Effects of Visual Fidelity on Biometric Cue Detection in Virtual Combat Profiling Training

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Abstract. Combat Profiling involves observation of humans and the environment to identify behavioral anomalies signifying the presence of a potential threat. Desires to expand accessibility to Combat Profiling training motivate the training community to investigate Virtual Environments (VEs). VE design recommendations will benefit efforts to translate Combat Profiling training methods to virtual platforms. Visual aspects of virtual environments may significantly impact observational and perceptual training objectives. This experiment compared the effects of high and low fidelity virtual characters for biometric cue detection training on participant performance and perceptions. Results suggest that high fidelity virtual characters promote positive training perceptions and self-efficacy, but do not significantly impact overall performance.

Keywords: Biometric Cue Detection, Visual Fidelity, Virtual Training.

1 Introduction

Combat Profiling training provides Warfighters with a valuable observational and decision-making skill set for dominating within the ever-changing irregular warfare environment. The U.S. Marines' Combat Hunter program provides Combat Profiling instruction, which trains Warfighters to observe the human terrain and establish a baseline for behavior along six domains including: atmospherics, biometrics, geographics, heuristics, kinesics, and proxemics [1]. Behavioral anomalies are analyzed to determine if a potential threat requiring further action is present. Combat Profiling skills equip Warfighters to be preemptive, rather than reactive, in their detection and mitigation of threats [2]. The apparent value of Combat Profiling has increased desires to expand the accessibility of training. Current research and development efforts are making strides toward cost-effective Combat Profiling training solutions including virtual simulation.

Design factors related to visual aspects in the Virtual Environment (VE) (e.g., graphics, visual fidelity, textures, 3D modeling, etc.) may significantly impact visual

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design requirements related to observational and perceptual training objectives in the Combat Profiling domain. This research aimed to identify an acceptable level of visual fidelity to elicit positive trainee perceptions and increased performance with virtual Combat Profiling applications.

Visual fidelity refers to the visual similarity of a representation to the original and the ability of that representation to communicate the intended concept [3]. In graphics-based computer applications, such as interactive VEs, users may quickly compare a current image to one previously presented, but will rarely attend to direct comparison of visuals [3]. This implies that users distinguish a visual element and interpret its significance for the current state of the system (e.g., application, simulation, or scenario) based on its similarity to the target representation and intended meaning. This also suggests that user perception of visuals play a role in the discrimination and interpretation of these images.

Combat Profiling skills are predominantly observational and perceptual. For example, trainees receive instruction on how to identify potential threats by observing various cues that may indicate a target's intent or emotional state. Therefore, in a virtual Combat Profiling training setting, inability to portray the intended cue and meaning may result in negative training and poor performance. When depicting domain relevant human emotions in virtual characters, evoking accurate user perceptions of the intended emotion is a critical design implication. Users perceive emotions differently depending on the character features available to represent emotions [4]. Communicative cues used in human-to-human contact appear to translate into interactions between humans and virtual characters [5]. Therefore, users may better interpret intended emotions in characters designed with more human-like features and expression capabilities [4], [6]. Some facial features and behaviors that affect perceptions of emotion include: wrinkling, blushing, sweating, and tears [4-7].

Each domain of Combat Profiling likely varies in visual requirements for virtual training; therefore, research is needed to investigate the dynamics of each domain separately. This research initiative addresses the biometrics domain. The biometrics domain involves involuntary behaviors exhibited by the body during various emotional states. Examples include: sweating, flushing, blushing, pallor, visible veins, and heart rate [8]. The scope of this research focuses on two biometric cues addressed in current Combat Profiling training—facial sweat and facial flushing. In Combat Profiling training, trainees are taught the significance of these cues and how to distinguish them when attempting to identify potential threats among the human terrain.

Sweat is the moisture secreted by the sweat glands of the skin. There are two types of sweat: thermal and emotional [7]. Within Combat Profiling, the focus is on emotional sweating. Emotional sweating is caused by nervousness and anxiety or an intense emotional state, such as anger or rage [7-11]. Threatening individuals may exhibit signs of emotional sweat if they are nervous about being caught, have anxiety about completing their attack, or are experiencing anger, hatred, or rage toward an adversary [8], [11]. Emotional sweating is also evident in non-threatening individuals that may be in distress. Distressed individuals may exhibit signs of emotional sweat if they are nervous or anxious around other individuals who pose a potential danger [11]. Visible sweat caused by emotion often appears as a collection of droplets or as a sheen on the forehead, upper lip, nose, and/or cheeks [5], [7].

Flushing is the reddening of the face, neck, chest, and ears and may appear when individuals feel shyness, shame, anger, embarrassment, rage, anxiety, distress, or are performing deceptive acts [10-11]. For Combat Profiling, the focus is on flushing caused by anger, rage, deceptive behavior, anxiety, or distress [8]. Threatening individuals may exhibit signs of flushing if they are attempting to commit deceptive acts or experiencing anger or rage. Non-threatening individuals may exhibit signs of flushing if they are anxious or distressed in the presence of others who may pose a danger [11]. Flushing caused by anger, rage, deceptive behavior, anxiety, and distress often appears as redness on the forehead, nose, cheeks, ears, neck, and/or chest [10].

The purpose of this research was to investigate participant perceptions of biometric cues in a VE. Results will have implications on the design of visual elements for modeling biometric cues in virtual Combat Profiling training. Specifically, this experiment targets visual fidelity of virtual characters used to model sweating and flushing cues. Visual fidelity was varied by manipulating the polygon count of the virtual models, a method consistent with previous visual fidelity research [3]. A high polygon count was considered the high fidelity condition and a low polygon count distinguished the low fidelity condition. The flushing and sweat cues were modeled on the virtual characters faces using shaders and texture mapping tools in Autodesk's 3ds_Max software.

This experiment compared participants' perceptions of the realism and effectiveness of high versus low fidelity virtual characters for biometric cue detection training. Performance measures were collected to compare participants' abilities to identify the biometric cues in the high versus low fidelity virtual characters. It is hypothesized that there is a difference in participant's perception of high fidelity virtual characters than low fidelity characters. Additionally, there is a difference in performance in scenarios using high fidelity virtual characters than low fidelity characters. As experience and previous research indicate, the modeling of realistic facial flushing cues is easier to accomplish than modeling realistic sweat cues [6]. Therefore, it is also hypothesized that participants will have higher performance measures in scenarios containing only targets exhibiting the flushing cue versus scenarios with only sweat cues. Additionally, performance self-assessment and emotional intelligence measures were collected to determine if these individual differences were predictors of scenario performance.

2 Method

2.1 Participants

Sixty-six undergraduate students from the University of Central Florida were recruited for participation. Participants were U.S. Citizens and at least 18 years of age. Participants received class credit upon completion of the experiment. The sample population was selected as their skills and abilities reflect those of novice soldiers and can be used as a baseline for data collection [12].

2.2 Measures

Measurement instruments for this experiment included a series of subjective questionnaires, and performance logging during experimental scenarios. The demographics questionnaire included questions pertaining to general biographical information (i.e., age, gender), military experience, video-game experience, and computer competence. The Trait Emotional Intelligence Questionnaire-Short Form (TEIQue-SF) consisted of 30 self-report items measuring emotional intelligence across emotional intelligence subscales including: well-being, self-control, emotionality, and sociability [13]. The Performance Self-Assessment Questionnaire (PSAQ) is designed for the participant to judge their performance based on nine task-related questions. This measure was used as an indicator of self-efficacy in the analysis. The Training Perception Questionnaire (TPQ) gauged the participant's awareness, understanding, and perception of the virtual characters displayed, using a ten question multiple choice format.

2.3 Discrimination Task

The discrimination task involved identifying virtual characters that display the specified biometric cue (i.e., sweat or flushing) within the simulation platform. The platform utilized was the Mixed Initiative eXperimental (MIX) testbed [14]. The VE gave a first-person perspective of a patrol route in a desert village (Figure 1). The display of sweating, flushing or neutral cues on characters was randomized within three separate scenarios including: sweat only, flushing only, or a combination. The participant was tasked with identifying which characters displayed the sweat or flushing cue in either the high or low fidelity condition. Accuracy was determined as the number of biometric cues detected correctly out of the total cues present within the scenario.

Fig. 1. Participant view within the MIX testbed

For each scenario, there were two visual fidelity conditions: low and high. The virtual characters used in this experiment were procured from a third party vendor. The initial state of each model was considered the high fidelity version. These original models were imported into Autodesk's 3dsMax, a commercial-off-the-shelf

3D graphics software application, and modified to create the low fidelity versions using the optimization filter. The optimization filter is a feature used to modify the polygon count, or number of polygonal faces, of a model. Designers adjust the polygon count of characters in VEs in order to optimize processing speeds. However, this may be detrimental to visual fidelity as users may misidentify cues and features due to changes in the polygon count.

Fig. 2. High and low fidelity models of virtual flushing and sweat cues

For experimental purposes, the optimization settings for the original, high-polygon models (i.e., high fidelity) were set to ten and edited to five for the low-polygon versions (i.e., low fidelity). Figure 2 provides an example of one civilian model used to exhibit the sweat and flushing cues in the high and low fidelity conditions. Scenarios included models depicting male and female civilians, foreign military, and U.S. military. The number of polygonal faces varied depending on the details of each model including: skin texture, size of facial features, and the presence of adornments (e.g., hats, helmets, and scarves). Table 1 lists the range of polygonal faces of each character type.

Table 1. Virtual character polygon ranges

Character Type	Low Fidelity	High Fidelity
Female Civilian	2300-2500 polygons	3200-3800 polygons
Male Civilian	2100-3200 polygons	3400-4300 polygons
Foreign Military	5300-6000 polygons	7100-7400 polygons
U.S. Military	5400-8700 polygons	7900-11,000 polygons

2.4 Procedure

Upon arrival, the participant was asked to read the informed consent, which also served as a debriefing form at the end of the session. The participant was randomly assigned to a high or low fidelity condition. After reading the consent form, the instructions were to complete the demographics questionnaire and the TEIQue-SF. After questionnaire completion, the participant read a task training slide presentation.

Following the task training presentation, the participant completed three, randomized scenarios. For consistency, each participant was positioned 30 inches from the monitor, which was established as a comfortable viewing distance during pilot experimentation. Scenario duration was approximately 20 minutes each. After each scenario, the participant completed a PSAQ and TPQ. The participant was given a five minute break between the first and second scenario. At the end of the final scenario and questionnaires, the participant was debriefed and dismissed.

3 Results

An independent samples t-test was conducted to compare the TPQ ratings for high and low fidelity conditions (Table 2). There was a significant difference in TPQ scores for high fidelity and low fidelity conditions in the flushing scenario and combination scenarios with the high fidelity condition yielding higher ratings. Although the difference in TPQ scores was not significant for the sweat scenario (p=.056), the descriptive statistics were consistent with results from the flushing and combination scenarios. Overall, the results suggest that individual's perception in the high fidelity condition were consistent with viewing high polygon models. Individuals in the low fidelity condition rated realism less certain and accurate.

Table 2. Training Perception Quesstionnaire (TPQ) independent samples t-test results

	High Fidelity		Low Fidelity		t	*p*	95% Confidence Interval	
	M	*SD*	*M*	*SD*			Lower	Upper
Flushing	2.94	.39	2.67	.48	(55)=2.48	.016	.056	.482
Sweat	2.90	.41	2.69	.48	(58)=1.95	.056	-.002	.434
Combo	2.93	.38	2.67	.40	(61)=2.68	.010	.067	.454

There was no significant difference between high and low fidelity conditions in PSAQ ratings for all three scenarios. Additionally, the performance scores (i.e., accuracy) revealed no significant difference between the high and low fidelity conditions. The percentage of correctly identified cues when compared to the total number of targets presented showed no significant difference between high and low conditions for all scenarios.

A multiple linear regression analysis was conducted to test if the PSAQ scores significantly predict the percentage of correctly identified cues. The results of the regression indicated that the PSAQ of the flushing scenario explained 15% of the variance in the flushing scenario; R^2=.17, F (1, 63) =10.57, p=.002, and 18% of the variance in the sweat scenario; R^2=.21, F (1, 63) =15.95, p<.001. However, the PSAQ was not a significant predictor of performance in the combination scenario.

A Spearman's rho correlation was computed to assess the relationship strength and direction between TPQ and PSAQ ratings for the high and low fidelity conditions collectively. There was a positive correlation between the two variables for the flushing scenario; rs (66)=.390, p=.001, the sweat scenario; rs (66)=.513, p<.001), and the combination scenario; rs (66)=.417, p=.001). There was also a positive correlation between the two variables for the total ratings across all three scenarios; rs (66)=.522, *p*<.001. Overall, there was a moderate, positive correlation between TPQ ratings and PSAQ scores. Increases in ratings on the TPQ were correlated to increases in the scores on the PSAQ.

A multiple regression was used to test if personality traits predict the percentage of correctly identified cues by identifying the correct targets located in the flushing scenario. Results suggest that personality traits account for 12% of the variance; R^2=.20, F (6, 59) =2.52, *p*=.031. This indicates that personality traits may predict ability to correctly identify cues from the total number of correct flushing targets found. Notably, participants high in well-being significantly predicted the percentage of correctly identified and located cues within the flushing scenario; R^2=.16, F (1, 64) =12.21, *p*=.001.

An analysis of data also supported personality as a predictor of the participants' percentage of correctly identified cues to the total number of sweat targets. The regression results suggest that 17% of the variance is explained by personality; R^2=.25, F (6, 58) =3.25, *p*=.008. It was also found that personality is a predictor for correctly identifying sweat cues for the total number of sweat targets.

4 Discussion

Results of the TPQ indicate that participants had a more positive perception of training effectiveness and realism for the high fidelity virtual character condition over the low fidelity condition. It was also observed that a positive perception of the training tool correlated to higher self-assessments of performance, as indicated by the correlations between TPQ and PSAQ scores. Combining these observations suggests that higher visual fidelity in virtual biometric cue detection training may be associated with greater self-efficacy for the task. Previous research suggests that greater self-efficacy contributes to increased motivation, engagement, and training transfer [15-16]. Therefore, higher levels of visual fidelity for the biometric domain may contribute to increased motivation, engagement, and training transfer for virtual Combat Profiling training. Future research may investigate this further by comparing results from self-efficacy scales between high and low visual fidelity conditions.

Self-assessment ratings on the PSAQ were found to be significant predictors of performance for identifying flushing and sweat cues in a VE. This suggests that self-efficacy has a bearing on virtual biometric cue detection ability. Likewise, having TEI-Que scores high in psychological well-being was also a predictor of performance, which suggests that fostering a greater sense of well-being during virtual biometric cue detection training may result in a positive performance outcome. These findings are consistent with previous research indicating that self-efficacy and psychological well-being affect learners' behaviors and attitudes, which may contribute to higher or lower quality in learner performance [17]. Future research may directly assess the impact of virtual Combat Profiling training quality on Soldiers' self-efficacy and psychological well-being.

Although results suggest that there were no significant performance differences between high and low fidelity conditions, the emergence of self-efficacy as a potential motivation and engagement factor support the use of high fidelity models for the biometric domain of Combat Profiling. Achieving a higher level of detail is no longer cost-prohibitive with the current technological advancements such as higher computer processing speeds and faster refresh rates of current video cards.

5 Conclusion

In anticipation of demands by the U.S. military to increase access to virtual Combat Profiling training and improve virtual training quality, this research sought to identify the impact of visual realism on trainees' abilities to detect biometric cues in a VE. The findings suggest that in the biometrics domain of Combat Profiling, it is recommended but not essential to include high fidelity virtual characters for the depiction of cues. It is further recommended that design requirements incorporate the use of high fidelity characters to improve the quality and perceptions of virtual training.

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