Assessing Performance of Kinesic Cue Analysis in Simulation-Based Training Environments

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ABSTRACT

Virtual training remains one of the core pillars of the military training community. The U.S. Armed Forces provide Warfighters with state-of-the-art Virtual Environments (VE) and Simulation-Based Training (SBT) to equip units with critical skills including marksmanship and crew coordination. Combat Profiling, described as the ability to rapidly discriminate between threatening and non-threatening situations, represents a skillset applicable to other task environments such as presence patrols that is ripe for widespread training distribution via simulated or virtual methods. In order to facilitate the transition from live Combat Profiling training methods to SBT, it is important to understand how and when to apply hardware elements from the continuum of VE tools. The VE continuum encompasses laptop/PC-based simulations, virtual reality, augmented and mixed reality; each possessing their own strengths and weaknesses for conducting operationally relevant training and mission rehearsal. This experiment focused on trainee performance and perceptions using a standard desktop display compared to a Virtual Reality (VR) system for detection and classification of kinesic cues (e.g., body language and movement) The software application Virtual Battlespace 2 was used to develop and present operationally relevant scenarios within each hardware configuration. Virtual agents displayed kinesic cues that indicated: lying, nervousness, and aggressiveness. Accuracy of cue detection and cue categorization served as the primary objective performance metrics. Subjective questionnaires focused on participants' qualitative assessments of system aspects such as realism, immersion, and technology acceptance. Upon initial review of the data, it may appear that PC-based systems are sufficient, but a careful review of the experimental results inform the training community of how best to apply traditional PC-based simulations and physically-based VR systems for developing kinesic identification skills.

ABOUT THE AUTHORS

Dr. Stephanie Lackey earned her Master's and Ph.D. degrees in Industrial Engineering and Management Systems with a specialization in Simulation, Modeling, and Analysis at the University of Central Florida (UCF). Her research focused on prediction, allocation, and optimization techniques for digital and analog communications systems. Dr. Lackey conducted high-risk research and development aimed at rapid transition of virtual communications capabilities to the Field and Fleet as a computer engineer with the United States Naval Air Warfare Center Training Systems Division (NAWC TSD). She joined UCF Institute for Simulation and Training's (IST) Applied Cognition and Training in Immersive Virtual Environments (ACTIVE) Lab in 2008, and assumed the role of Lab Director in 2010. Dr. Lackey leverages her experience in advanced predictive modeling to the field of human performance in order to develop methods for improving human performance in simulation-based training environments and human-robot interfaces. Dr. Lackey has a proven track record of delivering research and development products to the Warfighter training community through the skilled application of systems engineering principles, and her efforts have been recognized by the National Training and Simulation Association, the United States Navy, and internationally by the Joint Forces Simulation and Training community.

Ms. Crystal Maraj is a Graduate Research Assistant (GRA) at the Applied Cognition and Training in Immersive Virtual Environments (ACTIVE) Lab since summer 2010. She has attained her Bachelor's degree in Psychology and M.S. degree in Modeling and Simulation (M&S) from the University of Central Florida (UCF). Previous research and work experience focused on improving pilot training for the operation of automated aircrafts under the Federal Aviation Administration (FAA). Concurrently, she also worked and gained experience in the Mental Health field. Currently, Ms. Maraj is attaining her Ph.D. in the Human Systems track within UCF's M&S program. Her research interests center on Virtual Environments for training, specifically the design of technical attributes including improvement in trainee performance and training system utility.

Ms. Julie Salcedo joined the Applied Cognition and Training in Immersive Virtual Environments (ACTIVE) Lab as a Graduate Research Assistant in 2009. She holds a Bachelor's in Education, a Master's in Modeling and Simulation, and a Certificate in Instructional Design for Simulations all from the University of Central Florida (UCF). She is currently pursuing a Ph.D. in Modeling and Simulation from UCF. A former public school teacher, Ms. Salcedo leverages her education and instruction background to investigate learning and instructional design in simulation-based training systems.

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Mr. Irwin L. Hudson is the Science & Technology Manager responsible for leading STTC's Unmanned Ground Systems Research. This research focuses on Human–Robot Interaction, Physiologically-based Interaction, Unmanned Ground Vehicles, Remote Weapon Systems, Virtual Combat Profiling, and STEM Outreach. Mr. Hudson is Contract Officer Representative (COR) for The HRI Analysis for Training Simulations and Operational Neuroscience (HATS-ON) program. He also serves as the Assistant Contract Officer Representative (ACOR) to Dr. Neal Finkelstein for the Research Academic and Operational Support (RAOS) Indefinite Delivery, Indefinite Quantity (IDIQ) contract, which supports a large percentage of the research and development budget for STTC's Blended Systems Research Branch (BSRB). Mr. Hudson earned his Bachelor of Science degree in 1991 from Mississippi State University in Computer Engineering with minors in Math and Human Factors. He is currently pursuing his Ph.D. in Modeling and Simulation at the University of Central Florida.

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INTRODUCTION

Combat Profiling is a valuable skillset enabling a Warfighter to maintain a heightened sense of situational awareness. It is a culturally agnostic protocol involving human and environmental observations. This observational attention helps determine baseline behavioral cues, and detect potential danger, threats, or anomalies. Warfighters trained in Combat Profiling techniques demonstrate greater perceptual capabilities when assessing situations and taking proactive steps—rather than reactive—to opposing threats (Freeman, Walker, Puglisi, Geyer, Marceau, & Marc, 2011). Specific behavioral cues of interest are biometrics (autonomic physiological reactions), kinesics (non-verbal cues), and proxemics (spatial relationships). Combat Profiling training tools aim to develop Warfighter decision-making skills required to address the ever-changing demands of unconventional, irregular warfare. The typical Combat Profiling approach utilizes a multi-team effort aiding in observing and understanding the "complete picture" of what is happening in a specific location. Multiple teams situated in Observation Posts (OP) at varying distances (e.g., 100, 500, and 1000 meters from an area of interest), work together to operate and perform intelligence, reconnaissance, and surveillance operations and provide "over-watch" for teams working the street level. Over-watch supplies observational data from a wider perspective (i.e., Field of View, FOV) than is possible at the street level and from multiple angles. This provides a clearer understanding of the baseline behavioral cues and environmental anomalies across the "Ville" (i.e., city or town) as a whole. It is from these perspectives that a complete picture may be established. Traditional Combat Profiling training methods typically rely heavily on classroom-based curriculum and supplemental multimedia sources for instruction (Gideons, Padilla, & Lethin, 2008). However, in order to reduce implementation costs and increase accessibility, the research community is investigating alternative solutions such as virtual agents and VE applications (Schatz, Wray, Folson-Kovarik & Nicholson, 2012).

Although Combat Profiling techniques and training traditionally focus on OPs, the long distance observational and diagnostic skills can be adapted for close-range observational tasks such as presence patrols. A presence patrol's mission is to patrol an area regarded as relatively safe, and to meet with local residents to help establish bonds and trust. Thus, understanding baseline cues and identifying anomalies are critical to mission success and safety. Advancing the use of Combat Profiling training techniques to virtual patrol training presents an opportunity to leverage the benefits of this innovative approach and to further improve SBT in a high-risk domain.

Modeling and simulation technology implementations range from extremely low fidelity (e.g., sand table) to highly realistic recreations of complex operational systems (e.g., power plant control room). Between these distinct fidelity poles, a variety of simulation categories exist. VEs, "computer-generated environments used to simulate the real world," (Gupta, Anand, Brough, Schwartz, & Kavetsky, 2008) play a vital role in military training. The United States Marine Corps' Deployable Virtual Training Environment illustrates the portability of a laptop-based SBT system. Laptop/PC-based simulations offer portable, cost-effective platforms that support individual and team training. VR systems provide physically immersive experiences which incorporate varying degrees of sensory fidelity that include psychomotor skills by using a virtual representation of the weapon or system (Gupta, et al., 2008). VR systems provide an interactive virtual world and sensory feedback based upon physical position (Sherman & Craig, 2003). To enhance this experience, VR systems require greater space and provide less portability (Gupta, et al., 2008). Augmented Reality (AR) involves superimposing virtual imagery upon real-world objects or locations; usually through the use of a head-mounted display (Sherman & Craig, 2003). A Mixed Reality (MR) system produces a new environment by integrating real physical structures and virtual elements. In this sense, MR encompasses AR and Augmented Virtuality – a virtual environment augmented by real world data (Milgram, 1994).

To gain insight into the strengths and weaknesses of traditional and emerging SBT technologies, this effort applied existing training techniques from the Combat Profiling domain to the Fire Team Foot Patrol domain. A Fire Team Foot Patrol is comprised of four armed members assigned to conduct surveillance, reconnaissance, and/or target engagement tasks in a specific area of interest. The Fire Team employs various perceptual strategies to observe the environment, identify threats, and select appropriate courses of action. One strategy is human behavior analysis which involves the identification and interpretation of target behavior cues. This experiment will address one aspect of human behavior analysis called kinesic cue detection. Kinesic cues are non-verbal behaviors that indicate an individual's emotional state or pretense (e.g., nervousness, deception etc.). For this experiment, training focused on identifying specific kinesic cues that are indicators of three target states including lying, nervousness and aggressiveness. Lying indicates an individual is attempting to deceive, and examples of lying cues include rubbing the back of the neck and covering the mouth. Nervousness is also applied to a variety of kinesic cues, and the two cues included in this effort "check six" behavior (e.g., looking behind oneself) and wringing of the hands. Aggressiveness can indicate individuals who may be potentially hostile in a situation and the cues used for this experiment were slapping of the hands and clenched fists. A more detailed description of each kinesic cue can be found within Table 1. Skill acquisition and user perceptions were assessed using either a standard desktop configuration or a VR system. Performance data collected included kinesic cue detection and classification accuracy rates. Perception data was collected using subjective questionnaires that measured simulator sickness and presence. It was hypothesized that the VR system would yield higher accuracy rates, simulator sickness, and presence scores than the desktop simulator. Conclusions drawn from this research provide a launching point for leveraging Combat Profiling training techniques to other military, homeland security, and local law enforcement patrol applications.

METHOD

Participants

For this experiment, 90 undergraduate students from the University of Central Florida (UCF) were asked to participate using the UCF-SONA system, an online experiment management and participant recruitment website. Prior research suggests that performance data of non-military novices, namely undergraduate students, is comparable to military novice performance data in experimentation involving military task domains (Ortiz, Salcedo, Lackey, Fiorella, & Hudson, 2012). Participation was restricted to those who were 18 years and older (M=20.29, SD=4.14), U.S. citizens, and had normal or corrected to normal vision. After pilot data was removed, 80 students participated within the experiment. One participant from the desktop condition was excluded due to technical issues of the VBS2 software. No performance data was logged, and the participant was debriefed and dismissed. Finally, data from 43 males and 36 females were collected, and class credit was assigned after the conclusion of the experiment.

Experimental Design

The experiment assessed kinesic cue detection and classification performance between two SBT configurations. One configuration used a desktop computer with a 22-inch widescreen display. The second was an immersive trainer called the Virtual Immersive Portable Environment (VIPE). The dimensions of the VIPE included a seven foot high screen, angled at 120-degree (See Figure 1). Virtual Battlespace 2 (VBS2) Version 1.6 development software was selected for its capability to represent high-fidelity kinesic cues, and the ability to customize scenarios within a SBT platform.

Figure 1: VIPE display

Kinesic Cues

The use of kinesic cue training assists the Warfighter's ability to anticipate both voluntary and involuntary movement that can pose as a potential threat. For this effort, kinesic cues include body language, hand and arm gestures, as well as posture, and represented affective states such as lying, nervousness, and aggressiveness. The pre-training process allowed participants to learn the kinesic cues upon which they would be tested in the experimental scenarios. The target affective state had two cues per state. The following table reflects the affective state and kinesic cues (see Table 1).

Table 1. Kinesic cues by affective state

Kinesic Cues	Description	Target State Classification
Rubbing Neck	The palm or fingers of one hand strokes the nape and side of the neck.	Lying
Covering Mouth	The palm or fingers of one hand cover and rub the mouth and chin.	Lying
Wring Hands	Fingers and palm of one hand clasp the opposite hand and rub along the fingers.	Nervousness
Check Six	Abbreviated term for "check your six o'clock." The head turns to look over the shoulder or the body turns around 180º.	Nervousness
Slap Hands	The back of one hand strikes the palm of the other hand.	Aggressiveness
Clench Fists	Fingers are curled and squeezed into the palms.	Aggressiveness

Mission Environment

The mission environment presented scenarios to the user from the perspective of a Fire Team on patrol tasked with identifying kinesic cues and determining which of the target states was represented (i.e., lying, nervousness, or aggressiveness). The experimental scenarios created within VBS2 reflected three non-geo-specific environments including: a desert, suburban, and urban environment. General features included: houses, buildings, foliage, people, and vehicles. Figure 2 displays a scene within the urban mission environment.

Figure 2: Interface displayed on desktop and VR systems

Measures

Two types of performance were measured. Classification accuracy tracked the participants' ability to identify a virtual agent exhibiting a target kinesic cue and classify it correctly. It was calculated as a ratio of the number of kinesic cue targets that were both correctly detected and classified, according to the associated affective state, compared to the total number of kinesic cue targets. Detection accuracy focused solely on the identification of an agent exhibiting a target cue, and was calculated as a ratio of the number of correctly detected kinesic cue targets, regardless of classification, divided by the total number of kinesic cue targets. The resulting values for both calculations represent accuracy percentages.

The following measures were used to generate assessment of performance feedback within the experiment. The Demographic Questionnaire was used to gather biographical information (e.g., age, gender, computer experience etc.) about the participant. Using a seven point rating scale with values from one through seven, the Immersive Tendency Questionnaire (ITQ) considers individual differences when deeply immersed in an activity (Witmer & Singer, 1998). The Presence Questionnaire (PQ) comprised of 20 items related to the level of presence the participant felt within each configuration (Witmer & Singer, 1998). Reliability analyses using Cronbach's Alpha have resulted in r=0.81 for the ITQ and r=0.88 for the PQ (Witmer & Singer, 1998). The Simulator Sickness Questionnaire (SSQ) assesses a participant's health status before and after exposure to the simulated environment (Kennedy, Lane, Berbaum, & Lilienthal, 1993). The SSQ is comprised of a four point rating scale, with values from zero through three, to rate 16 symptoms related to disorientation, nausea, and occulomotor disruption as none, slight, moderate, or severe. SSQ reliability results presented in past VR research report a split-half correlation of r=0.80 and full measure correlation with Spearman's correction for attenuation of r=0.89 (Drexler, 2006). Performance data was also collected via automated computer logging.

Procedure

Permissions and approvals to conduct this human research experiment were obtained from the UCF Institutional Review Board. Upon arrival, the participants were greeted by the experimenters and randomly assigned to the desktop or VR system. At each designated lab area, the participant read the informed consent document, which disclosed the purpose, tasks and expectations, compensation (i.e., class credit), and minimal risks (i.e., simulator sickness) associated with the experiment. Next, the participant completed the Demographic Questionnaire, ITQ, and SSQ labeled as "Current Health Status Questionnaire." After completing the questionnaires, the participant completed the performance pre-test where he/she viewed several sets of photographs of individuals exhibiting the kinesic cues (see Table 1). For each set, the participant selected the photograph that exhibited lying, nervous, or aggressive behavior. Next, the participant viewed a training based upon existing practice that was comprised of a PowerPoint presentation that provided background information in behavior cue detection, instruction on identifying and classifying the kinesic cues, and photographs of individuals exhibiting each cue. After a five minute break, the participant completed a practice scenario within the simulation environment which was followed by three 15 minute experimental scenarios to assess detection and classification proficiency. Following each scenario, the participant completed the SSQ. After the final scenario, the participant completed the PQ and was then debriefed and dismissed. The duration of the experiment was approximately two hours per participant.

RESULTS

Five participants reported prior training in identifying body language or gestures. Three received training as part of pre-deployment exercises with the U.S. military, one received training in an acting course, and one received training in an unspecified college course. However, these instances of prior experience did not appear to affect pretest or performance results. There was no significant difference in pretest scores between groups as well as no significant difference in results on the ITQ indicating both groups are representative of the same population.

Independent samples t-tests were conducted to analyze performance results at three levels: overall, by affective state, and by each cue type. There was a significant difference in overall target classification accuracy between the desktop (M=55.75, SD=13.80) and the VR system (M=35.51, SD=14.69) conditions; $t(77)$=6.31, p<0.001, 95% CI [13.85, 26.62]. There was also a significant difference in the overall target detection accuracy between the desktop (M=61.54, SD=12.73) and the VR system (M=40.88, SD=14.25) conditions; $t(77)$=6.79, p<0.001, 95% CI [14.60, 26.72]. For each affective state, there was a significant difference in classification accuracy with the desktop yielding greater scores (see Table 2). In both conditions, classification accuracy was highest for the lying affective state. There was also a significant difference in detection accuracy for each affective state with greater scores in the desktop condition (see Table 3).

Table 2: Classification accuracy results by affective state

Affective State	Desktop		VR System		$t(77)$	p	95% Confidence Interval	
	M	*SD*	*M*	*SD*			Lower	Upper
Lying	62.82	17.53	37.22	24.72	5.30	<.001	15.97	35.22
Nervousness	51.42	21.81	33.89	19.07	3.81	<.001	8.36	26.71
Aggressiveness	52.99	12.99	35.42	12.69	6.08	<.001	11.82	23.33

Table 3: Detection accuracy results by affective state

Affective State	Desktop		VR System		$t(77)$	p	95% Confidence Interval	
	M	*SD*	*M*	*SD*			Lower	Upper
Lying	67.95	16.69	40.42	24.20	5.87	<.001	18.20	36.87
Nervousness	61.54	18.66	44.58	17.77	4.14	<.001	8.79	25.12
Aggressiveness	55.13	13.45	37.64	12.74	5.94	<.001	11.62	23.36

Comparisons of classification accuracy of each cue type revealed significant differences between conditions for all cue types except for the Check Six cue (see Table 4). Detection accuracy of each cue type also resulted in significant differences between conditions for all cue types with the exception of the Check Six cue (see Table 5). In both performance accuracy categories, the desktop group outperformed the VR system group for all cue types.

Table 4: Classification accuracy results by cue type

Cue Type	Affective State	Desktop		VR System		*t*(77)	*p*	95% Confidence Interval	
		M	*SD*	*M*	*SD*			Lower	Upper
Rubbing Neck	Lying	55.27	19.66	36.67	24.55	3.71	<.001	8.62	28.58
Covering Mouth	Lying	70.37	20.60	37.78	27.43	5.96	<.001	21.70	43.48
Check Six	Nervousness	57.26	31.99	44.72	27.73	1.86	.066	-.86	25.95
Wringing Hands	Nervousness	45.58	23.47	23.06	18.73	4.72	<.001	13.03	32.03
Slapping Hands	Aggressiveness	77.49	17.00	61.67	18.65	3.94	<.001	7.82	23.83
Clenched Fists	Aggressiveness	28.49	16.08	9.17	12.55	5.96	<.001	12.87	25.78

Table 5: Detection accuracy results by cue type

Cue Type	Affective State	Desktop		VR System		*t*(77)	*p*	95% Confidence Interval	
		M	*SD*	*M*	*SD*			Lower	Upper
Rubbing Neck	Lying	61.54	16.88	38.06	24.25	4.98	<.001	14.10	32.87
Covering Mouth	Lying	74.36	20.58	42.78	26.58	5.90	<.001	20.91	42.25
Check Six	Nervousness	69.23	26.79	60.83	22.92	1.50	.138	-2.76	19.56
Wringing Hands	Nervousness	53.85	19.34	28.33	19.32	5.87	<.001	16.85	34.17
Slapping Hands	Aggressiveness	79.20	16.36	63.89	18.27	3.92	<.001	7.54	23.09
Clenched Fists	Aggressiveness	31.05	17.32	11.39	13.19	5.69	<.001	12.78	26.55

Contrary to expectation, there was no significant difference in presence perceptions reported on the PQ. There was also no significant difference between conditions in the average SSQ scores across all scenarios. Likewise, there was no significant difference between conditions in the average SSQ subscale scores, including disorientation, nausea, and occulomotor, across all scenarios. Altogether, the data analysis results were not consistent with anticipated outcomes. The performance and perception results fared better in the desktop simulation condition as opposed to the VR system. Perhaps this divergence was influenced by experimental limitations.

LIMITATIONS

The desktop simulation had a limited FOV compared to the VR system. The VR system allows for a more realistic perspective as the angled screens engage users' peripheral view resources, while the desktop simulation skews the entire FOV to a forward facing perspective. The forward view in the desktop condition may prompt greater engagement and visual focus during kinesic cue detection training, thus, promoting better performance (Ortiz, Maraj, Salcedo, Lackey, & Hudson, 2013).

There was a previously unidentified inconsistency between the photos depicting the Check Six cue in the training slides and the behavioral agents exhibiting the same cue during experimental scenarios. Check Six is a cue for nervousness indicated by turning to look behind oneself. In the training slides, Check Six was described as an abbreviated term for the directional phrase "check your six o'clock" and indicated by turning around or looking over the shoulder to see behind oneself. The photos provided in the training slides depicted several human models with slight variations in the degree of head, neck, and shoulder rotations. The Check Six animation applied to the behavioral agents in the experimental scenarios was consistent with the cue description from the training slides, but involved a greater degree of rotation than the photos depicted. In addition to turning the head, neck, and shoulders, behavioral agents exhibiting the Check Six cue also turned the hips and feet. This discrepancy likely contributed to a higher number of false positive Check Six detections. Many participants selected non-target behavioral agents exhibiting conversational animations involving head nods and turns from side-to-side, but not looking behind. These non-targets were possibly associated with the photos from the training slides depicting less exaggerated head and neck turns. It is recommended that future research assess the images used for training, target stimuli, and non-target stimuli to verify such discrepancies do not emerge.

Another concern surrounds the display size for the PowerPoint training slides. In the VR system condition, the training slides were displayed on the seven-foot high VIPE screen as opposed to the 22-inch widescreen monitor of the desktop condition. It would appear participants in the VR system condition would have an advantage over participants in the desktop condition due to the larger screen size and, thus, larger depiction of cues displayed within the training slides. However, the results suggest that the display size for training slides did not impact participants' performance results as one would expect since the accuracy scores were higher in the desktop condition than the VR system condition.

Inconsistencies in the lighting between the two laboratory spaces, which separately housed the desktop simulation and VR system, may have affected performance results. In the desktop simulation laboratory, the overhead fluorescent lighting remained on for the duration of the experiment. For the VR system condition, the laboratory was dim, save for the display screen and residual light from several high windows. A lighted room for the desktop and a darkened room for the VR system were selected for consistency with real-world application of each platform. Typical desktop PC use occurs in lighted spaces, while too much light interferes with clear visual perception of simulations displayed on the VIPE. Future research may place both simulation platforms in identically dimmed rooms.

The experimental testbed utilized VBS2 Version 1.6 software originally designed with a 4:3 aspect ratio for simulation displays. When expanded to the widescreen views of the desktop and VR system displays, performance data that occurred outside the inherent display boundary was not detectable by the logging software. An additional software overlay was applied to override the existing display boundary, expanding the detectable region to include the full screen. The unreleased VBS2 Version 2.0 is projected to account for this limitation.

DISCUSSION

The VR system was anticipated to produce higher levels of average simulator sickness, more positive presence perceptions, and better performance than the desktop simulator. Simulator sickness and presence perceptions did not differ significantly between the simulation platforms. However, better performance was observed in the desktop condition. The performance results in conjunction with the FOV limitation suggest a deficiency in the use of VR systems for perceptual skills training. There is an opportunity presented by these findings to design better simulations that account for peripheral target detection skill development. The FOV offered by a VR system aligns with real-world perspectives much more closely than a desktop simulator. However, the results from this experiment suggest that performance degrades when visual resources are expanded from a forward focus to include a peripheral FOV. While there is insufficient data from this experiment alone, these results may be extended to suggest that perceptual skill performance on a desktop simulator may not be comparable to performance on VR systems or in the live environment. The peripheral FOV of a VR system affords a more authentic challenge for foot patrol perceptual skill practice (Ortiz, Maraj, Salcedo, Lackey, & Hudson, 2013). However, degradation in performance when utilized a VR system represents an opportunity to inform functional requirements and technological designs. The results serve as a baseline for further research exploring the relationship between perceptual skill performance and simulator FOV, and how the relationship may predict performance in the operational environment.

In addition to increasing the fidelity and efficacy of visual and display aspects in virtual simulations, perceptual skills training protocols would benefit from including instructional strategies guiding trainees to recognize and overcome visual limitations during a target detection task. Perceptual skills associated with the task assessed in this experiment include: attentional weighting, searching, scanning, and pattern recognition. Applicable instructional strategies for training these perceptual skills in military observation contexts include: Highlighting, Scaffolding, Controlling FOV, Massed Exposure, and Minimum Stimulus (Carroll, Milham, & Champney, 2009). Each strategy listed has the potential to provide a unique dimension to SBT for kinesic cue detection. Explicit Highlighting of critical targets in the training scenario with signals or other feedback may expedite development of attentional weighting. Scaffolding the acquisition of kinesic cue detection knowledge and procedures may assist trainees in mastering a smaller set of skills, leading to the recognition of patterns, and ultimately developing a common foundation upon which to layer more complex tasks. Controlling FOV through manipulations of the VE or simulation display system may allow for more dynamic practice of searching and scanning skills with the ability to broaden or narrow the FOV, provide multiple vantage points, and include physical or technological obstacles that may inhibit the FOV. The presentation of a high quantity of varied skill practice opportunities through Massed Exposure may reduce the overall training time required. Minimum Stimulus scenarios offer practice with more realistic target probabilities allowing for a more accurate level of challenge when all of the required perceptual skills are combined to detect cues. In order to identify specific instructional design recommendations for SBT of kinesic cue detection, further research is needed to assess the effects of each strategy on performance and identify the optimal strategy formats.

CONCLUSION

This paper assessed the performance of kinesic cue detection using a standard desktop display compared to a VR system. Participants were trained to accurately identify and classify kinesic cues and then practiced detecting cues in scenarios developed with VBS2. Based on the performance and perception results, it appears that the PC-based systems are sufficient for developing kinesic identification skills in SBT for Combat Profiling. However, the limitations aforementioned may have impacted participants' performance within the VR system. Regardless, the use of an immersive portable system has great potential as a tool for SBT and development of perceptual combat skills for close proximity situations. Additional research into this topic area should focus on the instructional systems design of immersive environments to include appropriate peripheral FOV during training scenarios, the inclusion of perceptual strategies to enhance instruction, and improved lighting conditions.

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