Analysis of the effect of emotion elicitation on the cardiovascular system

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Abstract

Emotions play an important role in our everyday life, influencing our decision-making process, and also affecting our physiology. Several studies in literature have proposed successful classification models for emotion recognition combining multimodal physiological measures without dwelling on the physiological significance of the measures. Our study aims at finding cardiovascular indices related to the autonomic nervous system that can explain how autonomic control of the heart responds with respect to specific emotions: happiness, fear, relaxation and boredom. Pulse arrival time and pulse pressure measurements have been shown to be significantly separating the 4 emotions, especially along the arousal dimension as expected from previous findings. Importantly, these blood pressure related indices also yielded relevant insights into characterizing the valence dimension when looking at high and low arousal subsets. In addition, these measures were found to be correlated with classical autonomic indices and explanatory in the cardiovascular and autonomic changes elicited by different emotions. Autonomic indices were then used to train a basic support vector machine model obtaining four-class test accuracy in discriminating happiness, relaxation, boredom and fear equal to 44%, 67%, 55%, 44% respectively.

1. Introduction

Emotions play a fundamental role in the life of human beings as they represent an evolutionary factor that ensures survival and reproduction through adaptation to the environment [1]. From a biological point of view, emotions are a very complex network of neuronal and hormonal interactions which generate cognitive processes, aimed at influencing the decision-making process.

Emotion recognition is finding many applications in many areas including Human-Computer and Human-Robot Interaction [2]. Emotion related technologies, indeed, have already been introduced in our daily life and in the very next future our mood could be perceived by our devices, appliances, cars, etc.

Many emotion recognition methods deal with the Central Nervous System (CNS) by using the Electroencephalogram (EEG) from which a large number of measures can be estimated to derive the emotional state. Affective elicitations arouse the prefrontal cortex which encodes the stimuli and transmit them to the brainstem through other central areas, producing this way an emotional response [3]. Many investigations regarding emotion elicitation have found significant links between the involvement of multiple cortical and subcortical regions with both positive and negative emotions [4].

Despite the importance of the CNS in regulating the emotional sphere of each of us, an important milestone is also being reached by the study of changes in the peripheral autonomic nervous system (ANS). Indeed, the ANS is controlled by the CNS network, stemming from brainstem dedicated areas that drive the vagus nerve and the sympathetic spinal derivations. These two branches are responsible for heart rate variability, sweating and also drive the pupil dilation mechanisms and the activity of some facial muscles which regulate social engagement via facial expression. The clear advantage of studying the ANS with respect to CNS is that nowadays many wearable systems can easily monitor physiological variables driven by the ANS resulting in less invasive than measuring central signals [5] and a less cumbersome instrumentation.

The general objective of our investigation is to find cardiovascular indices, linked to changes in the ANS, which can explain how, at a physiological level, control of the heartbeat and its cardiovascular effects on blood pressure is characterized with respect to four different emotions. In this study, we focus our attention on two measures derived by considering both ECG and BVP time series: pulse arrival time (PAT) and pulse pressure (PP).

1.1. Study design and data

The Continuously Annotated Signals of Emotion (CASE) dataset is considered for this analysis [6]. This database includes physiological recordings (1000 Hz) obtained from ECG, BVP, EMG, GSR, respiration and skin temperature on 30 subjects who watched video-stimuli. Both subjective and pre-study annotations of the videos are provided in form of *valence* and *arousal* scales ranging from 1 to 9. Four emotions (happiness, relaxation, boredom, fear) were elicited with 8 different videos, 2 for each emotion, randomized in the order of display and separated each by a 2-minute blue screen visualization.

The presented study considers only a subset of cardiovascular signals (ECG and BVP) and pre-study annotations in order to ensure balanced classes.

Due to the different length of the videos, only the last 100 seconds of each video were considered. The last part of the videos were considered in order to limit the influence of the previous emotion at the beginning of the following one. Moreover, by looking at the videos, we noticed that the last part was the more relevant for the emotion aroused. In order to compute the features needed for the study from the physiological signals, the lengths of the signal segments for each emotion were uniformed to compute the variation of each feature between every video and the previous blue screen video, used to bring emotional conditions back to baseline.

For each subject examined all signals were acquired in a single session, so the signals were processed as explained in the next section before being cut. Then, all the features were extracted from the cut signals.

1.2. ECG/BVP signal processing

The ECG signal was initially filtered with a zero-phase low-pass Butterworth filter of 4th order and then it was downsampled at 250 Hz.

R peaks on the ECG signal were identified through a Pan-Tompkins based algorithm [7]. Thanks to the extracted peaks a total of 11 features were computed. In this regard, different heart rate variability features were included. Considering both time domain and frequency domain features computed from the available 100 seconds signals. Specifically, frequency domain features were obtained from the autoregressive modeling of RR series with the Yule-Walker method. The order of the model was chosen as the lowest order in the range 7-15 that provided white residuals and/or minimized the Akaike information criterion.

The BVP signal was pre-filtered at 25 Hz with a zero-phase low-pass Butterworth filter of 4th order and successively down-sampled at 250 Hz. The obtained signal was then low-pass filtered with a 4th order Butterworth filter with cut-off frequency equal to 5 Hz. Fiducial points (systoles and diastoles) on the BVP signals were extracted and synchronized with the corresponding R-peaks on the ECG signal.

Pulse arrival time (PAT) series and pulse pressure (PP) series were computed as the time between the R-peak and the systolic event and the difference between systolic and diastolic values, respectively.

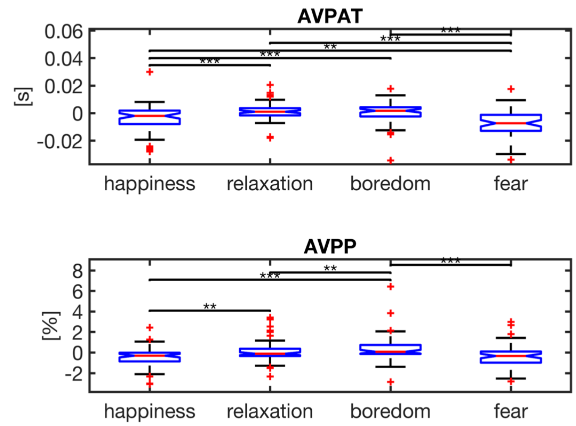

Figure 1. In the upper panel delta distributions for AVPAT feature are shown according the four emotions. In the lower panel delta distributions for AVPP feature are shown as well. Significances are marked with *. ** if the p-value resulted lower than 0.01and *** if the p-value resulted lower than 0.001.

For statistical analysis, the following features were included: ***ECG features****: average and standard deviation of NN intervals (AVNN, SDNN), power spectral density of RR in very low (RR VLF), low (RR LF) , high (RR HF) frequencies and LF/HF, normalized power spectral density of RR in low (RR LFn) and high (RR HFn) frequency ranges.* ***BVP features****: average pulse pression (AVPP), average and standard deviation of systolic amplitude pressure (AVSAP, SDSAP), diastolic amplitude pressure (AVDAP, SDDAP).* ***ECG-BVP features****: average pulse arrival time (AVPAT) and power spectral density of PAT in very low (PAT VLF), low (PAT LF) and high (PAT HF) frequency ranges.*

2. Statistical analysis

After computing all the delta features, the Wilcoxon signed-ranked test with Bonferroni correction was performed for each feature among the four different emotions. Most of the features showed less than 4 significant comparisons, with the exception of the average pulse pressure (AVPP) and the average pulse arrival time (AVPAT) which showed respectively 4 and 5 significant comparisons out of 6 comparisons. Figure 1 shows the boxplots for the two most relevant features.

The standard heart variability measures confirm previous results on the ability of these indices to resolve discrimination along the arousal scale [8]. On the other hand, both AVPP and AVPAT are able to separate emotions on both valence and arousal dimensions, although not for all emotions. In particular, AVPAT alone is able to discriminate all the emotions except relaxation

Table 1. Correlations between AVPAT and AVPP with respect to ANS features. Bold numbers represent significant correlations (p<0.05).

Correlation	AVNN	RR VLF	RR LF	RR HF
AVPAT	**0,59**	**-0,32**	**-0,19**	-0,05
AVPP	**0,24**	-0,06	-0,09	0,004
Correlation	RR LFn	RR HFn	RR LF/HF	
AVPAT	**0,13**	**0,24**	**-0,15**	
AVPP	**-0,13**	**0,19**	-0,09	

and boredom (high-low valence), which are successfully separated by AVPP though.

In order to characterize the relationship between these features with respect to classical autonomic indices, their correlations are shown in Table 1.

AVPAT results to be slightly and negatively correlated with RR LF and RR LF/HF, positively correlated with normalized RR HF and strongly (positively) correlated with AVNN. Normalized RR LF results slightly and positively correlated with AVPAT. AVPP is slightly and positively correlated with AVNN and normalized RR HF as well as slightly negatively correlated with normalized RR LF.

In order to estimate how AVPAT and AVPP behave, on average, according to each emotion, standard errors and 95% confidential intervals were computed. In particular, we tried to see whether the combination of these two features could manage to separate the 4 emotions. In this regard, Figure 2 shows 2D boxplots given by the combination of the values of the two features. The asterisks represent the average values of AVPAT and AVPP, while inner rectangles represent the average +/- the standard errors computed as the standard deviation over the root of the number of samples and outer rectangles represent the average +/- 95% confidential intervals, computed as 1.96 multiplied by the standard error. This measure can give us insights about the capability of these two features in estimating their averages for each emotion.

In order to quantify the measure of average estimations, we computed for each emotion the ratio between the area of intersection of each couple of outer rectangles and the area of each outer rectangle itself. As we can notice from Figure 2, the rectangles relating to happiness and fear do not intersect with relaxation and boredom and vice versa. Thus, we obtained percentages of non-intersection of 85.70% for happiness, 65.59% for relaxation, 76.32% for boredom and 92.47% for fear.

Both AVPAT and AVPP seem to separate better the arousal dimension with respect to the valence one. Fear and happiness, which belong to high arousal, create indeed a different cluster with respect to relaxation and boredom,

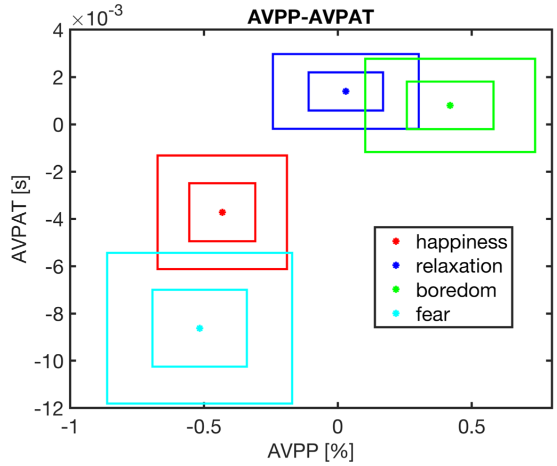

Figure 2. 2D boxplots are represented. * represent the averages of AVPP on x axis and AVPAT on y axis. Inner rectangles are linked to the average features +/- the standard error and outer rectangles are linked to the average features +/- 95% confidential intervals for the average estimations.

belonging to low arousal instead. Regarding the valence dimension, on the other hand, the difficulty in separating emotions can be appreciated in Figure 2, as happiness and relaxation theoretically should form a cluster different from fear and boredom.

3. Support Vector Machine classifier

We created a simple model for emotion recognition by means of a Support Vector Machine classifier. In order to provide a simple interpretable model we decided to consider only the six most important cardiovascular features. To this extent we chose the most significant features from the ECG identification (RR HF, RR HFn, AVNN), from the BVP identification (AVDAP and AVPP) and from the combined identification (AVPAT).

The dataset was split randomly into training (70% of the sample, 168 records) and test (30% of the sample, 72 records) datasets. Stratification was applied to maintain the same percentage of records in the four classes in the original dataset and in the training and test partitions.

Given the small size of the dataset, including 240 records (8 videos*30 subjects), the classification model was optimized using 5-fold cross-validation on the training dataset. The performance of the model was evaluated by measuring accuracy on the training and test sets. The model was built by using a linear kernel and standardized features with respect to their standard deviation. The average training accuracy for the 4 class problem was found equal to 44% (47% of the best model), an average validation accuracy equal to 33% (41% of the best model) and an average test accuracy equal to 53%, in discriminating the 4 emotions. Dividing by emotion, happiness reached a test accuracy of 44%, relaxation of 67%, boredom of 55% and fear of 44%.

4. Discussion

The aim of the study is to introduce and characterize new indices (AVPP and AVPAT) for emotion recognition. The statistical characterization obtained from computing AVPAT and AVPP suggests that cardiac and peripheral vascular activities are strongly affected by autonomic changes elicited by emotions. AVPAT conveys information from both the activity of the heart and the state of the vessels, whereas AVPP is mainly influenced by vasodilation, vasoconstriction and respiration phenomena [9]. In this perspective, as shown in Figure 1, the decrease in AVPAT and AVPP, associated with happiness and fear (high arousal), might be due to the strong sympathetic activation, inducing an increase in heart rate and vasoconstriction, consequently decreasing the time of pulse event with respect to R-wave occurrence and reducing the excursion of the pulse pressure. Vice versa, low arousal emotions are associated with an increase in pulse arrival time and pulse pressure with respect to baseline, thus indicating that cardiovascular changes elicited by these emotions are mainly related to a peripheral vasodilation. These considerations are in accordance with the results obtained in the correlation analysis. Importantly, as it can be noticed in Figure 2, AVPAT measurements are effective in distinguishing emotions along the valence dimension when dealing with high arousal emotions (happiness and fear). This is possibly due to the higher sensitivity in estimating the sympathetic activation (both cardiac and peripheral). On the other hand, AVPP shows a good ability in discriminating the valence dimension when low arousal emotions (relaxation and boredom) are considered. This could be attributed to the high sensitivity in estimating the sympathetic peripheral deactivation associated with valence.

In conclusion, as usually ECG derived measures have been found useful in separating the arousal dimension, the main problem lies on being able to estimate the valence dimension, which is more difficult to be recognized since it is less related to the ANS. In this perspective, AVPAT and AVPP do show a specific ability to stratify the valence dimension, in particular when looking at high and low arousal emotion subsets, respectively. The higher difficulty in separating boredom from relaxation might be associated with the computation of differences with respect to baseline. It is reasonable to deduce that, depending on the subject, the blue screen can be considered either relaxing or boring, thus creating a mixing effect between the two emotions.

5. Conclusion

We here present an original characterization of emotional states through physiological measures extracted from the ECG and BVP time series. In particular, we focus attention on two indices related to cardiovascular control dynamics: the average pulse arrival time, computed as the time between an R peak in the ECG and the following systolic value in the BVP and the average pulse pressure derived from the difference in amplitudes between each systolic and diastolic pressures. Results highlight the importance of these features in describing cardiovascular and autonomic changes elicited by emotions, particularly along the valence dimension. To further validate our assessment, we developed a basic machine learning model including also these new features and observed an improved performance in identifying the different emotions with a very limited number of features extracted from non-invasive cardiovascular signals.

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