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Real-Time Emotional State Estimator for Adaptive Virtual Reality Stimulation

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Abstract. The paper presents design and evaluation of emotional state estimator based on artificial neural networks for physiology-driven adaptive virtual reality (VR) stimulation. Real-time emotional state estimation from physiological signals enables adapting the stimulations to the emotional response of each individual. Estimation is first evaluated on artificial subjects, which are convenient during software development and testing of physiology-driven adaptive VR stimulation. Artificial subjects are implemented in the form of parameterized skin conductance and heart rate generators that respond to emotional inputs. Emotional inputs are a temporal sequence of valence/arousal annotations, which quantitatively express emotion along unpleasant-pleasant and calm-aroused axes. Preliminary evaluation of emotional state estimation is also performed with a limited set of humans. Human physiological signals are acquired during simultaneous presentation of static pictures and sounds from valence/arousal-annotated International Affective Picture System and International Affective Digitized Sounds databases.

Keywords: Real-Time Emotional State Estimator, Adaptive Virtual Reality Stimulation, Artificial Neural Network, Stimuli Generation, Physiological Measurements

1 Introduction

Research described in this paper is a part of ongoing efforts to design and develop the physiology-driven adaptive stimulation for VR exposure therapy (VRET) [1,2]. In VRET, a treatment method for various anxiety disorders, the therapist (*the supervisor*) operates a user interface to deliver gradually to the patient (*the subject*) the virtual stimuli of anxiety-provoking situations [3,4,5]. Physiology-driven adaptive VR stimulation attempts to optimize and customize the therapy by relieving the supervisor of repetitive interface manipulation and monitoring of the subject's physiology. However, it may also be useful in a broader range of human-computer interaction applications.

Physiology-driven adaptive VR stimulation includes [1]: time-synchronized stimuli generation, acquisition of the subject's physiological response, subject's emotional state estimation, and closed-loop control that leads to subsequent generation of new stimuli. Control signals may specify semantics, emotional properties, and media form of the stimuli. The stimuli are presented in various media forms, like static pictures, sounds and synthetic virtual stimuli combined with real-life video clips. Emotional state estimation is based on the dimensional model of emotions organized along the axes of valence (unpleasant-pleasant) and arousal (calm-aroused) [6]. Mappings to other emotion representations may be added if necessary. For example, representation of relevant emotional states in VRET may be more coarse-grained [2]: non-aroused, aroused and overly aroused.

The paper is focused on the real-time Emotional State Estimator component of the physiology-driven adaptive VR stimulation. This component is crucial for adaptation of VR stimulations to the emotional response of each individual. The remainder of the paper lays out design and preliminary evaluation of the real-time Emotional State Estimator based on artificial neural networks, also describing accompanying stimuli generation and physiological measurements.

2 Stimuli Generation

Within the physiology-driven adaptive VR stimulation, the Stimuli Generator is responsible for finding the best-matching stimuli with respect to the semantics, emotional properties and media form specified by the control signals. In this process, it is important that the signals result in emotionally and semantically aligned stimuli, which are individually conformed to a specific subject's mental state.

The Stimuli Generator uses emotionally and semantically annotated stimuli databases. International Affective Picture System (IAPS) [7] and International Affective Digitized Sounds (IADS) [8] are such publicly available databases of static pictures and sounds. Valence and arousal emotional annotations of IAPS and IADS stimuli are decimal numbers in the range from 1.00 through 9.00, representing maximum unpleasantness through maximum pleasantness, and maximum calmness through maximum arousal, respectively. These databases also use free-text keywords, or tags, to describe the semantics of stimuli. However, the keywords are semantically scattered, taxonomically disordered, and subsequently cumbersome for information extraction.

Stimuli generation plans to introduce ontology-based tagging in the existing emotionally and semantically annotated databases, in order to achieve more informative descriptions of stimuli and more efficient extraction of context knowledge [9]. This work builds on the current Stimuli Generator that generates IAPS and IADS stimuli [10]. Media forms supported by the Stimuli Generator are also being extended to virtual stimuli in the context of VRET [11].

3 Physiological Measurements

Two physiological measurement approaches are used during the research and development of the physiology-driven adaptive VR stimulation. One approach involves artificial subjects that computationally generate physiological signals, and the other acquisition of physiological signals from real human subjects. Artificial subjects approach is convenient for software development of the physiology-driven adaptive VR stimulation. It allows generating numerous subjects and measuring their physiological reactions to a large number of stimuli. This facilitates development of the real-time Emotional State Estimator without requiring time-consuming and sophisticated emotion elicitation and physiological measurements on real humans. Approach with human subjects is relevant for the ultimate goal of estimating human emotional state, as artificial subjects provide only crude approximations of human physiological response to stimuli.

Artificial subjects consist of parameterized skin conductance (SC) and heart rate (HR) generators that accept valence/arousal of the generated stimuli (Fig. 1). Generated SC and HR signals exhibit simpler and more deterministic behavior than human physiological signals. However, some principles from the literature on relationship between physiology and valence/arousal have been incorporated, including initial post-stimulus HR deceleration dependent mostly on valence [12], HR acceleration affected by increase of arousal [12], and SC increase with increase of arousal [12]. Approximate parameter values of SC response have been found in [13] and the basic SC response model has been adopted from [14]. HR generator is a modification of the open-source generator ECGSYN [15] with parameter adjustments based on valence/arousal inputs. Description of the underlying modeling used in ECGSYN generator can be found in [16].

Human physiological signals can be acquired by a variety of multi-channel physiological acquisition systems. Acquisition system used in the paper is BIOPAC MP 150. This system is synchronized with SuperLab stimulus presentation system, which presents emotion eliciting stimuli to the human subjects. In order to collect the same signals for humans as for the artificial subjects, acquired physiological signals include

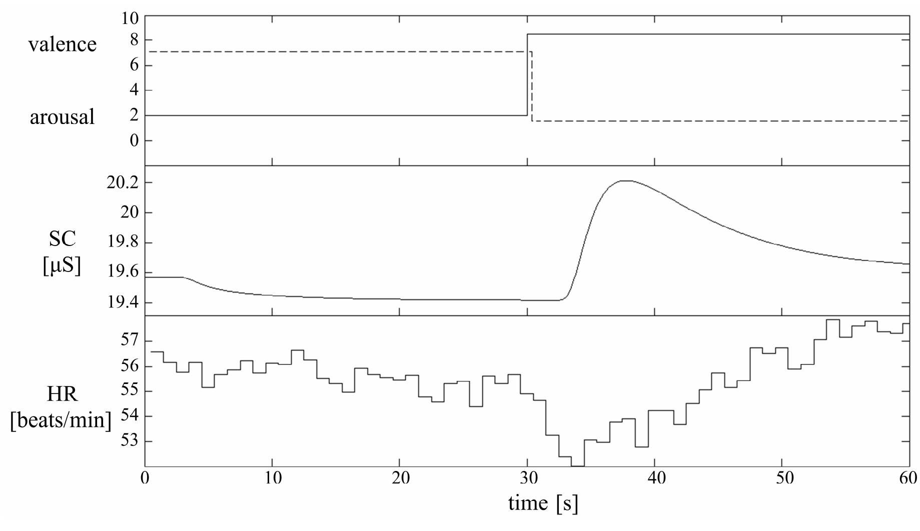

Fig. 1. An example of generated SC and HR reaction to a “step” input, a change from a pleasant relaxing stimulus to an unpleasant arousing stimulus.

SC and ECG signal. RR interval algorithm provided with the acquisition system is used in computing the HR signal from the ECG. In-house physiological acquisition system has also been developed, which is more convenient for physiology-driven adaptive VR stimulation.

4 Real-Time Estimation Concept Design

Real-time Emotional State Estimator in physiology-driven adaptive VR stimulation estimates the subject's emotional state repeatedly as physiological signals are acquired (Fig. 2). Subject's emotional state is changed in response to the presented stimuli and is generally affected by other influences, internal or external to the subject. The paper investigates emotional state estimation with sequential delivery of stimuli. *Stimuli sequence* is represented as s^1, s^2, ..., s^m, where stimulus s^i has an associated valence/arousal annotation (v^i, a^i) in the stimuli database. Corresponding *stimuli durations* in seconds are d^1, d^2, ..., d^m, and *stimuli onset times* $t^1 := 0$, t^2, ..., t^m, with $t^i := t^{i-1}+d^{i-1}$, for $i = 2, ..., m$.

Frequency of outputting the estimated valence/arousal is a predetermined fixed number of outputs per second, called the estimator *framerate* f_e. Acceptable real-time framerate in VRET is 1 Hz. Estimator *frame* is a time interval, in seconds, that extends from the beginning to the end of computation eventually producing one estimator output. *Frame duration* is $T_e := 1/f_e$.

For each frame, valence/arousal emotional state is estimated from physiological samples acquired during a time interval that starts a number of seconds in past and ends at the beginning of the frame. This interval is the *frame window* w_j^i, indexed in the same manner as the beginning of the frame. Physiological samples from the frame window are used in computing the *features* required for valence/arousal estimation. Generally, frame windows can have equal fixed *length*, in seconds, or the length may

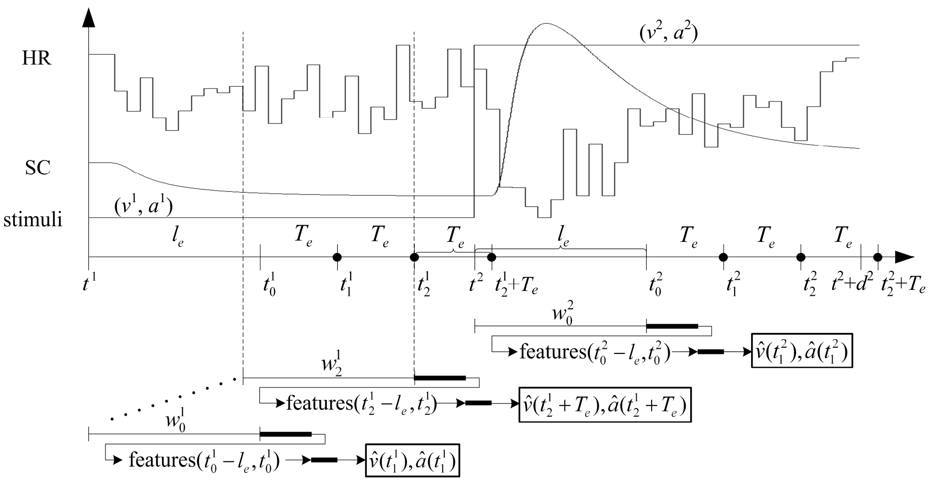

Fig. 2. Real-time emotional state estimation.

vary from frame to frame, e.g. to adjust to the dynamics of the features. Frame windows of fixed length l_e are applied, since the logic that may adjust window length to the feature dynamics is beyond the scope of the paper.

The Emotional State Estimator is *disabled* (does not estimate valence/arousal) whenever the frame window includes onset time of a stimulus; otherwise, it is *enabled*. Frame windows that overlap with a change from one stimulus to the next are avoided in emotional state estimation, as they introduce conceptual difficulties in defining the subject's emotional state. Illustration is given in Fig. 2, where no frame window overlaps with stimulus onset time t^2 and, therefore, no black-point markers of estimator output appear on time axis between $t_2^1 + T_e$ and t_1^2. Ability to disable and enable the estimator may rest in some higher-level logic with information regarding the frame windows and stimuli onset times.

5 Emotional State Estimator based on Artificial Neural Networks

There is a variety of research works that address emotion recognition based on physiology. Numerous methods for emotion recognition have been used, like k-nearest neighbor [17,18,19], discriminant analysis [17,18,20], support vector machine [19, 21], artificial neural network (ANN) [17,18,22,23], Bayesian classification methods [19] or regression tree [19]. In the surveyed articles, majority of the focus is on discrete emotion recognition, like pleasure, sadness, fear, anger etc. One encountered article [22], investigates valence and arousal estimation.

Complementing the previous research, the Emotional State Estimator presented in this paper gives unquantized real-time estimation of valence and arousal based on extracted physiological features. This is important in order to implement the closed loop of adaptive control presented in [1,2].

Estimator design is based on ANNs, due to their ability to model complex relationships between inputs and outputs. Unlike previous similar research [22], several ANN designs are tested:

1. One multi-input multi-output feedforward ANN with two output nodes, for valence and arousal,
2. Two separate feedforward ANNs for valence and arousal, each with a single output node,
3. One multi-input multi-output ANN with two output nodes, for valence and arousal, with feedback from output to input,
4. Two separate ANNs for valence and arousal, with feedback from output to input.

All designs have one hidden layer with 10 neurons, tansig activation function for hidden layer and purelin for output layer.

Training samples for the ANN are obtained by joining the features extracted from the physiological signals with the emotional annotations of the presented stimuli. Training samples are generated according to the concept of real-time estimation in the previous section; one training sample is obtained from each frame window. SC and HR signals of each subject are firstly divided by their respective mean at baseline, obtained during the initial neutral stimulus, for robustness to inter-subject baseline variation. After this transformation, two preliminary feature sets are extracted from both signals. Common features in both sets are mean, standard deviation and slope; the first set (FS1) further includes minimum and maximum, and the second (FS2) includes difference of maximum to minimum and difference of means between the current and the previous frame window. Every feature is normalized to [–1, 1] range, across all subjects used in training, by linearly mapping the minimum value of the feature to –1 and maximum value to 1. Stimuli emotional annotations in the training samples are normalized by linear mapping of their original range [1.00, 9.00] to [–1, 1]. The supervised training is performed with Levenberg-Marquardt learning algorithm, including early stopping for enhanced generalization.

Using emotional annotations of the presented stimuli for estimator training, as in this paper, is one of the possible training approaches (e.g. [22]). Another approach includes training the estimator with the subject's self-reported emotional state for each presented stimulus (e.g. [19]). Selected approach avoids the effect that human subjects' mental construction of self-report may have on physiology. Downside of the selected approach, however, is its inability to incorporate inter-subject differences in emotional experiences of the same stimulus.

6 Preliminary Estimator Evaluation

Accuracy of the estimated valence/arousal is evaluated against the valence/arousal values from the stimuli emotional annotations. Evaluation results are reported separately for valence and arousal, in terms of mean absolute error (mean AE) and maximum absolute error (maximum AE) over all subjects and stimuli sequences in the testing set. Testing set is kept separate from both the training set and the validation set, which is used for early stopping of the training process. Each subject's collected data are exclusively assigned either to the training, validation or testing set.

Evaluation is performed separately for artificial and human subjects, thus assessing inter-subject generalization in both cases. This differs from the protocol in reference [22], which performs valence/arousal estimation with a single human subject. Results are reported only for the best ANN design and feature set, which minimize the Euclidean norm of valence and arousal mean AEs.

Even though evaluation is performed offline in MATLAB, it is carried out in a manner suitable for real-time implementation. Estimator frame duration is set to 1 second, in order to achieve 1 Hz real-time framerate. Normalization of each feature during evaluation relies only on the minimum and maximum values computed during the training. Frame window length is 5 seconds.

6.1 Artificial Subjects

Artificial subjects process the sequences in which stimuli are represented as valence/arousal pairs with associated onset times. Two analyzed cases include evaluation on a variety of stimuli sequences, and evaluation on the sequence that is also used with human subjects. Duration of each stimulus in any sequence is set to 30 seconds.

In the first case (called “stimuli 1”), 10 artificial subjects are exposed to 10 stimuli sequences, each sequence having 21 stimuli. The first stimulus in each sequence has valence and arousal values of 5.00, and represents the ideal neutral stimulus for measurement of the subject’s baseline values. Other valence/arousal pairs are randomly selected from IAPS. Six artificial subjects are used for training of the estimator, two subjects for validation and two for testing. The best results are presented in Table 1, achieved by ANN design 4 and feature set FS2.

Table 1. Estimation errors for the best ANN designs and feature sets with artificial subjects (rounded to two decimal places).

		mean AE	maximum AE
stimuli 1	valence	0.64	4.37
	arousal	0.34	3.58
stimuli 2	valence	0.46	1.77
	arousal	0.32	1.42

In the second case (“stimuli 2”), valence/arousal pairs and onset times from the human stimuli sequence are used as inputs for the artificial subjects. Human stimuli sequence starts with a teal background, to establish the baseline physiology of the subject. Teal color has been chosen as the intermediate hue with the best ratio of elicited positive to negative emotions in a study with college students [24]. The sequence proceeds with 8 pairs of IAPS pictures and looping IADS sounds of matching onset and duration, having as similar as possible semantics and valence/arousal values. The first 2 stimuli are neutral, followed by a group of 3 pleasant relaxing stimuli and, finally, a group of 3 unpleasant highly arousing stimuli. Averages and standard deviations of valence and arousal within each group of stimuli, rounded to two decimal places, are (5.69±0.33, 4.50±0.48), (7.46±0.51, 3.27±0.05), (1.92±0.30, 6.90±0.31), respectively. Four randomly selected artificial subjects are used in training, one in validation and one in testing, to match the numbers of human subjects whose results are given in the next section. The best results are again achieved by ANN design 4 and feature set FS2 (Table 1).

With many random stimuli, arousal estimation is superior to valence estimation, as exemplified by the nearly twice lower arousal than valence mean AE in “stimuli 1”. Generated physiological signals indeed provide more information regarding arousal than valence, as valence affects only initial HR deceleration after the stimulus onset. Improvements in valence mean AE and maximum AEs from “stimuli 1” to “stimuli 2”, may reflect heavily polarized structure of the human stimuli sequence, i.e. strong negative correlation between valence and arousal.

6.2 Human Subjects

Six male students, 24.0±0.9 years of age, participate in the experiment. Stimuli are delivered via eMagin Z800 3DVisor head mounted display (HMD) with earphones, in order to help the subjects focus on the stimuli. Experiment is conducted in a dim air-conditioned technical laboratory with ambient temperature of 23–24°C. After reading of instructions to the subject, applying the electrodes and the HMD, the subject is left to rest for about three minutes, and the stimuli presentation and physiological acquisition are started. Four subjects are used in the estimator training, one in validation and one in testing. The best results are in Table 2, achieved by ANN design 3 and feature set FS1.

Table 2. Estimation errors for the best ANN design and feature set with human subjects (rounded to two decimal places).

		mean AE	maximum AE
stimuli 2	valence	1.33	5.09
	arousal	0.74	3.24

Mean and maximum AEs exhibit twofold to threefold increase from artificial to human subjects (cf. "stimuli 2" in Table 1). Therefore, generalization of estimation to the testing set, which includes a subject not encountered during training, is more problematic for humans. This underscores complexity of human individuality relative to SC and HR generators, mentioned in section 3.

Evaluation of different ANN designs and feature sets indicates that they may also affect generalization of estimation to previously unseen subjects. Moreover, feature set FS2 seems better suited for artificial subjects, probably because artificial physiological signals exhibit stronger tendency than human signals to settle in a steady state after each stimulus. Reasons behind the differences in the best ANN design for artificial versus human subjects remain to be elucidated by further experiments.

In order to assess if any generalization might have happened with human subjects, valence and arousal mean AEs from Table 2 are benchmarked against the expected mean AEs of two simplified estimators. The first one performs unbiased constant estimation that always returns the mean values of valence and arousal for the stimuli sequence; the human stimuli sequence has both mean values equal to 4.94. The second estimator returns random numbers from uniform distribution on [1.00, 9.00]. Expected mean AEs for valence and arousal, after rounding, are 2.27 and 1.47 for the first estimator and 2.76 and 2.32 for the second, based on the following derived formulas:

$$\mathrm{E}_{\text{unbiased constant}}[\text{mean AE}] = \frac{1}{N}\sum_{i=1}^{N}(|X_i - \overline{X}|)\,, \tag{1}$$

$$\mathrm{E}_{\text{uniform random}}[\text{mean AE}] = \frac{1}{8N}\sum_{i=1}^{N}(X_i^{\,2} - 10X_i + 41)\,. \tag{2}$$

In the formulas, N stands for the number of estimated valence/arousal outputs, X_i represents valence, or arousal, in the corresponding stimuli annotations, and $\overline{X}$ is the mean value of all X_i. Therefore, valence mean AE from Table 2 is about two times lower, and arousal mean AE is about two or three times lower, than the corresponding expected mean AEs of the two simplified estimators.

7 Conclusion

The paper has presented design and evaluation of the real-time Emotional State Estimator, using both artificial subjects and real humans. Inconveniences of using human subjects in early development and testing of the physiology-driven adaptive VR stimulation have been among the motivating factors for development of artificial subjects. Estimation accuracy is superior for artificial subjects, which is expected and acceptable with regard to their purpose.

In future work, comparative analysis is planned between different emotional state estimation methods, like various modifications of ANNs, hidden Markov models etc., different feature sets, as well as additional sensor inputs, like EEG, EMG etc. Larger homogenous samples of human subjects and more sophisticated fusion of multiple estimators' outputs might also improve real-time emotional state estimation. However, in order to emphasize human individuality, some form of estimator customization to each individual will also be applied.

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