Predicting Navigation Performance with Psychophysiological Responses to Threat in a Virtual Environment

Christopher G. Courtney[1,2], Michael E. Dawson[1], Albert A. Rizzo[2], Brian Arizmendi[3], and Thomas D. Parsons[4]

[1]Department of Psychology, University of Southern California, USA
[2] Institute for Creative Technologies, University of Southern California, USA
[3]Department of Psychology, University of Arizona, USA
[4] Department of Psychology, University of North Texas, USA
courtney@ict.usc.edu, {dawson,arizzo}@usc.edu, arizmendi@email.arizona.edu, thomas.parsons@unt.edu

Abstract. The present study examined the physiological responses collected during a route-learning and subsequent navigation task in a novel virtual environment. Additionally, participants were subjected to varying levels of environmental threat during the route-learning phase of the experiment to assess the impact of threat on consolidating route and survey knowledge of the directed path through the virtual environment. Physiological response measures were then utilized to develop multiple linear regression (MLR) and artificial neural network (ANN) models for prediction of performance on the navigation task. Comparisons of predictive abilities between the developed models were performed to determine optimal model parameters. The ANN models were determined to better predict navigation performance based on psychophysiological responses gleaned during the initial tour through the city. The selected models were able to predict navigation performance with better than 80% accuracy. Applications of the models toward improved human-computer interaction and psychophysiologically-based adaptive systems are discussed.

Keywords: Psychophysiology, Threat, Simulation, Navigation, Route-Learning.

1 Introduction

The incorporation of simulation technology into neuroergonomic and psychophysiological research is advancing at a steady rate (see [1], [2]). The range and depth of these simulations cover a large domain, from simple low fidelity environments to complex fully immersive simulators, which are factors that may affect psychophysiological response within the environment [3]. All of these simulators rely on some type of representation of the real world [4]. The current study utilized a high fidelity, highly immersive virtual environment, as increased applicability to real-world performance was the goal. Specifically, the virtual

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environment (VE) utilized herein was that of a virtual Iraqi city [5], which included a route-learning and navigation simulation to assess landmark and route knowledge of the newly experienced VE [6]. Psychophysiological responses were monitored throughout the experiment and were used to predict navigation performance following threat exposure during the route-learning phase.

1.1 Navigation in Virtual Environments

Numerous studies have conveyed the benefits of ecologically valid simulated navigation tasks as predictors of real-world functioning [4], [7], [8]. Navigation abilities are customarily broken down into three knowledge based components, each adding to the cognitive map developed by the participant. The first is landmark knowledge, which involves learning to recognize landmarks or salient features of the environment upon initial exploration of said environment [9]. In the current study, zone markers indicating the entrance into a new zone were the key landmarks involved. The second component is referred to as procedural or route knowledge and involves information gleaned from first-hand experience with a route which provides the ability to create distance and orientation relationships connecting landmarks [9], [10]. Real-world and virtual reality (VR) experiments suggest that active navigation, which was utilized in the current research, is more effective for route-learning than passively being exposed to the environment [11]. The third component of navigation ability is referred to as survey knowledge, which can be described as having developed a “bird’s eye view” of the environment. Survey knowledge affords the development of a cognitive map that provides associations between locations with increased levels of exposure to the environment [9], [12]. Survey knowledge is valuable as a means of finding shortcuts through the environment, but is not necessarily useful in the present study, as participants were instructed to follow a specific route without deviating. Thus, this study is primarily concerned with landmark and route knowledge.

The current research design afforded the opportunity to investigate the effects of exposure to threat on route-learning. To our knowledge, no study has examined the effects of varying levels of threat on route-learning, making this a novel approach. We hypothesized that threatening stimuli in the environment would serve as distractors and would hinder route-learning in highly threatening areas of the VE. Past research involving distractors presented during route-learning typically involve cognitive workload tasks and tend to interfere with route-learning. Walker and Lindsay [13] reported decreased efficiency in wayfinding performance in a virtual city when a secondary speech discrimination task was introduced. They postulate that this was due to the switch of attentional resources to the completion of the secondary task. A similar result was found in a between-subjects study involving examination of the effects three separate types of cognitively distracting tasks presented during the route-learning phase compared to a no task condition. All groups that experienced distracting tasks performed less efficiently on a wayfinding task than the group that was not presented with any distracting task [14]. Knowledge of psychophysiological states gleaned during the route-learning phase may serve as an indicator of wayfinding abilities. For example, participants with lower psychophysiological response levels during the route-learning phase may prove more efficient during the navigation phase.

1.2 Toward Adaptive Simulations

The current research was concerned with informing psychophysiological computing strategies for creation of VEs capable of adapting to the participant's affective and cognitive state to foster optimal performance. Psychophysiological computing represents an innovative mode of human-computer interaction (HCI) wherein system interaction is achieved by monitoring, analyzing and responding to covert psychophysiological activity from the user in real-time [15], [16]. Psychophysiological computing represents a means of creating for the computer system a more empathic link to the user.

The strategy employed herein for creation of a psychophysiological computing system initially required assessment of psychophysiological response patterns associated with varying affective states. The current research manipulated environmental threat to create response variability in order to perform such assessments. Data analytic approaches designed for prediction were then compared and tested for effective development of a psychophysiological computing system capable of predicting performance outcomes. Namely, the efficacy of multiple linear regression (MLR) and artificial neural network (ANN) models were compared for prediction of navigation performance based on psychophysiological responses to threat and cognitive workload during the route-learning phase of the experiment.

In summary, participants were exposed to varying levels of threat while concurrently completing a route-learning task, and the responses collected were submitted to MLR and ANN models to predict performance on the subsequent test of route-learning efficacy during a navigation task.

2 Methods

2.1 Participants

A total of 53 participants (67.9% female; mean age = 19.79; age range = 18 to 22) took part in the experiment. Participants were recruited through the psychology subject pool at the University of Southern California. Inclusion criteria included normal or corrected to normal vision, and English fluency. Participants were between the ages of 18 and 35.

2.2 Stimuli

A virtual environment depicting an Iraqi city was presented to participants with use of an eMagin Z800 head mounted display complete with head tracking capabilities to allow the participant to explore the environment freely. The virtual environment was created using graphic assets from the virtual reality cognitive performance test

(VRCPAT) [6], [17], using the Gamebryo graphics engine to create the environment. A tactile transducer floor was utilized to enhance the ecological validity of the VE by making explosions and other high threat stimuli feel more lifelike. Auditory stimuli were presented with a Logitech surround sound system. Psychophysiological measures related to electrodermal and electroencephalographic activity were collected using a Biopac MP150 system. Participants experienced the VE while residing in an acoustic dampening chamber, which had the added benefit of creating a dark environment to remove any peripheral visual stimuli that were not associated with the VE, resulting in increased immersive qualities of the simulation.

2.3 Procedural Design

Following a baseline procedure, participants were exposed to the route-learning task. The task consisted of following a guide through six zones that alternated between high and low levels of threat. All environmental stimuli were pre-scripted, allowing each participant to experience exactly the same environmental stimuli at the same time to enhance experimental control of stimulus presentation. The high and low zone presentation order was counterbalanced across subjects as to which type of zone was experienced first. During the high threat zones, participants experienced an ambush situation in which bombs, gunfire, screams and other visual and auditory forms of threat were present, whereas none of these stimuli were presented in the low threat zone. Each zone was preceded by a zone marker, which served as landmarks to assist in remembering the route.

The route-learning task was followed immediately by the navigation task in which the participants were asked to return to the starting point of their tour through the city. Participants were to pass through each zone in reverse order until reaching the original starting point. If the participant strayed too far from the path, which was quantified as the distance it would take to walk for 10 seconds in a perpendicular direction from the original path, an arrow appeared in the corner of the screen that assisted the participant in finding his or her way back to the original path. During the navigation task, there were no longer any threatening stimuli presented in the high threat zones. The navigation task ended when the participant crossed the zone 1 marker.

2.4 Analytic Approach

Data were scored using an in-house custom designed Matlab scoring program. The program includes graphical representations of each channel of psychophysiological data for manual inspection of scoring accuracy.

Electrodermal Data Scoring. The scoring program was used to partition response levels into each zone, and then calculate the median skin conductance level (SCL) and the number of spontaneous fluctuations (SFs) in each. The median SCL was chosen for analyses rather than the mean because it is a more robust feature as it is less susceptible to influences of artifacts, which will be especially useful in future adaptive applications. SFs, which were also scored during trimmed zones, were quantified as any change in slope of the response curve resulting in a > 0.01 µS response, with a peak latency of 1 to 3 seconds following onset.

Electrocardiographic Data Scoring. ECG data were scored as inter-beat intervals (IBIs), which were calculated as median values for each zone. Accuracy of the peak detection scoring program was assessed manually, with visual inspection of all selected R-waves. Missed R-waves were manually added to the calculation of zone medians. Power spectral density analyses of heart rate variability (HRV) were also performed with use of a fast Fourier Transform based algorithm. The algorithm was used to calculate the spectral power of the low frequency (LF) component and the high frequency (HF) component of HRV associated with each zone. The frequency range of the LF component is between 0.04 and 0.15 Hz, while the HF component is between 0.15 and 0.4 Hz [18].

Respiratory Data Scoring. Respiration was scored in a similar fashion to the ECG data, and reported as interbreath intervals. Peak detection of each positive deflecting curve in the breathing cycle was manually reviewed in order to ensure accuracy of the scoring program, and median intervals were calculated for each zone.

MLR and ANN Approach. The experimental conditions described herein are designed to provoke responses typical of high and low extremes of experienced threat. The ultimate purpose of the proposed ANNs is to develop a strategy for creating adaptive systems for future research and eventual real-world applications including enhanced training scenarios and adaptive assistance for any individual who must fulfill tasks that involve high levels of threat, stress, or cognitive effort. A backpropagated algorithm was utilized to train the ANN models mainly because it can be thought of as a specialized case of the general linear model that is capable of more effectively fitting curvilinear data distributions than is possible with a linear regression model. Additionally, because the ANN model can be thought of as a special type of regression, and provides similar output, results can be compared directly to predictive results generated with the use of more standard and widely used MLR. This sets the backpropagated algorithm apart from numerous machine learning algorithms, such as support vector machines, which can lead to difficulties when trying to compare causes for predictive differences with other algorithms.

First, a MLR model that used the psychophysiological data gathered during the initial tour through the city to predict the navigation performance was developed. The navigation performance was quantified as the time needed to return to the starting point. A set of six psychophysiological predictors were utilized. Included in the analyses were SCLs, SFs, IBIs, interbreath intervals, and the LF and HF components of the HRV measure. Due to the relatively small sample size in this experiment, an attempt to condense the number of predictors was made by calculating difference scores between the high and low threat zones for each of the psychophysiological predictors. Difference scores were calculated in two ways. First, the overall difference between all three high and low threat zones was calculated as a representation of the response levels associated with the task as a whole. Next, a difference score that would serve as an index of the habituation involved in the responses to the high threat zones compared to the low threat zones was calculated. To accomplish this, difference scores between the high and low threat zones in the first pair of zones experienced in the route-learning phase (zone pair A) and the third pair (zone pair C) were calculated. The zone pair C difference score was then subtracted from the zone pair A difference score. This threat habituation index was calculated to account for the waning response levels during high threat zones present in a number of response measures. Analyses not reported here determined that the habituation-sensitive predictors were preferable. A backward-elimination stepwise regression was utilized for the MLR model.

The ANN model was developed in a manner analogous to the above MLR model, such that the predictor variables, or inputs, were the same in each model. The output node will again represent the continuous navigation performance outcome measure of the time needed to return to the starting point. The primary goal of the BPN used herein is prediction. In order to increase the probability of generalization and to avoid over-fitting of the observed sample, three data sets were considered, including the training set, validation set, and the test set (see [18] for review of these data sets). The test set contains a set of examples that had not been previously considered during the training or validations phases, which is used to calculate the global predictive ability of the network for generalizations to future practical applications. After the development and implementation of the ANN, comparisons were made (following [18]) between its output and that of the general linear model's regression for the predicted outcome measure.

3 Results

3.1 Regression Results

The MLR model was able to explain a significant proportion of the variance in navigation performance, $R^2 = 0.27$, $F(7, 45) = 2.32$, $p < 0.05$. Significant predictors included SFs, $\beta = -0.34$, $t = 2.66$, $p < 0.05$, and interbreath intervals, $\beta = 0.28$, $t = 2.13$, $p < 0.05$. The negative correlation coefficient related to the SF measure indicates that participants who had a greater difference between the high and low threat zones during zone pair A than zone pair C, due to habituation in high threat zones, took less time navigating back. Though interbreath intervals correlation coefficient was positive, the results are analogous to those of the SFs. Increased activation leads to more SFs and shorter interbreath intervals, so the response patterns are reversed. Thus, greater reduction in differential activation between high and low threat zones during zone pair C resulted in more efficient navigation performance.

Table 1. MLR model summary statistics

RMSE = root mean squared error.

R	R^2	Adj. R^2	Std. Error	RMSE	*F*	*P*
0.52	0.27	0.17	48538.0	220.3	2.32	*<0.05*

3.2 ANN Results

The backpropagated ANN that was developed included the same six predictor variables used in the preferred MLR model, here entered as inputs to the system. In the preliminary tests to assure that the ANN achieved its optimal output, the network model was developed with different numbers of nodes in the single hidden layer. The hidden layer learns to provide a representation for the inputs through an alteration of the weights associated with each node and then connects to the output layer. The experimental method involved developing a hidden layer that contained a minimum of four nodes and a maximum of twenty-four nodes. It was found that six hidden layer nodes resulted in optimal model performance. A tanh activation function was applied to the hidden and output nodes, which is recommended when the sum of squares error function is employed, as it was in this case. Descriptive statistics associated with the training, validation, and test set samples are included in Table 3.

Following network training, the test set was applied to the network to test the generalizability of the model. It should be noted that the predictor values of the test set were not involved in the training of the model, providing a "test" of the generalizability of the model to new data. A gradient descent learning algorithm was applied along with a sum of squares error function. Hyperbolic tangent activation functions were applied to the hidden and output nodes. The ANN was able to predict the outcome measure with 76.0% accuracy (training performance = 0.938; test set performance = 0.871).

A global sensitivity analysis was performed in order to determine the relative importance of each input (i.e., predictor variable) to the successful prediction of the output. A sensitivity analysis tests how the error rates would increase or decrease if each individual input value were changed (see [20] for review). More specifically, the data set is repeatedly submitted to the network, and in turn each input variable is replaced with its mean value calculated from the training sample, and the resulting network error is recorded. Important inputs cause for a large increase in error, while the error increase was small for unimportant inputs. Thus, sensitivity analysis allows for a rank order of the importance of the individual inputs [21, 22]. Ratio values less than 1 indicate that the network actual performs better without inclusion of the associated input. All inputs had ratio values of greater than 1, indicating that all contributed to the performance of the model. The highest ranked inputs were SCLs, IBIs, SFs, and interbreath intervals, each having a ratio value greater than 4.

3.3 ANN and MLR Comparisons

Examination of the squared correlation coefficient associated with each model reveals that there is a 49.0% increase in prediction of navigation performance when the ANN is employed. The drop in root mean squared error related to use of the ANN (RMSE = 205.39) in comparison the MLR model (RMSE = 220.30) signifies that the neural network model better fits the data. Direct comparison of correlation coefficients associated with each model with use of the Fisher z transformation revealed that the ANN had significantly greater predictive ability than the MLR model, $z = 3.84$, $p < 0.001$. Thus, the ANN was determined to be the preferable model due to the increase in the squared correlation coefficient in addition to the decrease in RMSE.

4 Discussion

The current research offers a number of beneficial design advances for potential use in future training simulation technologies and adaptive systems in general. A VE was developed that was capable of providing a route-learning scenario and the ability to test route-knowledge with use of a navigation task. Manipulations embedded within the VE also afford the opportunity to test the effects of varying levels of threat in the environment. Models were designed to predict navigation performance based on psychophysiological response measures collected during the route-learning phase. Evidence presented led to the conclusion that ANNs were better able to predict performance outcomes, and were generalizable to previously unseen data following training of the model. The goal of this study was to develop strategies for the successful development of systems that utilize psychophysiological computing to adapt to the individual in such a way that an optimal pace for training is achieved in order to foster ideal learning settings. A number of findings reported in the current research provide informative material for such adaptive system development.

Adaptive automation systems generally utilize psychophysiological responses to assess user-states in order to determine the necessity of automated assistance to facilitate optimal system performance [1]. In the current study, habituation effects on threat responses led to the calculation of predictor variables better suited for navigation performance prediction. Responses to threat habituated almost universally throughout the task. Thus, a set of predictors designed to account for habituation effects produced better prediction of navigation performance. This distinction could be used to inform future adaptive system design in that thresholds for adaptations based on responses to threatening stimuli must be concerned with the change in response levels with repeated exposure to the stimuli and must allow for dynamic adjustment to thresholds for adaptive change.

Finally, the current research provided encouraging support for the use of ANNs for prediction of performance outcomes based on psychophysiological response measures. The ANN provided significantly enhanced predictive abilities compared to a traditional MLR model. This demonstrated that psychophysiological responses to varying levels of threat during a route-learning task could be used to predict performance on a subsequent navigation task with better than 76% rates of accuracy.

Recently, researchers have begun applying advanced algorithms such as ANNs for data classification in real-time. For example, a number of studies have utilized ANNs for the initiation of adaptive assistance when features meet classification requirements for a state of overload [23, 24]. These techniques are often used for assessment and classification of nonlinear data (see [19]). The models produced in the current research lend themselves well to use in adaptive training simulations to enhance route-learning abilities when confronted with threatening stimuli. An adaptive automation approach can be employed to training making use of the VE developed herein, such that psychophysiological responses gleaned during the route-learning phase can be assessed for hyper- or sub-threshold criteria related to overload or fear, and adaptive assistance may be provided during the navigation task to fit the needs of the individual and promote optimal performance.

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