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Do men and women have different ECG responses to sad pictures?

Ateke Goshvarpour, Ataollah Abbasi [*,1], Atefeh Goshvarpour

Computational Neuroscience Laboratory, Department of Biomedical Engineering, Faculty of Electrical Engineering, Sahand University of Technology, Tabriz, Iran

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ABSTRACT

Gender differences in emotional experience are the subject of many physiological and psychological investigations. However, the effect of gender differences on the affective electrocardiogram (ECG) signals has not been well established. This study was aimed to compare the emotional ECG responses of males with that of females by means of signal processing techniques. It has been also attempted to determine which features can properly show the physiological differences of two groups during sad stimuli. For this purpose, time-, frequency-, wavelet-, and nonlinear- based approaches were examined. Applying the Wilcoxon rank sum test, significant differences between the groups were inspected. The analysis was performed on 47 college students. The effect of data length on the results was also investigated. The best results were achieved using the data length of 10 s with an overlap of 50%. In this case, the nonlinear features outperformed the other measures. 82.43% of nonlinear features, 73.33% of Db4 wavelet measures, and 64.29% of time and frequency indices showed significant differences between ECG parameters of men and women. Specifically, recurrence quantification measures and lagged Poincare indices have the best performance. In conclusion, the results of this study emphasize the efficiency of nonlinear features in the analysis of physiological signals in a negative emotional state. In addition, ECG signals can confidently serve as an indicator of emotional responses.

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1. Introduction

In terms of dimensional model, emotions grouped into the positive and negative valences [1]. Negative emotions usually caused undesirable impacts on the physical and mental health of a person and they could have also led to some cardiovascular and mental diseases [2]. Therefore, it is important to study the mental and autonomic effects of these emotions. Sadness is a basic emotional state which belongs to the negative valence.

Different physiological responses to the sad inductions have been reported. Decreased HR and SCL have been documented in response to the sad pictures [3]. Furthermore, sadness associated with the distinctive brain regions; specifically, motivates the right hemisphere [4]. On the other hand, these changes alter with respect to the individual characteristics. One of the most important factors is gender. It has shown that a wider portion of the limbic system is activated in women than that of men during sadness; however, comparable changes in mood have been self-reported [5].

Electrocardiogram (ECG) is a biological signal which noninvasively indicates the activity of the heart in different situations. It has been considered as an effective tool in diagnosis of physical and mental diseases. Due to the time-consuming, complexity, and low precision, visual inspection of ECG is not applicable. Instead, automated, computer aided algorithms have been developed. Various time and frequency methods as well as nonlinear approaches have been introduced to analyze ECG. For the sake of nonstationary and chaotic nature of the biological signals, time and frequency parameters cannot present hidden and subtle information about the signals. To overcome the shortcomings, nonlinear methodologies are implemented.

To date, several ECG derived indices were applied to the problem of emotion. Recognition of two emotions of joy and sadness was fulfilled by means of wavelet transform (WT) indices of ECG [6]. Similar work was reported in [7]. To classify affective states, wavelet based indices were also applied in other works [8]. The empirical mode decomposition (EMD) technique was appraised to detect the evolving emotion patterns on ECG [9]. Jerritta et al. [10] computed Hurst using Rescaled Range Statistics (RRS) and Finite Variance Scaling (FVS) methods and combined it to the Higher Order Statistics (HOS) to classify emotional states. Then [11], they examined power and entropy features of Intrinsic Mode

* Corresponding author.
E-mail address: ata.abbasi@sut.ac.ir (A. Abbasi).
[1] CNLab: http://ee.sut.ac.ir/Labs/CNLab/index.html

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Functions (IMF) derived from EMD to develop a user-independent emotion recognition system. In [12], Lyapunov Exponents (LE) and Approximate Entropy (ApEn) were assessed during emotional visual elicitation. In the other work, the authors [13] included that spectrum, bispectrum, and the LE can provide accurate real-time characterizations of emotional responses through ECG. Recently, for classification of arousal and valence dimensions of emotion, some indices from time domain and Power Spectral Density (PSD) analysis as well as the ApEn, the Detrended Fluctuation Analysis (DFA) and the lagged Poincare plot, as nonlinear features, were implemented [14]. More recently [15], DFA, LE, and ApEn along with some standard features were implemented to investigate the effect of affective picture sequences. Despite, the huge amount of features proposed in the literature to deal with the problem of affect recognition, there is not any consensus about the features which have significant roles in emotion classification.

The purpose of this article was to examine if there is any difference between men and women in the affect detection using ECG signal. Among the various categories of emotions, sadness was chosen. Therefore, a comprehensive evaluation of ECG signal was provided through several linear and nonlinear features to determine the best features affected by sad induction. These features can serve to identify the emotional pattern associated with ECG signals. Specifically, to show the significant differences between men's and women's physiological responses during sad picture viewing. These measures can provide additional and comparative information about the underlying mechanism of the heart during the sad inductions.

The structure of the remaining parts of the article is as follows. First, the signal acquisition procedure is introduced. Then, the proposed methodology is described in detail. Next, the results are presented. Finally, the article is concluded.

2. Material and methods

The proposed methodology consists of three steps: ECG signal acquisition, feature extraction, implementing statistical test (Mann-Whitney *U* test). Fig. 1 summarizes the feature extraction step.

2.1. Data

The ECG signals of 47 college students were recorded, while watching sad pictures chosen from the International Affective Picture System (IAPS) [16]. The subjects under study were 47 college students (31 women with the age range of 19–25 years and mean age of 21.90 ± 1.7 years and 16 men with the age range of 19–23 years and mean age of 21.1 ± 1.48 years). The ECG signals were taken in Computational Neuroscience Laboratory using a 16-channel PowerLab (manufactured by ADInstruments) at 400 Hz sampling rate. A digital notch filter is applied to remove power line noise. More information about signal acquisition procedure can be found in [15].

2.2. Time domain features

The time domain parameters are mean, standard deviation, maximum, minimum, median, mode, root mean square (RMS), second-, third-, and fourth- moments.

2.3. Frequency domain analysis

Applying the Fast Fourier transform (FFT) [17], power spectral density (PSD) of ECGs is estimated. Then, maximum and mean values of the power as well as their frequency are calculated as frequency based parameters.

2.4. Discrete wavelet transform

Applying the Discrete Wavelet Transform (DWT), the signal is converted from the time domain to the wavelet domain and different coefficient values are obtained [18]. In the DWT, the given ECG signal is passed through two kinds of filters: a high pass and a low pass one. Employing the first filtering, as it is sub-sampled by a factor of two, the halves of the samples are excluded. Then, the extracted coefficients from the low pass filter are subjected to another low pass and high pass filters. This procedure is repeated until the last level of decomposition is realized. As a result, some approximate (low pass) and detailed (high pass) coefficients are excluded from a signal.

Mathematically, a low-pass filter, *h*, of the WTs should fulfil the standard quadrature mirror filter condition as follows:

$$H(z)H\left(z^{-1}\right) + H(-z)H\left(-z^{-1}\right) = 1 \tag{1}$$

Where *H(z)* refers to the z-transform of *h*. Then, the definition of the high-pass filter is presented as follows:

$$G(z) = zH\left(-z^{-1}\right) \tag{2}$$

By taking into consideration the initial condition of $H_0(z) = 1$, a chain of filters with increasing length is accomplished:

$$\begin{aligned} H_{i+1}(z) &= H\left(z^{2^i}\right) H_i(z) \\ G_{i+1}(z) &= G\left(z^{2^i}\right) H_i(z), \quad i = 0, \ldots, I-1 \end{aligned} \tag{3}$$

Its' time domain transform is presented as follows:

$$\begin{aligned} h_{i+1}(k) &= [h]_{\uparrow 2^i} * h_i(k) \\ g_{i+1}(k) &= [g]_{\uparrow 2^i} * h_i(k) \end{aligned} \tag{4}$$

where the up-sampling by a factor of *m* is shown by $[\cdot]_{\uparrow m}$. The sampled discrete time reflected by *k*. Next, the calculation of standardized wavelet $\phi_{i,l}(k)$ and scale basis function $\psi_{i,l}(k)$ is performed by:

$$\begin{aligned} \phi_{i,l}(k) &= 2^{i/2} h_i\left(k - 2^i l\right) \\ \psi_{i,l}(k) &= 2^{i/2} g_i\left(k - 2^i l\right) \end{aligned} \tag{5}$$

where $2^{i/2}$ shows the inner product normalization, *i* and *l* are the scale and the translation parameters, respectively. Consequently, the DWT decomposition is accomplished as follows:

$$\begin{aligned} a_{(i)}(l) &= x(k) * \phi_{i,l}(k) \\ d_{(i)}(l) &= x(k) * \psi_{i,l}(k) \end{aligned} \tag{6}$$

where $a_{(i)}(l)$ and $d_{(i)}(l)$ are the approximation and the detail coefficients at resolution *i*, respectively.

Several wavelet families have been introduced. Selection of an appropriate wavelet function and the number of decomposition levels are important issues in DWT. However, there is no special rule for selecting the wavelet families. It is important to select wavelet family in a way that is closely matched to the signal being processed. On the other hand, the number of breakdown levels is designated based on the signals' dominant frequency components. In the present study, several wavelet families and levels were examined. Among them, daubechies, coiflet, and symlet wavelet functions (db4, coif5, sym8) with eight levels outperformed the others. In addition, the previous literature also used similar wavelet mothers for ECG signals [19–21].

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