

Optimal Arousal Identification and Classification for Affective Computing Using Physiological Signals: Virtual Reality Stroop Task

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Abstract—A closed-loop system that offers real-time assessment and manipulation of a user's affective and cognitive states is very useful in developing adaptive environments which respond in a rational and strategic fashion to real-time changes in user affect, cognition, and motivation. The goal is to progress the user from suboptimal cognitive and affective states toward an optimal state that enhances user performance. In order to achieve this, there is need for assessment of both 1) the optimal affective/cognitive state and 2) the observed user state. This paper presents approaches for assessing these two states. Arousal, an important dimension of affect, is focused upon because of its close relation to a user's cognitive performance, as indicated by the Yerkes-Dodson Law. Herein, we make use of a Virtual Reality Stroop Task (VRST) from the Virtual Reality Cognitive Performance Assessment Test (VRCPAT) to identify the optimal arousal level that can serve as the affective/cognitive state goal. Three stimuli presentations (with distinct arousal levels) in the VRST are selected. We demonstrate that when reaction time is used as the performance measure, one of the three stimuli presentations can elicit the optimal level of arousal for most subjects. Further, results suggest that high classification rates can be achieved when a support vector machine is used to classify the psychophysiological responses (skin conductance level, respiration, ECG, and EEG) in these three stimuli presentations into three arousal levels. This research reflects progress toward the implementation of a closed-loop affective computing system.

Index Terms—Affective computing, arousal classification, affect recognition, virtual reality, Stroop task, Yerkes-Dodson Law.

1 INTRODUCTION

AFFECTIVE computing [42] is “computing that relates to, arises from, or influences emotions.” It has been gaining popularity rapidly in the last decade because it has great

potential in the next generation of human-computer interfaces [42], [57], [59]. One goal [53] of affective computing is to design a computer system that responds in a rational and strategic fashion to real-time changes in user affect (e.g., happiness, sadness, etc.), cognition (e.g., frustration, boredom, etc.), and motivation, as represented by speech [16], [24], [51], [65], facial expressions [12], [35], physiological signals [11], [22], neurocognitive performance [40], and multimodal combination [4], [32], [72]. Potential applications of affective computing include the following:

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- *Learning* [6], [9], [44], e.g., a computer tutor that recognizes the student's affective and cognitive status to individualize its teaching strategy.
- *Affective gaming* [14], [27], [29], [55], e.g., a game that changes its settings (difficulty, visualization, music, etc.) automatically to keep the gamer engaged.
- *Robotics* [2], [13], [46], e.g., a personalized robot companion that understands and displays affect.
- *Healthcare and behavioral informatics* [26], [43], [45], e.g., assessment in autism.

Our research focuses on closed-loop affective computing systems, i.e., how to build interactive environments [11], [56], which adapt automatically to move the user's affective and cognitive state to the desired state. A diagram of such a system is shown in Fig. 1. It consists of three main blocks:

- *Controller*, which outputs the control signal to change the environment and, hence, the user's affect.

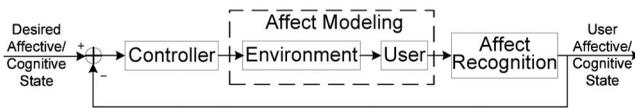


Fig. 1. A closed-loop affective computing system.

- *Affect modeling*, which models the relationship between the environment surrounding the user and the change of the user's affect.
- *Affect recognition*, which recognizes the user's affect from various signals, e.g., speech, facial expressions, gestures, physiological signals, etc.

Additionally, we also need to know the desired affective/cognitive state so that we can regulate the user's actual affective/cognitive state toward it. This paper presents an approach for this problem and also a method for affect recognition using physiological signals.

Research on affect [47], [49] has shown that affect can be represented as points in a multidimensional space. One of the most frequently used affect spaces consists of three dimensions [8], [21]:

- *Valence*, which ranges from *negative* to *positive*.
- *Arousal*, which ranges from *low* to *high*.
- *Dominance*, which ranges from *weak* to *strong*.

Among them, arousal is closely related to a subject's performance in mental tasks. According to the well-known Yerkes-Dodson Law [69], performance is a nonmonotonic function of arousal, as shown in Fig. 2. Performance increases with arousal when the arousal level is low, then reaches its peak at the optimal arousal level, and then decreases as arousal continues to increase. So, in an affective computing system which aims to improve the user's performance in mental tasks, such as learning and affective gaming, it is very important to be able to identify the user's optimal arousal level and to recognize whether or not the user's actual arousal level is close to that optimal level.

In this paper, we make use of the Virtual Reality Stroop Task (VRST) from the Virtual Reality Cognitive Performance Assessment Test (VRCPAT) [37], [38], [39], [41] to find the optimal¹ arousal level. We chose the Stroop color interference task because it is among the most extensively studied paradigms in neuropsychology and it has known relation to the anterior cingulate cortex (ACC). The Stroop color interference task produces a classical behavioral effect [54] that consists of a lengthening in reaction time to color naming when the word meaning and the presentation do not match (i.e., they are "incongruent") relative to when they correspond (i.e., they are "congruent" [33]). The ACC is known to be involved in a form of attention that serves to regulate both cognitive and emotional processing [3], [61]. The ACC's involvement in the Stroop color interference task has been delineated by cognitive neuroimaging studies [25], [36], [58]. The extensive distributed network of activated regions suggests that the Stroop interference effect cannot be

1. As presented in Section 2.2, we chose three scenarios from VRST and identified the best arousal level among them. This best arousal level should be close to the optimal arousal level in Fig. 2; however, it may not be exactly the same as it is. For simplicity, it is referred to as "optimal arousal level" in this paper.

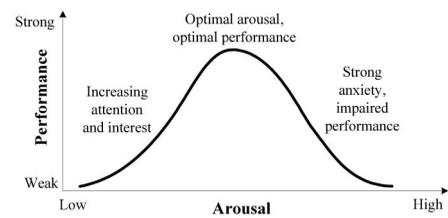


Fig. 2. The Yerkes-Dodson Law.

explained simply in terms of stimulus encoding or response interference. Further, the increased difficulty found in the Stroop interference task has been shown to directly evoke autonomic changes in cardiovascular arousal [19].

The aims of this study are to

1. assess whether or not it is possible to identify a subject's optimal level of arousal using three stimuli presentations from VRST, based on user test performance, and
2. investigate the extent to which it is possible to accurately classify a subject's arousal state into three levels, based on the user's physiological responses.

Successful achievement of the objectives will allow for construction of the input signal and the affect recognition block in Fig. 1. The classifier built above can be used to indicate whether or not the subject is near his/her optimal level of arousal. If not, one may also know whether it is excessively high or low. Results will be important steps in implementing the closed-loop affective computing system in Fig. 1.

The remainder of the paper is organized as follows: Section 2 introduces VRCPAT's VRST and the experimental setup. Section 3 explains how a subject's performance on the VRST can be used to identify the user's optimal arousal level. Section 4 presents a support vector machine (SVM) approach to distinguish among three arousal levels. Finally, Section 5 draws conclusions and proposes future research directions.

2 VIRTUAL REALITY COGNITIVE PERFORMANCE ASSESSMENT TEST (VRCPAT)

2.1 Introduction

At the University of Southern California's Institute for Creative Technologies we have developed an adaptive virtual environment for assessment and rehabilitation of neurocognitive and affective functioning. This project brings together a team of researchers to incorporate cutting edge neuropsychological and psychophysiological assessment into state-of-the-art interactive and adaptive virtual Iraqi/Afghani scenarios. These scenarios consist of a virtual city, a virtual vehicle checkpoint, and a virtual Humvee driving scenario in simulated Iraqi and Afghani settings. Two primary goals define these virtual and adaptive environments: 1) a Virtual Reality Cognitive Performance Assessment Test (VRCPAT 1.0) that includes a battery of neuropsychological and psychophysiological measures for diagnostic assessment and treatment of subjects with affective disorders, brain injury, or neurocognitive deficits; and 2) a Virtual Reality for Cognitive Performance and

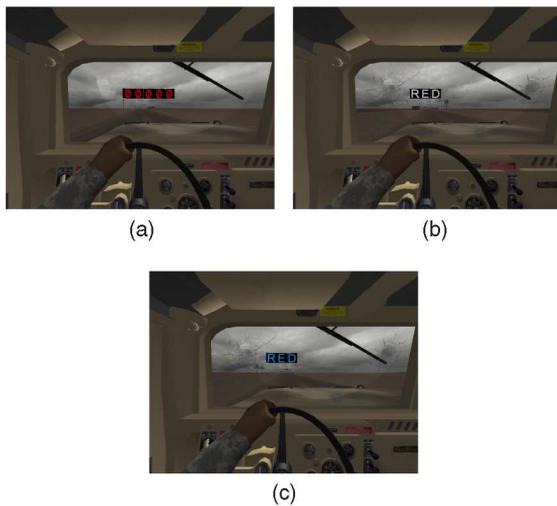


Fig. 3. The Humvee Stroop Scenarios: (a) color naming, (b) word reading, and (c) interference.

Adaptive Treatment (VRCPAT 2.0) that develops an adaptive environment in which data gleaned from the assessment module (VRCPAT 1.0) will be used for refined analysis, management, and rehabilitation of subjects who have suffered blast injuries (varying levels of traumatic brain injury) and/or are experiencing combat stress symptoms (e.g., post-traumatic stress disorder [18]).

While immersed in the VRCPAT, a subject's neurocognitive and psychophysiological responses are recorded in an attempt to understand how the activation of particular brain areas is related to given tasks. It is hoped that this will allow us to better uncover the relationship between the neural correlates of neurocognitive functioning in virtual environments for generalization to real-world functioning. Following the acquisition of these data, we will use nonlinear approximation to model specific neurocognitive and affective processes of persons immersed in VRCPAT.

The VRST utilized in the current study involves the subject being immersed into a virtual Humvee as it travels down the center of a road, during which Stroop stimuli [54] appear on the windshield, as shown in Fig. 3. The VRST stimuli are presented within both "safe" (low-threat) and "ambush" (high-threat) settings: start section, palm ambush, safe zone, city ambush, safe zone, and bridge ambush. Low-threat zones consist of little activity aside from driving down a desert road, while the more stressful high threat zones include gunfire, explosions, and shouting among other stressors.

The VRST assesses simple attention, gross reading speed, divided attentional abilities, and executive functioning. The task requires the subject to inhibit an overlearned response in favor of an unusual one. It takes advantage of the subject's ability to read words more quickly and automatically than s/he can name colors [28]. If a word is displayed in a color different from the color it actually names, for example in Fig. 3c, the word "red" is displayed with a blue colored font, the subject would press the button corresponding with the word "red" more readily than s/he can respond with the color in which it is displayed, which in this case is "blue." The subject must correctly respond to each Stroop stimulus immediately after it appears. In the

"Color Naming" condition, the subject must respond with the name of the color that appears on the screen. In the "Word Reading" condition, the subject must respond with the word that appears on the screen. In the "Interference" condition, the subject must press the button corresponding with the color of the word that appears on the screen, ignoring what the word says.

Psychophysiological measures of skin conductance level (SCL), respiration (RSP), vertical electrooculograph (VEOG), electrocardiographic activity (ECG), and electroencephalographic activity (EEG) are recorded continuously throughout exposure to the virtual environment.

2.2 Experiment Setup

There are many different scenarios eliciting different levels of arousal in VRST. In this study, we chose the following three of them to affect different arousal levels:

- Scenario I: low threat, color naming.
- Scenario II: high threat, color naming.
- Scenario III: high threat, interference.

Each scenario consisted of 50 tests. Three colors (blue, green, and red) were used, and they were displayed with equal probability. In Scenario I, 50 colored numbers were displayed at random locations on the windshield one by one while the subject was driving through a safe zone. Scenario II was similar to Scenario I, except that the subject was driving through an ambush zone. Scenario III was similar to Scenario II, except that Stroop tests instead of color naming tests were used.

Given the known ACC involvement in cognitive and affective processing of Stroop interference stimuli, the three scenarios are in the order of $I < II < III$. Our conjecture is that the arousal level in Scenario I is too low for peak performance, i.e., the arousal level is on the left of the optimal arousal level in Fig. 2; on the contrary, the arousal level in Scenario III is too high for peak performance, i.e., the arousal level is on the right of the optimal arousal level in Fig. 2. Finally, the arousal level in Scenario II, which is between those of Scenarios I and III, is close to or at the optimal arousal level in Fig. 2; hence, the subject should have the best performance in Scenario II.

A total of 19 college-aged students participated in this experiment. Strict exclusion criteria were enforced so as to minimize the possible confounding effects of additional factors known to adversely impact a person's ability to process information, including psychiatric (e.g., mental retardation, psychotic disorders, diagnosed learning disabilities, attention-deficit/hyperactivity disorder, and bipolar disorders, as well as substance-related disorders within 2 years of evaluation) and neurologic (e.g., seizure disorders, closed head injuries with loss of consciousness greater than 15 minutes, and neoplastic diseases) conditions. The University of Southern California's Institutional Review Board approved the study. After informed consent was obtained, basic demographic information was obtained.

3 OPTIMAL AROUSAL LEVEL IDENTIFICATION

The optimal arousal level was identified based on a subject's test performance in the three VRST scenarios. Each subject's performance was evaluated using two criteria:

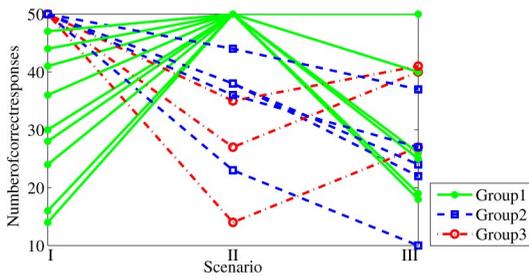


Fig. 4. Number of correct responses for the 18 subjects. Note that a larger number of correct responses correspond to a better performance.

- *Number of correct responses*, which is the number of times that the subject indicated the correct color.
- *Reaction time*, which is the time between the stimulus onset and the subject's correct response. Incorrect responses were not considered in this study.

Our conjecture is that Scenario II has an arousal level close to or at the optimal arousal level, and hence, the subject should have better performance than that in Scenarios I and III. This conjecture is tested next using both performance measures.

3.1 Performance Based on the Number of Correct Responses

One of the 19 subjects did not respond at all in one of the three scenarios and was excluded as an outlier. Only the remaining 18 subjects were studied in this paper.

The numbers of correct responses for the 18 subjects are shown in Fig. 4. We partitioned these 18 subjects into three groups:

- Group1: those subjects whose *maximum* number of correct responses was obtained in Scenario II.
- Group2: those subjects whose *maximum* number of correct responses was obtained in Scenario I.
- Group3: those subjects whose *minimum* number of correct responses was obtained in Scenario II.

These groups are indicated by different line patterns in Fig. 4. Observe that:

1. Ten of the 18 subjects belong to Group1, i.e., their optimal arousal levels were elicited in Scenario II. These subjects' performances were consistent with the Yerkes-Dodson Law and also our conjecture.
2. Five of the 18 subjects belong to Group2, i.e., their optimal arousal levels were elicited in Scenario I. These subjects' performances were also consistent with the Yerkes-Dodson Law. A subject's number of correct responses decreasing from Scenario I to II and then to III means that this subject has a very low optimal arousal level, lower than or equal to the arousal level elicited in Scenario I.
3. Three of the 18 subjects belong to Group3. These subjects' performances were inconsistent with the Yerkes-Dodson Law, i.e., in theory, we should not have performance that first decreases and then increases as arousal increases.

In summary, when the number of correct responses is used as a performance measure, $15/18 \approx 83.3\%$ of the subjects'

TABLE 1
Mean and Standard Deviation of the Two Performance Measures in Different Scenarios

Scenario	Mean			Standard Deviation		
	I	II	III	I	II	III
Number of correct responses	40.222	41.944	33.667	10.268	11.526	13.960
Reaction time (second)	0.805	0.776	0.866	0.072	0.076	0.089

performance-arousal profiles were consistent with the Yerkes-Dodson Law. Furthermore, $10/18 \approx 55.6\%$ of the subjects' performance-arousal profiles satisfied our conjecture, that is, their optimal arousal level was close to or at the arousal level elicited in Scenario II.

The mean and standard deviation of the number of correct responses for all 18 subjects in one group across each of the three scenarios are shown in Table 1. An ANOVA showed no significant affect between the number of correct responses across the three scenarios ($F(2,51) = 2.26, p = 0.1142$). This suggests that the number of correct responses may not be an adequate performance measure for distinguishing among the three arousal levels. Reaction time is a better performance measure, as we will demonstrate next.

3.2 Performance Based on the Reaction Time

The reaction times for the 18 subjects are shown in Fig. 5. We again partitioned these 18 subjects into three groups:

- Group1: those subjects whose shortest reaction time was obtained in Scenario II.
- Group2: those subjects whose shortest reaction time was obtained in Scenario I.
- Group3: those subjects whose shortest reaction time was obtained in Scenario III.

These groups are indicated by different line patterns in Fig. 5. Observe that:

1. Eleven of the 18 subjects belong to Group1, i.e., their optimal arousal levels were elicited in Scenario II. These subjects' performances were consistent with the Yerkes-Dodson Law and also our conjecture.
2. Four of the 18 subjects belong to Group2, i.e., their optimal arousal levels were elicited in Scenario I. These subjects' performances were also consistent with the Yerkes-Dodson Law. A subject's reaction time increasing from Scenario I to II and then to III means that this subject has a very low optimal arousal level, lower than or equal to the arousal level elicited in Scenario I.

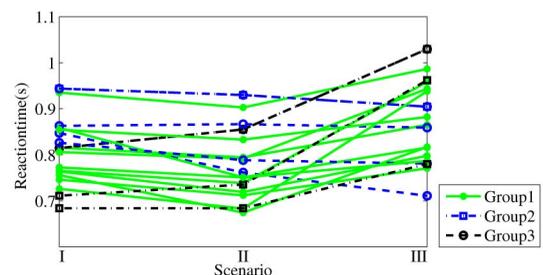


Fig. 5. Reaction time for the 18 subjects. Note that a shorter reaction time corresponds to a better performance.

3. Three of the 18 subjects belong to Group3, i.e., their optimal arousal levels were elicited in Scenario III. These subjects' performances were also consistent with the Yerkes-Dodson Law. A subject's reaction time decreasing from Scenario I to II and then to III means that this subject has a very high optimal arousal level, higher than or equal to the arousal level elicited in Scenario III.

In summary, when the reaction time is used as a performance measure, all subjects' performance-arousal profiles were consistent with the Yerkes-Dodson Law. Furthermore, $11/18 \approx 61.1\%$ of the subjects' performance-arousal profiles satisfied our conjecture, that is, their optimal arousal level was close to or at the arousal level elicited in Scenario II.

The mean and standard deviation of the reaction time for all 18 subjects in one group across each of these three scenarios are also shown in Table 1. An ANOVA showed a statistically significant difference between the mean reaction times across the three scenarios ($F(2,51) = 6.02$, $p = 0.0045$), indicating that reaction time provides a superior performance measure to correct responses for distinguishing the level of arousal. Our results also support the popularity of the use of reaction time in Stroop tests [28].

4 AROUSAL CLASSIFICATION

In the previous section, we have demonstrated that most of the subjects' performance-arousal profiles are consistent with the Yerkes-Dodson Law, particularly when reaction time is used as a performance measure. In addition, 61.1 percent of the subjects' performance-arousal profiles also satisfy our conjecture. In summary, it is possible to elicit different levels of arousal and identify the optimal arousal level using VRST. The next question is whether or not these arousal levels can be recognized accurately from physiological signals. If so, then the classifier can be used in a real-time affective computing system. This section presents our classification results using a SVM [5], [7], [50].

4.1 Feature Extraction

Twenty-nine features were extracted from the data, including three from SCL, three from RSP, two from ECG, and 21 from EEG, as shown in Fig. 6. To do this, the data were first split into overlapping 3-second epochs² which were time locked to the stimulus presentation such that the epoch began 1 second before the stimulus and ended 2 seconds after stimulus presentation. From the SCL and the RSP data, we extracted minimum, mean, and maximum values throughout the epoch, while we extracted the number of beats per epoch and inter-beat-interval (IBI) from the ECG. EEG was recorded at the Fp1, Fp2, Fz, Cz, Pz, O1, and O2 electrode sites, based on the International 10-20 system for EEG electrode placement [20]. Before extracting the 21 EEG features, we first removed the ocular artifacts from EEG signals using the VEOG data in conjunction with the regression analysis method introduced in [52]:

2. This 3-second window was chosen empirically. The classification performance in Section 4.3 could vary if longer scoring windows were used, or different window lengths were used for different features. The latter approach is currently under investigation.

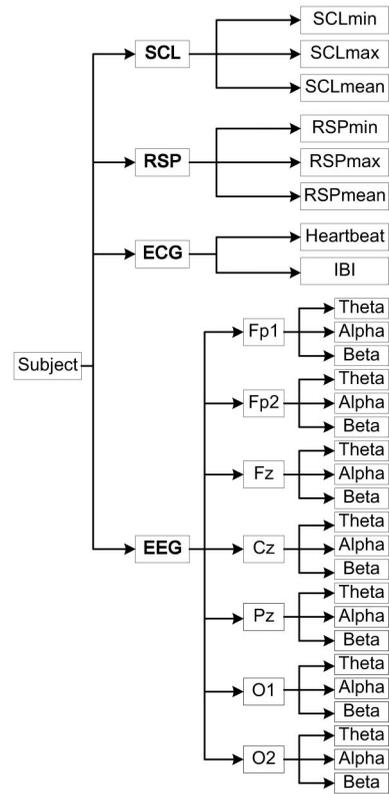


Fig. 6. The 29 features extracted from four physiological signals.

$$EEG = \text{"raw"} EEG - \alpha \cdot VEOG \quad (1)$$

where

$$\alpha = cov(VEOG, \text{"raw"} EEG) / var(VEOG). \quad (2)$$

We then filtered each EEG channel by a [1, 30] Hz bandpass filter and detrended each channel within each epoch. Finally, from each channel, we derived the spectral power for several brain activity oscillations within each epoch [34]. Specifically, we used the ranges [3.5, 7] Hz for theta waves, [7.5, 13.5] Hz for alpha waves, and [13.5, 19.5] Hz for beta waves.

After all 29 features were extracted across all epochs for each subject, each feature was normalized to the interval [0, 1].

4.2 Feature Ranking and Selection

Given that all of the 29 features may not be useful in classification, it is necessary to select a subset of the best features because redundant features may deteriorate the classification performance while increasing the computational cost [17].

Feature ranking is often used as a preliminary step in feature selection [17]. In this paper, we rank the features using the iterative sequential forward selection (SFS) method [23]. Initially, the *best feature set* is empty, and the *remaining feature set* consists of all the 29 features. In each iteration, one feature that maximizes the fivefold cross-validation performance of the SVM is moved from the remaining feature set to the best feature set. SFS iterates until the remaining feature set is empty, so it takes 29 iterations to finish. The rank of the features is the order in which they are added to the best feature set.

For feature selection, we started with the single best feature and gradually added the next best feature to the

TABLE 2
Subject-Dependent Feature Selection and Classification Results

Feature	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	#Subject
SCLmin		✓	✓	✓	✓		✓	✓	✓	✓		✓	✓		✓	✓	✓	✓	13
RSPMax		✓				✓		✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	10
RSPmin	✓						✓		✓			✓	✓		✓	✓	✓	✓	8
RSPMean	✓		✓		✓	✓			✓		✓	✓	✓		✓	✓	✓	✓	8
SCLmax	✓						✓			✓	✓	✓	✓			✓			7
IBI	✓				✓			✓		✓	✓		✓	✓					7
SCLmean	✓		✓							✓	✓		✓		✓				7
thetaPZ							✓	✓	✓				✓	✓	✓		✓	✓	5
thetaO1							✓		✓	✓			✓	✓					5
thetaO2	✓						✓		✓	✓						✓			5
alphaFP2		✓					✓		✓	✓	✓								4
alphaFZ					✓		✓		✓	✓				✓		✓			4
betaFP1							✓		✓	✓						✓			4
betaO1		✓					✓		✓	✓						✓			4
thetaFP1			✓				✓		✓	✓									3
thetaFZ							✓		✓	✓				✓					3
thetaCZ							✓		✓	✓				✓					3
alphaFP1							✓		✓	✓	✓								3
alphaCZ		✓					✓		✓	✓									3
alphaPZ							✓		✓	✓				✓		✓			3
alphaO1							✓		✓	✓									3
beta2							✓		✓	✓						✓		✓	3
betaFZ							✓		✓	✓						✓			3
thetaFP2							✓		✓										2
alphaO2									✓	✓						✓			2
Heartbeats						✓													1
betaCZ									✓	✓									1
betaO2									✓	✓									1
betaPZ										✓									0
#Feature	6	5	4	1	4	3	16	4	15	18	5	4	6	9	3	11	4	4	
Accuracy (%)	100	99.3	99.3	100	98.7	99.3	98.7	94.0	84.7	95.3	84.0	100	91.3	96.0	100	98.0	100	98.0	

feature subset until the fivefold cross-validation performance stops improving.

4.3 Feature Selection and Classification Results

In this section, we present the subject-dependent and subject-independent classification results, respectively.

In the subject-dependent case, we want to study whether or not a subject's arousal level in a new experiment can be predicted from his/her responses in previous experiments. So, we considered each subject separately, and trained an SVM to classify his/her responses into three groups. Fivefold cross-validation was used: We used 120 of the subject's 150 responses in feature selection and training and the remaining 30 in testing, and repeated this procedure five times until all 150 responses were tested. The features selected by SVM for different subjects are shown in Table 2, and the corresponding fivefold cross-validation classification rates are shown in the last row. An average classification rate of 96.5 percent was achieved. Observe from the feature selection results that:

1. generally a small number of features were enough for classification, and
2. different features were used by the SVM for different subjects, a fact which is intuitively explained by individual response profiles across the same physiological signals.

Among the four physiological signals, SCL and RSP features were the most important. EEG features were moderately important. For EEG features, among the three waves (theta, alpha, and beta), theta waves seem to be the

most important. This is reasonable, as theta waves seem to be related to the level of arousal [15], [48]. For ECG features, IBI was much more important than Heartbeats.

In the subject-independent case, we want to study whether or not a subject's arousal level in an experiment can be predicted from other subjects' arousal levels in the same experiment. We used a leave-one-out cross-validation approach: Each time, 17 subjects' $50 \times 3 \times 17 = 2,550$ experiments were used in training and the remaining subject's $50 \times 3 = 150$ experiments were used in testing. This procedure was repeated 18 times so that all 18 subjects were tested. The average classification rate of the 18 runs was 36.9 percent, very close to random guess. This was not surprising since the selected features in the subject-dependent case are quite different from subject to subject, i.e., the individual difference was too large to find a good subject-independent classifier.

In summary, it is possible to classify a subject's arousal level accurately by comparing his/her responses with his/her own previous responses, but it is difficult to do that by comparing his/her responses with other subjects' responses. So, in practice, it is necessary to run VRST individually for each subject in order to accurately capture his/her arousal profile.

5 CONCLUSIONS AND FUTURE RESEARCH

In this paper, we used the VRST from the VRCPAT, a virtual environment for assessment of neurocognitive and affective functioning to identify the optimal arousal level in mental tasks. Two performance measures, the number of

correct responses and the reaction time, were compared, and we found that the reaction time is a better performance measure to distinguish among different arousal levels experienced by users of the VRST. We also found that a moderate level of arousal can lead to improved performance, as suggested by the Yerkes-Dodson Law. We have also presented a subject-dependent SVM-based classifier which achieved over 84 percent accuracy in distinguishing among three arousal levels using physiological signals. The results in this paper enable us to identify the optimal arousal levels and recognize whether or not the user is close to or at that optimal level. These are two important steps in building a closed-loop affective computing system that adapts automatically to keep the user at the optimal arousal level.

5.1 Future Directions

We have achieved a high subject-dependent classification rate using SVM, but SVM is a black-box approach and, hence, gives us little insight about the underlying patterns of how subject's physiological responses are affected by different arousal levels. To do this, we need more transparent methods. The following two approaches will be considered in our future research:

1. A rule-based method, where a rule in the following form is constructed for each physiological feature:
IF feature > threshold1, THEN Class1; IF feature < threshold2, THEN Class2; Otherwise, Class3.
 The thresholds can be found from the distribution of the feature. If we use the 29 features above, then we will have 29 such rules. These rules could be combined using majority vote.
2. A Naive Bayes approach [10], where we assume that the features are independent of each other and find the class using the *maximum a posteriori* (MAP) rule.

When reaction time is used as a performance measure, we are able to identify that 61.1-percent subjects have optimal arousal level at or close to that elicited in Scenario II. The optimal arousal levels for the rest 38.9-percent subjects are either no higher than that elicited in Scenario I or no lower than that elicited in Scenario III. To accurately identify the optimal arousal level for all subjects, we need to increase the range of elicitable arousal levels in our future development of VRST. Additionally, currently VRST uses virtual Iraqi/Afghani scenarios. Whether or not the optimal arousal levels identified from these scenarios are identical or close to those in other scenarios, e.g., classroom, games, or everyday life, is also worth investigation.

Our research goal is to fully implement a closed-loop affective computing system, as shown in Fig. 1. So far, we have been able to construct the input signal, i.e., we can identify the optimal arousal level, and we have also been able to recognize the user's actual arousal level from physiological signals. Our future research will focus on the other two essential blocks of the closed-loop affective computing system, i.e., affect modeling and controller design.

For affect modeling, we need to model the relationship between the environment surrounding the user and the change of the user's affect. For example, in games, possible environment parameters are difficulty levels, music, background color, etc. We need to perform experiments or

surveys to establish the relationship between the change of these variables and the change of the user's arousal level. We expect that it will be difficult to represent these relationships using precise functions. Linguistic rules based on interval type-2 fuzzy sets [30], [71], which are better able to model linguistic uncertainties than traditional fuzzy sets [70], are viewed very favorably. We have developed procedures to extract such rules from databases [62], [63] and surveys [31], [62], [64], and have successfully applied the rules to social judgments [31], [62], [64].

Once affect modeling is completed, we need to design a control algorithm that changes these variables to move the user's arousal level toward the optimal level. This algorithm should be able to handle individual differences, and also be able to perform the regulation smoothly and quickly. Again we believe fuzzy rule-based controllers [60], [66], [67], [68] are more favorable than traditional PID controllers [1], as it is difficult to represent the desired affective/cognitive state and the user's actual affective/cognitive state by precise numbers.

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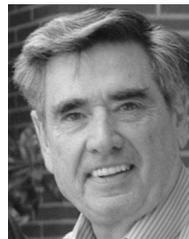
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