise at this temperature (p. 860). The authors report how multiple variables aside from heat can contribute to performance decrements: "Mean performance change alone is insufficient to represent a full picture of what is going on as stress increases and, instead, that increasing variability in performance scores represents a crucial indicator" (p. 860). The authors believe that multiple confounding variables such as exposure time to the temperature, type of task, and "other environmental factors" serve as the basis for observation (p. 860). We attempt to replicate the importance of variability observed by Hancock et al. (2007).

In sum, Hancock et al. (2007) assert that their findings in the meta-analysis support the Maximal Adaptability Model put forth by Hancock and Warm (1989). Hancock and Vasmatzidis (2003) reference the work of Kahneman in stating that this model "assumes that heat exerts its detrimental effects on performance by competing for and eventually draining attentional resources" (as cited in Hancock & Vasmatzidis, 2003, p. 367). This idea appears quite similar to Wickens et al.'s (2013) discussion of attention as a fuel. Ultimately, we utilized effect size statistics from the meta-analysis pertaining to perception and the 85°F ET threshold in our model.

A* Search

To alter agent pathfinding illustrating worsened cognitive performance due to heat and humidity, we modified the A* search algorithm. We refer the reader to Russell and Norvig (2010), Stout (2000), and Tozour (2003) to gain a basic understanding of the algorithm and waypoint graphs. Similar to Russell and Norvig's (2010) naming conventions, we will use Equation 1 to refer to the different aspects of a path node's cost.

$$f = g + h \tag{1}$$

According to Stout (2000), the *g* cost to reach the node usually consists of total "distance traveled" to that node, but "other factors can be added into this function, such as penalties for passing through undesirable areas" (Stout, 2000, p. 259). Our work was inspired by Stout (2000) and Darken (2016) to achieve our desired agent behavior by manipulating this *g* cost.

We also utilized aspects of van der Sterren's (2002) "*tactical path-finding*" approach to the A* algorithm to manipulate the paths of our agent (p. 294). Specifically, we make use of van der Sterren's (2002) observation that the "distance to the threat and the threat's weapon might also have a large influence on the risk of being in the line-of-fire" in increasing the *g* cost of a node based upon its distance to the IED danger area within our model (p. 301). Our model implementation also draws from Abdellaoui, Taylor, and Parkinson (2009), Harder and Darken (2016), Straatman, van der Sterren, and Beij (2005), Wray, Laird, Nuxoll, and Jones (2002), and van der Sterren (2001) in allowing our model's agent to know the position of the IED danger area in advance of path execution.

RELATED WORK

A number of relevant military simulations and their implementations of environmental modeling help to better define previous approaches within the problem space that our modeling effort resides in.

Virtual Battlespace 3

A summary investigation into VBS 3's modeling and CGF AI capabilities show it is not possible to manipulate the temperature of the game environment, although, weather effects such as fog, rain, and snow can be implemented (Bohemia Interactive Simulations, 2015). Tactically speaking, the VBS 3 manual reports the AI of the agents within VBS 3 can be influenced as far as behavior in terms of combat posture that can account for tactical considerations such as cover locations, or alters behavior based upon enemy presence. Notably, the agent's pathfinding has the ability to account for enemy threats (Bohemia Interactive Simulations, 2015). One can also modify a unit's navigation capability, and adjust it to induce errors that impact the unit's arrival at the correct location of a waypoint (Bohemia Interactive Simulations, 2015).

Improved Performance Research Integration Tool

The U.S. Army's Improved Performance Research Integration Tool (IMPRINT), a discrete event simulation, provides a key usage capability for determining how well system operators can interact with a system even while performing under the influence of "environmental stressors" (United States Army Research Laboratory, n.d., para. 2). Our model implementation is inspired by some of the approaches used within IMPRINT.

Behavior Moderators, Cognitive Architectures, and Constructive Simulations

Pew and Mavor (1998) and Ritter and Avraamides (2000) provide a useful framework for thinking about how to model human behavior moderators, specifically within military simulation. Ritter and Avraamides (2000) provide valuable enumeration of the many behavior moderators that one could model, and how these moderators could impact agent performance. The authors even provide use cases with operational examples that helped provide ideas for how to model cognitive performance issues within our model's agent.

Cognitive architectures have found use in driving human behavior models within CGF. Wray et al. (2002) outline their plans and previous work for applications of Soar (Laird, Newell, & Rosenbloom, 1987) to the FPS game platform Unreal Tournament as a part of an ONR program. An example of some of this work came in a Soar integration with Unreal Tournament in a game called *Haunt 2* that links environmental temperature to fatigue, exertion, and body temperature level of the CGF (Laird et al., 2002). The authors describe how a decline in temperature has a direct influence in causing the CGF to become more fatigued.

Woodill, Barbier, and Fiamingo (2010) conduct an experimental effort using the Infantry Warrior Simulation (IWARS), a small unit constructive simulation (Borgman, 2007), that sought to analyze an appropriate squad size based upon conducting urban combat operations in a hot, dry environment of over 45º C (113ºF). IWARS serves as the experimental test bed, which allows the authors to model the environmental temperature, Soldier equipment, ambient air temperature, and the activity of the Soldier and the resultant effects on core body temperature (Woodill et al., 2010).

Ubink, Aldershoff, Lotens, and Woering (2008) describe work accomplished in the Netherlands called the Capability-based Human-performance Architecture for Operational Simulation (CHAOS) that serves as the underlying cognitive architecture for the Soldier Capability Optimization for Projected Efficacy (SCOPE) infantry analysis model. The authors describe an implementation of CHAOS where the interplay of the Dutch and Afghanistan weather climates with acclimatization, fitness level, and body armor influenced the tactical and behavioral actions of agents within SCOPE executing a peacekeeping operation in terms.

Blais (2016) describes the discrete-event military analysis simulation, Combined Arms Analysis Tool for the 21st Century (COMBATXXI), as needing to provide better human behavior models that mimic actual human behavior instead of the behavior of unmanned systems. Interestingly enough, COMBATXXI actually contains the software infrastructure to model human physiology, and this comprises an area of opportunity for creating better human behavior models that could include non-visual properties of human behavior (e.g. "fatigue, hunger, and thirst") (Blais, 2010, p. 10).

METHODOLOGY

Based on Hancock et al.'s (2007) work, we understand that certain temperature conditions in a given environment can deleteriously affect one's attention and vigilance to their surroundings. To model this relationship, we develop an agent behavior model that represents decremented perceptual capabilities due to thermal heat factors and its resultant effects on path finding decisions of an agent executing a common military patrolling task. The task scenario envisions a ground combatant encountering a bridge over a culvert which provides passage over a small, dry streambed—a potential IED danger area (United States Marine Corps, n.d.). The ground combatant agent must navigate around the danger area to the opposite side in order to continue the patrolling mission. We incorporate recommended minimum standoff distances for personnel in the course of a unit's standard reaction to an IED based on the general premise that if one senses an IED danger area in their path they will take measures to avoid the danger posed by that location by offsetting their direction of travel (United States Marine Corps, n.d.). We also take note of the fact that many types of IEDs require outdoor standoff distances greater than the recommended minimum standoff distance in our extra cost implementation according to van der Sterren's (2002) methods within the A* algorithm (National Ground Intelligence Center, n.d.).

Using empirical evidence provided by Hancock et al. (2007) relating to human performance perceptual decrements in hot environments, we make an assumption that the agent will choose a path closer to the recommended offset from an IED danger area as the agent patrols around it in mild temperatures. Conversely, a hot temperature environment will result in agent paths exhibiting less than the recommended offset distance due to decremented vigilance and attention to the danger area in the environment. We conduct experimental testing to determine if our model adhered to these assumptions.

All model development took place within the Unity game engine utilizing Microsoft Visual Studio 2015 as the underlying code development environment for scripting behaviors (Microsoft Corporation, 2016; Unity Technologies, 2016). The *Apex Path* pathfinding library served as the mechanism for implementing the waypoint grid and A* algorithm, as well as provided a model representing the agent (Apex Game Tools, 2016). The source for modeling the danger area consisted of models provided by the *Modular Prison Fortress* library (Aquarius Max, 2016). Experimental testing of the model took place on an Asus Notebook UX303UB running Microsoft Windows 10 Home Edition with an Intel Core i7-6500U two-core 2.50 GHz processor with 12.0 GB of Random Access Memory (RAM).

A* Algorithm Modifications

Our model's waypoint graph covers a 500 by 500-meter open terrain space in order to provide more realistic offset distances for the agent's navigational path in accordance with the recommended offset distance from an IED. This waypoint graph consists of a 100 x 100 grid with cell sizes of ten by ten meters.

As previously mentioned, to manipulate the A* algorithm according to our desired behavior we add more cost to each node within the waypoint graph via the g portion of the node's total f cost. We maintain the heuristic cost (h) based upon the "straight-line distance" between the current node and the goal node in order to preserve A* graph search optimality according to Russell and Norvig (2010), who state that such a straight line heuristic "is a consistent heuristic" (p. 95).

To determine the amount of cost to add to each node and how much the environment's conditions affect the agent for a specific path, we first randomly generate a circular danger area radius value, called the *randomNumberDASize* (corresponding to the IED's circular danger area radius). We then calculate the g cost of the currently searched node based upon the node's distance relationship from the IED danger area. In most cases, if the node's location falls within the IED's circular danger area radius the g cost would receive a minimum additional cost of 10,000 units, discouraging the A* algorithm from choosing a path that would pass through this area. However, if the node's location falls outside of the IED danger area radius, the g cost would increase based upon slightly different methods of calculation due to the environmental temperature condition.

Environmental Temperature Statistics Foundation

Our A* algorithm's modifications depend largely upon the choosing of the *randomNumberDASize* value. We desired an empirically-based behavior model founded upon Hancock et al.'s (2007) meta-analysis. In order to create this, we utilize a mean effect size statistic from the meta-analysis that comes from an outlier analysis focusing on perceptual tasks conducted in greater than 85°F ET. This mean effect size statistic describes worse performance for the "experimental" hot temperature condition relative to the "room-temperature control" mild temperature condition (Hancock et al., 2007, p. 854-855). We make a number of assumptions based on portions of Hancock et al.'s (2007) approach to convert this effect size statistic to means and standard deviations for hot and mild temperature condition normal distributions designed to represent performance accuracy. We chose to calculate the means and standard deviations as representative of performance accuracy due in part to Hancock et al.'s (2007) finding that "heat stressors deleteriously influence perception through a reduction in response accuracy and an increase in response time" (p. 868). The authors also note, from the outlier analysis, a "high degree of consistency in the effect of heat on perceptual performance accuracy" (p. 869-870). We also ensure that the hot temperature condition has a larger standard deviation, based in part on Hancock et al.'s (2007) earlier discussed observations on variability. The results of our statistical derivation produce the normal distributions for each temperature condition depicted in Figures 2 and 3 (we used $\bar{y}_H = 2.83$ for hot temperature condition mean performance accuracy and $\bar{y}_M = 3.00$ for mild temperature condition mean performance accuracy, while the standard deviation for the hot temperature condition, s_H, equaled 0.8 and the standard deviation for the mild temperature condition, s_M, equaled 0.6).

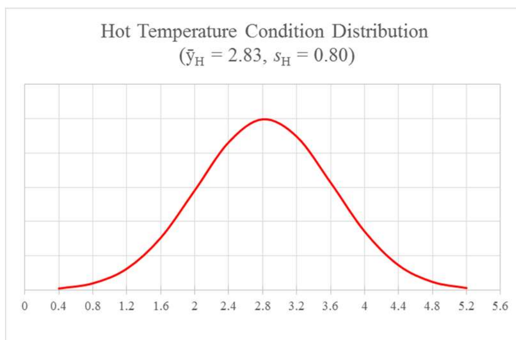

Figure 2. Hot Temperature Condition Distribution for Performance Accuracy. Adapted from Hancock et al. (2007).

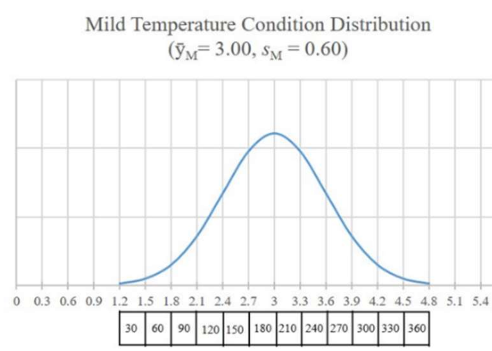

Figure 3. Mild Temperature Condition Distribution for Performance Accuracy. Adapted from Hancock et al. (2007).

Notice that we split the mild temperature condition's normal distribution into "brackets" by splitting the distribution up into half-standard deviation increments between plus or minus three standard deviations from the mean. The text box below the x-axis displays the possible values assigned to the *randomNumberDASize* variable. No interpolation of *randomNumberDASize* takes place between brackets. Any randomly sampled values that falls outside of the range are treated as if they had fallen within the range of the nearest two-and-a-half to three standard deviations from the mean bracket (Oferei, 2014). We determine the value assigned for each path by sampling from the respective temperature condition distribution currently present in the environment, and then compare this sample draw to its location on the mild temperature condition distribution. The bracket that this sample falls into determines the associated value assigned to *randomNumberDASize* for the path subsequently produced.

Smaller danger area values exist at the left end of the distribution, coinciding with degraded performance accuracy indicating poor attention and vigilance, and thus less offset achieved by the agent from the IED danger area. Larger danger area values on the right side of the distribution indicate better performance accuracy due to better attention and vigilance in the respective temperature environment, and consequently more offset of the agent's path from the IED danger area. This implementation provides a means for linking human statistical performance as seen in Hancock et al.'s (2007) meta-analysis to tactical path-finding decisions by the agent. It also derives inspiration from a NATO report observing a discrete event simulation technique where error modeling can be derived by sampling from the "extremes of the distribution of the task times or accuracies" (North Atlantic Treaty Organization (NATO), 2009, p. 8–10). We utilize the *MathNetForUnity* package to provide a Mersenne Twister (Matsumoto & Nishimura, 1998) random number generator, as well as the mechanism for conducting random number sampling from normal distributions (Bismur Studios Ltd., 2017a). The *MathNetForUnity* package utilized the Box-Muller Algorithm (Box & Muller, 1958) for sampling from the normal distributions (Bismur Studios Ltd., 2017b).

The statistically-generated circular danger area radius generates the most notable feature of the agent's path—the path's lateral offset from the IED danger area at the path's midpoint. The influence of the different *g* cost calculation method's due to the environmental temperature condition results in differences to both the A* algorithm's search space size and aesthetic differences in path appearance. In the examples shown in Figure 4 that illustrate 150 meter offset paths in both the hot and mild temperature condition, all nodes within a radius of 150 meters of the IED danger area received such a high *g* cost that the A* algorithm found other nodes to search that proved much cheaper. One can also see the subtle variations in path differences, and that the mild temperature condition exhibited a smaller search space for the agent's path.

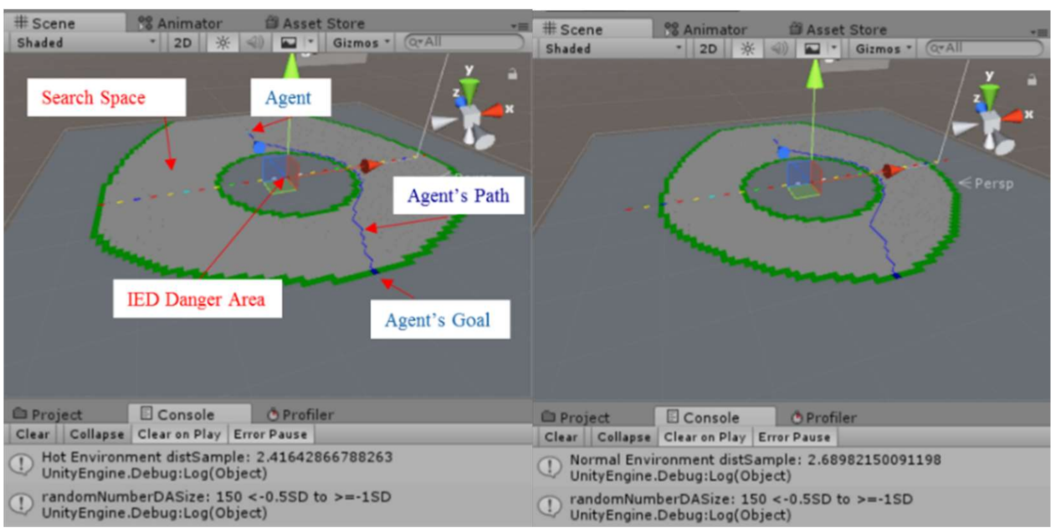

Figure 4. Left - Model under Hot Environmental Conditions: 150 Meter Agent Offset Path; Right - Model under Mild Environmental Conditions: 150 Meter Agent Offset Path

Depicting Performance Degradation to Adjacent Agents

To aid in comprehension of the environmental temperature conditions felt by the agents within the simulation to trainees, we place additional features to describe the environment in terms of environmental flag conditions above the agent. The Marine Corps utilizes a system of environmental flag conditions to describe the current WBGT of the environment; this system provides "guidance" for outdoor training in hot environments depending on the environmental flag condition (Commandant of the Marine Corps, 2003, p. 5). Inspired by the flag condition system, in our model a white flag condition sphere appears above the agent in a mild temperature environment, while a red flag condition sphere appears in a hot temperature environment (Commandant of the Marine Corps, 2003; Marines.mil, n.d.). Figure 5 depicts this flag condition feature.

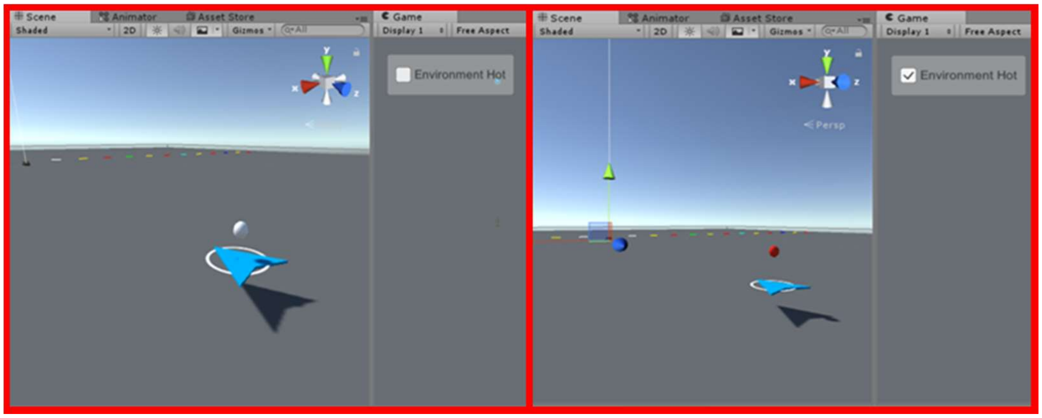

Figure 5. Flag Condition Status of Environment for Mild Temperature Environment (Left) and Hot Temperature Environment (Right)

RESULTS

We create a model version for executing mass trial runs for statistical testing. We use *JMP 12.0* to conduct our statistical analysis (SAS Institute Inc., 2015). To reduce variability while measuring the length of time needed to execute trial runs, we only allow the Unity model and Visual Studio project window to remain open. Further, the trials for each temperature condition take place during separate runs of the model. We also control for variability by using the "common random numbers (CRN)" technique described by Law (2015) (p. 588). Essentially, we use the same seed for the Mersenne Twister pseudo-random number generator to sample from each temperature condition's normal distribution. According to Law (2015), in doing so we hope to "induce…positive correlation" (p. 589) between each temperature condition's outputs, ultimately yielding less variance and a "much smaller confidence interval" of the mean of the differences between the two conditions (p. 563). Our results confirm these findings.

We conduct an experiment with 205 trials for each temperature condition. We utilize paired-*t* tests, unless otherwise noted, in accordance with Law's (2015) instructions on the proper use of CRN. Our α-level for all tests is 0.05. The run time for the 205 trial experiment for both the hot and mild temperature conditions took thirty-seven seconds each.

We first test if the mean difference between random number generator (RNG)-generated temperature condition normal distribution samples equals zero. Results for the experiment ($\bar{y}_M = 3.00$, $s_M = 0.66$ and $\bar{y}_H = 2.84$, $s_H = 0.88$) indicate that we can be ninety-five percent confident that the true mean difference between the RNG-generated temperature condition normal distribution samples is between 0.13 and 0.19. Therefore, we reject the null hypothesis. We also conduct a check to determine how accurately the RNG-generated distribution samples adhere to the specified means and standard deviations of the temperature condition normal distributions. We do so via a one sample *t*-test to assess if a difference exists between the mean of the respective temperature condition RNG-generated distribution sample and the specified mean of the same temperature condition's normal distribution. For this experiment, we fail to reject the null hypothesis for both the hot and mild temperature condition's ($t(204) = 0.20$, $p = 0.83$ for both temperature conditions), meaning we have an accurate enough distribution sample.

Our test to determine if the mean difference between each temperature condition sample's IED danger area radius sizes equals zero results in interesting findings. Results of our experiment indicate, with $\bar{y}_M$ for danger area radius = 195.21, s_M for danger area radius = 66.46 and $\bar{y}_H$ for danger area radius = 180.14, s_H for danger area radius = 84.14, that we can be ninety-five percent confidence that the true mean difference between each temperature condition sample's danger area radius sizes is between 12.02 and 18.12. Therefore, we reject the null hypothesis.

Finally, we test our model to determine if the mean difference between each temperature condition sample's path lengths equaled zero. Our findings, with $\bar{y}_M$ for path length = 806.73, s_M for path length = 107.33 and $\bar{y}_H$ for path length = 798.74, s_H for path length = 132.00, suggest that we can be ninety-five percent confident that the true mean difference between each temperature condition sample's path lengths is between 3.35 and 12.62 meters. We again reject the null hypothesis.

DISCUSSION

The results presented confirm that we can create agent performance exhibiting more decremented path finding around an IED danger area in hot temperature conditions relative to mild temperature conditions. Our findings show that the agent travels paths demonstrating greater offset around an IED danger area in mild temperature conditions compared to path offsets in hot temperature conditions. Furthermore, the agent paths travel a longer distance in mild temperature conditions than in hot temperature conditions. We also note that the confidence intervals found in our test results showcase the desired behavior of performance decrement in a hot temperature environment without producing unrealistically large values for the mean differences between the two temperature conditions. Another key contribution from our experiment demonstrates that we can show greater variability of performance in the hot temperature condition compared to the mild temperature condition in accordance with Hancock et al.'s (2007) observations. We also achieved a model that would simultaneously allow for our desired decremented behavior, while at the same time demonstrating plausible behavior of ground combatants that can make both good and bad decisions in mild and hot temperature conditions.

CONCLUSION

A primary limitation of the model stems from the source of the model's statistical data from the meta-analysis done by Hancock et al. (2007). Ideally, the data used for our model would come from studies of military personnel executing similar tasks as the one in our model, but the meta-analysis draws from studies across numerous domains. Hancock et al. (2007) also draws attention to the general limitation of the meta-analysis in that it does not account for all of the "moderator variables" likely to be present in the studies utilized (p. 856). Given limited resources for a human subjects experiment, the meta-analysis offered the best breakdown of the data according to perceptual types of tasks in a hot, humid environment. Thus, the meta-analysis proved sufficient for our model. Another limitation of our model stems from the fact that Hancock et al. (2007) conducted their task breakdowns according to the ET scale. Even though the authors required studies to contain enough information for WBGT calculation to become a part of the meta-analysis, Hancock and Vasmatzidis (2003) identify some issues of incompleteness of information in the ET conversion to WBGT that our model does not account for.

A human subjects experiment to provide a basis for validating our model comprises the most important area of future work. Doing so would provide a remedy for some of the aforementioned limitations offered by utilizing Hancock et al.'s meta-analysis as a data source. Another key area of future work would entail creating and implementing our model proof-of-concept in a constructive simulation such as COMBATXXI, aligning with recommendations by Blais (2016) to improve human behavior models within constructive simulation. Incorporating our work into multiple agents navigating as a team (see Darken, McCue, & Guerrero (2010)) provides another area of future work in order to provide a solution for more realistic training to Marines and soldiers operating as a part of larger units.

Ultimately, we have provided a model for virtual simulation entities based upon the environmental impacts of heat and humidity on human information processing. This model makes use of the A* path finding algorithm to demonstrate how heat and humidity can negatively impact the performance of an agent's vigilance and attention paid to their surrounding environment, resulting in decremented path finding performance of the agent as they attempt to navigate around an IED danger area location. We believe that including implementations similar to the one proposed in this paper within military training simulations can greatly improve the accuracy of simulation agent behavior. More importantly, we believe that such enhanced accuracy could improve the training of military personnel utilizing the simulation so that they gain a better understanding of the potential issues that they may encounter on the battlefield while operating as a member of a unit.

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