Recognizing the Effects of Voluntary Facial Activations Using Heart Rate Patterns

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Abstract: - Continuously measured physiological signals have the potential to act as non-invasive, real time indicators of human psychophysiological phenomena. Recently, several non-intrusive, wireless, and discrete measurement devices have been developed. For these reasons, there has been growing interest for using physiological signals for estimating emotions and other psychological processes during human-computer interaction. In the current work, we present the first steps towards constructing a person-independent online system that automatically identifies heart rate responses and estimates subjective experiences during voluntary facial activations. The preliminary results of our study showed that voluntarily produced facial expressions had an effect on subjective emotional experiences and physiological processes. Further, our results suggest that heart rate responses to facial activations can be detected and classified in order to support more accurate and efficient emotion detection.

Key-Words: - Affective computing, emotion recognition, heart rate patterns, pattern classification, psychophysiology, biosignal processing, voluntary facial activations.

1 Introduction

Recently, there has been growing interest for using physiological signals in human-computer interaction [e.g., 1,2]. In addition to providing new modalities to act as voluntary input, physiological measures have potential as continuous estimates of the cognitive and emotional state of a person. In fact, it is quite difficult to acquire as accurate information on a competitively fine time scale using other measures [3]. For these reasons, physiological data can be considered to be one of the most important sources of information for affective computing, that is, computing that relates to, arises from, or deliberately influences emotions) [4,5]. Further, many non-invasive and unobtrusive physiological measurement techniques have recently been developed. For example, an ordinary looking office chair embedded with electromechanical film can be used to measure heart rate non-invasively [6]. Such techniques allow measurements to be taken discreetly and ubiquitously, which suggests that these measures could soon become common in everyday human-computer interaction.

Physiological measures of emotion have been studied extensively. A well-tried measure of emotional state is facial electromyography (EMG) which reflects the electrical activity of facial muscles. For example, *corrugator supercilii* muscle (activated when frowning) activity increases during negative experiences and decreases during positive experiences [7]. *Zygomaticus major* muscle (activated when smiling) activity changes in the opposite manner during affective stimulation. Based on these correlations, Partala and others [8,9] developed person-dependent online and person-independent offline classifiers for emotional experiences with accuracies of about 70% to 80% depending on stimuli.

As another example of physiological measures that reflect experienced emotions, heart rate responses have been found to differ between different emotional stimulations [6,10,11]. In these studies both negative and positive visual stimuli produced a similar heart rate response pattern of decelerations and accelerations. However, as reported in [10], unpleasant stimuli provoked the greatest initial deceleration, while pleasant stimuli resulted in the highest peak acceleration. Also voluntarily produced facial activations have been found to induce emotion-specific patterns of autonomic central nervous system activity, including changes in heart rate [11].

The variability of heart rate has been associated with emotions as well. For example, low frequency heart rate variability accentuates when the person experiences anger [12]. However, both heart rate and heart rate variability are affected by attentional as well as emotional processes [10,13]. For example, Anttonen and Surakka [6] found in their study that only about 62.5% of individual heart rate responses to emotional visual stimulation were well or adequately in line with the overall mean response.

As illustrated by the previous discussion of EMG and heart rate measures, recognizing mental states and responses based on one physiological signal is challenging because physiological responses are person-dependent and they reflect several overlapping reactions and mental processes. For these reasons, simultaneous psycho-physiological measures are often used to augment each other and provide converging data for conclusions [e.g., 14]. However, these additional measures complicate the setup required for measurement, especially compared to novel methods for detecting heart rate [6]. Further, often these systems have to be adapted to each person, that is, they are person-dependent. This limits the scope of these systems, as they are not readily applicable for multiple users, for instance, in public spaces.

The present work investigated the construction of a person-independent online system for detecting psychophysiological reactions based on heart rate patterns alone. The system consisted of two stages. First, meaningful events were detected based on changes in heart rate patterns. Next, patterns of heart rate and heart rate variability measures were extracted and automatically classified using several classification methods. Finally, the performance of the system was analyzed, in both detecting events and classifying them.

2 Methods

2.1 Materials

Twenty-seven students (4 female) participated in an experiment investigating the effects of voluntary facial muscle activations on subjective experiences and heart rate patterns [15]. During the experiment, heart activity was registered with a wireless electrocardiography (ECG) measurement patch [16] while participants performed voluntary activations of two facial muscles (*corrugator supercilii* and *zygomaticus major*). Activity was held at one of three intensity levels for 30 seconds. Each participant performed each of the six tasks five times, for a total of 30 tasks per participant. After each task, participants were asked to rate the experienced emotional valence and the ease of the task with two bipolar scales from 1 (unpleasant, difficult) to 9 (pleasant, easy). An interval of 30 seconds preceded each task.

The data for present study consisted of subjective ratings of emotional valence and both non-uniformly and uniformly sampled heart rate (HR) values which were extracted from the ECG. First, recordings with malfunctioning ECG equipment were recognized and discarded, leaving data from 17 participants for further stages. Instantaneous HR sampled at 5 Hz was used as the material for the event detection stage in the present study. In addition, a non-uniformly sampled heart rate signal was computed from the data in order to provide additional material for the pattern classification stage.

2.2 Procedure and Data Analysis

The event detection stage was performed as follows. First, an autoregressive moving average (ARMA) model with AR order of 1 and MA order of 2 was trained using instantaneous HR data from all subjects. Then, the model was used to predict the succeeding heart rate value based on two previous samples. A series of prediction error (PE) values was computed by subtracting the true value from the prediction. Finally, potential events were extracted from squared PE data using Eq. (1), where 1 signifies a suggested onset or offset of a task and 0 signifies a non-event.

$$Event(t) = \begin{cases} 1, if \sum_{n=t}^{t+3} PE^2(n) \Big/ \sum_{n=t-4}^{t-1} PE^2(n) > 10^4 \\ 0, otherwise \end{cases} \quad (1)$$

When Eq. (1) suggested a potential event during the first fifteen seconds after a task had begun or ended, the suggestion was counted as a hit. Subsequent suggestions during the same fifteen-second period were disregarded. Periods without a hit were counted as misses. If a suggestion occurred at any other time, it was counted as a false alarm.

Pattern classification was based on five features extracted from instantaneous and non-uniformly sampled HR data. The mean, minimum, and maximum heart rate values during the task were computed from instantaneous HR with five-second baseline correction. Low frequency (0.04 to 0.15 Hz) and high frequency (0.15 to 0.40 Hz) heart rate variability was extracted using the Lomb periodogram [17,18]. The true class labels were based on three different data: the voluntarily activated muscle, intensity level of activation, and the subjective ratings of emotional valence experienced during the task. Ratings were divided into three classes: negative (1 to 3), neutral (4 to 6), and positive (7 to 9) experiences.

The classification was performed as follows. First, an unbiased sample was created by randomly selecting an equal numbers of samples (as many as in the smallest class) from each class. Second, a projection to a two-dimensional space was computed using multiple discriminant analysis. Third, projected samples were used to train a classifier using leave-one-out cross validation and either the nearest neighbor (NN) or the minimum squared error (MSE) algorithm [e.g. 19]. The former was used for classification to three categories, while the latter was used for classifying data from two classes. The procedure was repeated 1000 times (starting from random selection of samples). Each result was treated as a sample in later statistical analysis.

Pattern classification results were analyzed by computing the true class rate (TCR), the false class rate (FCR), the precision, and the accuracy of classification. TCR of class **A** indicates the percentage of samples correctly classified to **A**. FCR of **A** shows the percentage of samples from other classes incorrectly classified to **A**. Precision of **A** tells how many samples classified to **A** were correctly classified (i.e. their true label was **A**). The accuracy of the classifier shows the total percentage of correctly classified samples in all classes. Roughly stated, higher values signify better performance in every metric with the exception of FCR for which lower values are better.

The performance of event detection and pattern classification stages was compared to the values expected by chance (i.e. random guessing) using two-tailed t-tests. For example, the expected performance of event detection corresponds to the number of hits resulting from a random placement of suggestions from Eq. (1).

3 Results

Using the event detection algorithm, the onsets and offsets of tasks were detected with accuracies of 66.4% and 70.2%, respectively. The overall accuracy was 68.3%. This was significantly better than expected by chance, $t(16) = 4.0166$, $p < 0.001$, $MD = 4.566 \pm 1.048$ (*S.E.M.*). However, 59.7% of suggestions from Eq. (1) were false alarms, which can be considered quite a high percentage.

The results of pattern classification are presented in Table 1 which shows that all classification metrics

Table 1. The results of pattern classification in percentages (± S.E.M.). Statistically non-significant results are presented in bold.

Method	Accuracy	Class	TCR	FCR	Precision
NN with intensity level of facial muscle activation	36.63 (±0.06)	Low intensity	36.04 (±0.09)	29.63 (±0.06)	37.83 (±0.08)
		Medium intensity	31.46 (±0.11)	31.41 (±0.06)	**33.34 (±0.09)**
		High intensity	42.38 (±0.09)	34.01(± 0.07)	38.42 (±0.08)
NN with experienced emotional valence	35.80 (±0.15)	Negative	34.45 (±0.24)	28.95 (±0.13)	37.24 (±0.22)
		Neutral	31.48 (±0.23)	31.18 (±0.13)	**33.46 (±0.22)**
		Positive	41.46 (±0.22)	36.18 (±0.14)	36.46 (±0.18)
MSE with activated facial muscle	50.65 (±0.00)	Corrugator	20.35 (±0.11)	19.04 (±0.12)	51.81 (±0.05)
		Zygomaticus	80.96 (±0.12)	79.65 (±0.11)	50.40 (±0.01)
MSE with intensity level of facial muscle activation	65.83 (±0.02)	Low intensity	61.42 (±0.04)	29.76 (±0.02)	67.36 (±0.01)
		High intensity	70.24 (±0.02)	38.58 (±0.04)	64.56 (±0.02)
MSE with experienced emotional valence	58.56 (±0.15)	Negative	56.26 (±0.57)	39.14 (±0.66)	61.17 (±0.25)
		Positive	60.86 (±0.66)	43.74 (±0.57)	59.20 (±0.21)

besides the precision in medium intensity and neutral classes are significantly different from expected values, $p<0.0001$ for all.

Classification to the three classes of activation intensity using NN algorithm achieved quite modest results. Classifying data to the three categories of emotional valence using NN algorithm produced similar, modest results. TCR was significantly below the value expected by chance for both medium intensity activations and neutral emotional ratings. Further, as the precision in classifying these categories did not significantly differ from random guessing, samples from these categories were excluded and another round of classification was performed with a MSE classifier. As shown in Table 1, this classification resulted in significantly better performance for recognizing both activation intensity and experienced emotional valence as compared to random guessing.

4 Conclusion

The current study presented the first steps towards building a person-independent online system for recognizing psychophysiological reactions. The preliminary results of our study showed that heart rate is a promising measure for detecting and recognizing meaningful events. Changes in the voluntary behavior of a person, that is, when muscle activations started or ended, could be detected with an overall accuracy of 68.3%. Although the rate of false alarms was quite high as well (59.7%), these suggested events are useful for a complete system as an indication when more detailed analysis is required. This way, processing resources can be saved for other tasks at other times, supporting a more efficient system.

Event detection was achieved using a simple ARMA(1,2) model and some basic arithmetic operations with less than one second worth of heart rate samples. Thus, our algorithm reacts quickly to changes in heart activity and requires very little effort to perform. As such, it is feasible as a preprocessing step for these kinds of systems.

Our results also showed that, in most cases, heart rate based classification was significantly better than random guessing in classifying events according to the activated muscle, the intensity of activation, and the experienced emotional valence. However, when classifying to three categories, the accuracy in recognizing the middle category (i.e. neutral experience, medium intensity activation) was worse than expected from random placement. Further, the overall accuracy in classifying to three categories was only few percentages better than expected by chance. This suggests that the range of psychophysiological reactions was limited and sufficient only for recognizing the two clearest opposites. The performance was even more modest when recognizing which of the two muscles was activated (accuracy = 50.7%).

Nonetheless, whether the experience was rated emotionally negative or positive could be predicted with an overall accuracy 58.6%. More importantly, the precisions in recognizing these classes were 61.2% and 59.2%, respectively. Thus, a system reacting according to the recognized class, for example, calming a negatively aroused person, would take the correct action more often than not. The accuracy of recognizing the intensity of facial activation was even better, 65.8% in overall.

In summary, our preliminary results indicate that heart rate can be used to make automatic inferences about both the emotional valence and intensity of a psychophysical reaction, and heart rate seems to be suited for the latter task in particular. Further, these inferences can be made with person-independent methods which are suitable for online classification.

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