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An Emotion Recognition Approach based on Wavelet Transform and Second-Order Difference Plot of ECG

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Abstract

Emotion, as a psychophysiological state, plays an important role in the human communications and daily life. Emotion studies related to the physiological signals have recently been the subject of many research works. In this work, a hybrid feature-based approach is proposed to examine the affective states. To this effect, the electrocardiogram (ECG) signals of 47 students are recorded using the pictorial emotion elicitation paradigm. Affective pictures are selected from the International Affective Picture System and assigned to four different emotion classes. After extracting the approximate and detailed coefficients of Wavelet Transform (WT/Daubechies 4 at level 8), two measures of the second-order difference plot (CTM and D) are calculated for each wavelet coefficient. Subsequently, Least Squares Support Vector Machine (LS-SVM) is applied to discriminate between the affective states and the rest. The statistical analysis results indicate that the CTM density in the rest is distinctive from the emotional categories. In addition, the second-order difference plot measurements at the last level of WT coefficients show significant differences between the rest and the emotion categories. Applying LS-SVM, a maximum classification rate of 80.24% was reached for discrimination between the rest and the fear. The results of this study indicate the usefulness of WT in combination with the non-linear technique in characterizing the emotional states.

Keywords: *Combining Features, Electrocardiogram, Emotion, Second-Order Difference Plot, Wavelet Transform.*

1. Introduction

Electrocardiogram (ECG) signals are a valuable tool used to study the physiological changes of the heart in different situations. These signals have been used for the detection of various ailments such as heart diseases, arrhythmia, and epilepsy [1-6]. Cardiac fluctuations somehow represent the performance of the autonomic nervous system (ANS), particularly the sympathetic and parasympathetic functions [7-9]. As a result, ECG signals have also been applied to evaluate various mental and psychological conditions [10-11]. Emotion is known as a psychophysiological state. Various theories have shown that ANS and, in particular, the heart functions play a major role in the presentation of emotional states (for a brief review, see [12]). In addition, there are several attempts to evaluate and classify the emotional modes using the heart measures [13-15]. There are several emotion recognition applications in the human life. Human-computer interfaces, interaction between patient and doctor in some diseases such as schizophrenia and autism, and computer games and entertainments are some examples [16-19]. This crucial role has resulted in the advent of a new discipline called "affective computing". In this field of research, there have been many attempts to develop some automatic devices that can deal with the problem of human affect recognition and interpretation.

In the past, different analytical methodologies have been presented using ECG signals. Over the past decades, Wavelet Transform (WT) has become an interesting tool for evaluating the biomedical signals [20]. It has been extensively employed for feature extraction and classification of heart beats in different conditions. WT is able to demonstrate the temporal and spatial information of the signals, simultaneously. Owing

to the use of window with variable width, it is more flexible than a short-time Fourier transform. In this sense, long-term information with low-frequency and short-term information with high-frequency can be displayed concurrently. The procedure is very useful for analyzing the non-stationary signals owing to the outstanding of the subtle changes in the morphology of the desired scale of a signal.
On the other hand, due to the chaotic behavior of biological systems including the heart, the application of non-linear methods has been suggested [21]. Up to the present time, several non-linear approaches have been studied. One of the most common non-linear approaches is based upon the graphical representation of the signals. The Poincare plots, recurrent-based analysis, and Central Tendency Measure (CTM) are some examples. CTM is defined as a chaotic modeling approach [22]. It is usually applied to quantify the degree of variability in a time-series. In the current work, this non-linear technique was combined with the wavelet coefficients to evaluate the heart functions in different affective states. We believe that by combining the wavelet-based methods with non-linear approaches, a detailed information can be obtained from the signals that cannot be recognized with each one of the methods separately. As a result, this combination may improve the recognition rates.
The structure of the remaining parts of the article is as what 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. Methods

In the current work, a six-step procedure was adopted. First ECG signals were recorded during affective visual stimuli. Secondly, the preprocessing stage was performed, which involved line noise removal and signal segmentation according to the blocks of emotion classes. Thirdly, the WT coefficients (db4 at level 8) were extracted. Fourthly, the second-order difference plot measurements were implemented to the WT coefficients. Next, the statistical Mann-Whitney U-test was performed. Finally, the classification accuracy was evaluated based on the extracted features. Figure 1 summarizes the adopted steps of this work.

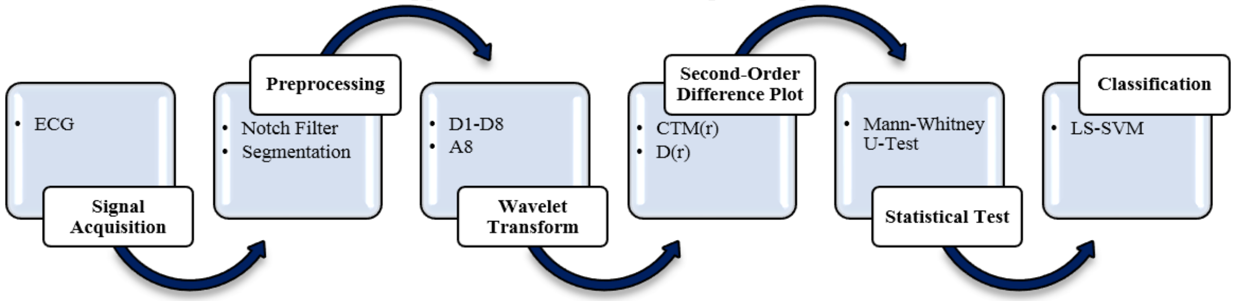


Figure 1. Block-diagram of proposed methodology applied in current study.

2.1. Data collection

In order to recognize emotions based on ECG signals, images gathered from the International Affective Picture System (IAPS) were employed [23]. Based on the dimensional structure, four emotion classes including happy, sad, relaxed, and afraid were chosen.
By combining the two scores arousal and valence, the designation of four different emotional states can be provided. Exactly, employing empirical thresholds on arousal and valence scores, each picture was assigned to one of the mentioned emotional categories. Figure 2 demonstrates the emotional load of the stimuli on a 2D emotion space using the valence and arousal axis. 47 college students including 31 females (age range: 19-25 years; mean age: 21.90±1.7 years) and 16 males (age range: 19-23 years; mean age: 21.1±1.48 years) participated in this study; they were naive to the purpose of the experiment. All the participants were asked to read an agreement form and sign it if they agreed to take part in the study. They were also requested to determine if they were in a very relaxed or very aroused state. Filling out a preliminary questionnaire, it was indicated that they were all healthy subjects. In addition, no history of any epileptic, cardiovascular, neurological, and hypertension ailments was reported. They were instructed not to consume salty and fatty foods or caffeine two hours before the test.During the experiment, the participants were asked to sit in front of a laptop screen, particularly avoid movements of their fingers, hands, and legs, and watch the images. Her/his ECG signals (Lead I) were measured simultaneously [24]. Totally, the ECG signals of 47 students were acquired in Computational Neuroscience Laboratory (CNLab) using a 16-

channel PowerLab (manufactured by ADInstruments). All signals were recorded at a 400 Hz sampling rate. A digital notch filter was applied to remove power line noise. After 2 minutes of rest, in which the subjects were asked to keep their eyes open and watch a blank screen, 28 blocks of emotional stimuli were brought to the screen.

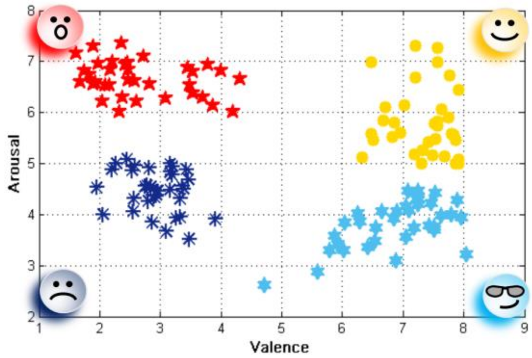


Figure 2. Valence and arousal distributions of pictorial stimuli. Fear: Red pentagrams; Happy: Yellow circles; Relaxed: Blue hexagram; and Sad: Dark blue asterisk.

Constructing a random sequence of the emotional blocks, a similar protocol was applied for all the volunteers. Each block contained 5 pictures from the same emotional class, and was displayed by random to prevent habituation in subjects. Each image was presented for 3 s on the screen leading a total of 15 s per block. 10 s of a blank screen period was applied at the end of each block to allow the return of physiological fluctuations to the baseline. The blank screen was followed by a white plus (for 3 s) in the middle of the screen to attract the subject attention to the center of the screen and prepare for the next block. The whole data acquisition took about 15 min.

After data recording, the subjects watched the same stimuli and their feelings were rated using self-assessment questionnaires. In other words, similar stimuli were brought to the screen, and each subject selected the best-matched emotion for each emotion block on a paper sheet in terms of sad, fear, happy or relaxed. Figure 3 demonstrates the protocol description.

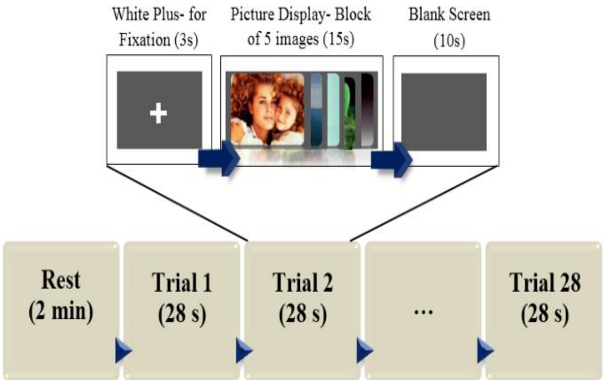


Figure 3. Proposed protocol.

2.2. Feature extraction

2.2.1. Discrete wavelet transform (DWT)

Applying DWT, the signal was transformed from the time domain to the wavelet domain, and different coefficient values were obtained [25].

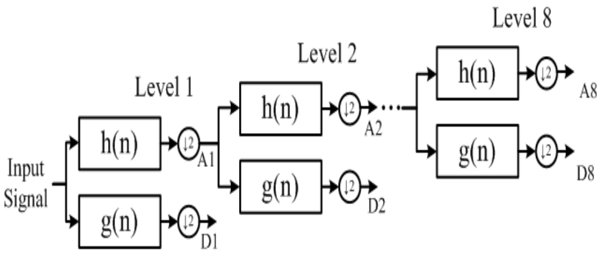


Figure 4. Sub-band decomposition of DWT. g[n] and h[n] are high-pass filter and low-pass filter, respectively.

In DWT, a given ECG signal was passed through two kinds of filters: a high-pass filter and a low-pass one. Employing the first filtering, as it is sub-sampled by a factor of two, half of the samples was excluded. This process resulted in the first level of decomposition. In the next stage, the extracted coefficients from the low-pass filter were subjected to other low-pass and high-pass filters. In order to have different decomposition levels, this procedure was repeated. The frequency band and the number of samples were divided into two equal parts at each level [26]. Therefore, a signal was converted into the approximate (low-pass) and detailed (high-pass) coefficients. It was important to select an appropriate wavelet function and the number of decomposition levels. In the current protocol, the Daubechies mother wavelet function (db4) with eight levels was used. Consequently, A8 corresponded to the eighth level of the approximate coefficients. D1 and D8 were the first to the eighth level of the detailed coefficients. Figure 4 depicts the schematic representation of this.

2.2.2. CTM

Central Tendency Measure (CTM(r)) is an index used to calculate the degree of variability in the second-order difference plot (x(i+2)-x(i+1), x(i+1)-x(i)). To compute CTM, at first, a circular region of radius r was selected. Around the origin (0,0), the number of points existing within the radius was counted. Dividing the achieved number by the total number of points, CTM was calculated. Considering the time series with n points, the quantity of the points on the graphic was n-2:

$$CTM(r) = \frac{\left|\sum_{i=1}^{n-2} \delta(d(i))\right|}{n-2}, \quad (1)$$

where

$$\delta(d(i)) = \begin{cases} 1 & if \ \left([x(i+2)-x(i+1)]^2 + [x(i+1)-x(i)]^2\right)^{0.5} < r \\ 0 & Otherwise \end{cases} \quad (2)$$

where, n and r are the total number of points and the radius of the central area, respectively.

The average distance of the points within a certain radius is characterized by D(r); these distances were calculated by (3):

$$d(i) = \left([x(i+2)-x(i+1)]^2 + [x(i+1)-x(i)]^2\right)^{0.5} \quad (3)$$

2.3. Classification

Support Vector Machine (SVM) is a popular binary classifier, which uses an ideal separating hyper-plane in the feature space. The system results in robust classification rates. More explanation about SVM has been presented by Hu and Hwang [27]. Least Squares Support Vector Machine (LS-SVM) Classifier is a least square version of traditional SVM, which keeps the characteristics and the benefits of SVM [28]. In addition to the good generalization performances and low computational costs [29], it also provides a simpler training compared to SVM [30].

3. Results

Figure 5 demonstrates three different time series with a constant, periodic, and random configuration. The capability of this approach in the discrimination of these time series was evaluated by means of the second-order difference plots.

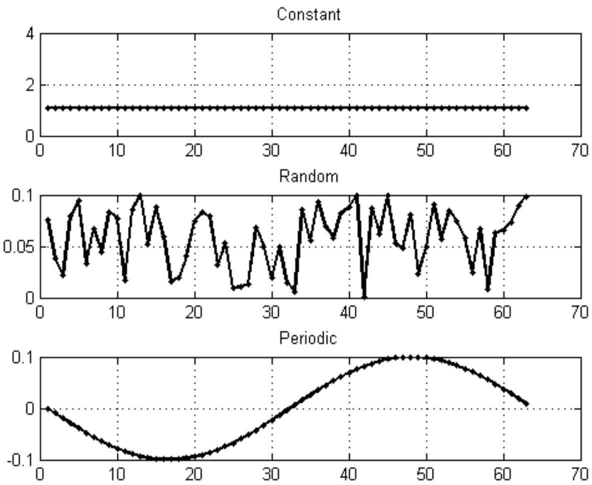


Figure 5. Different time series with 63 points: (top) constant, (middle) random, and (bottom) periodic time series. Vertical axis represents Xi, where i is number of samples, presented by horizontal axis.

Figure 6 exemplifies the arrangement of the points in a typical graphical representation.

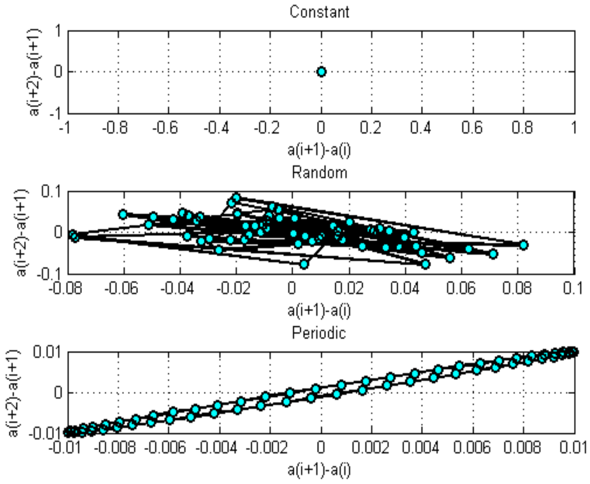


Figure 6. Second-order difference plot: (top) constant, (middle) random, and (bottom) periodic time series. Vertical axis represents X(i+2)-X(i+1), whereas horizontal axis demonstrates X(i+1)-X(i).

As shown in figure 6, a constant time series is converged into a single point in the center of the coordinates; whereas a periodic signal (like sinusoid) exhibits a circular pattern. In contrast, for a random data, there is no specific pattern of the points, and they just scatter in the space accidently. The CTM parameter with different radius was also evaluated for the above-mentioned time series. Figure 7 demonstrates the results.

As expected, the CTM values for different radii remain persistent in a constant data; whereas increasing the radius of the circle surrounding random points result in a gradual increment in the CTM values. Higher CTM values denote the focus of the points adjacent to the center, while the spreading points in the plot can be demonstrated by lower CTM values. A combined pattern is demonstrated for a periodic one.

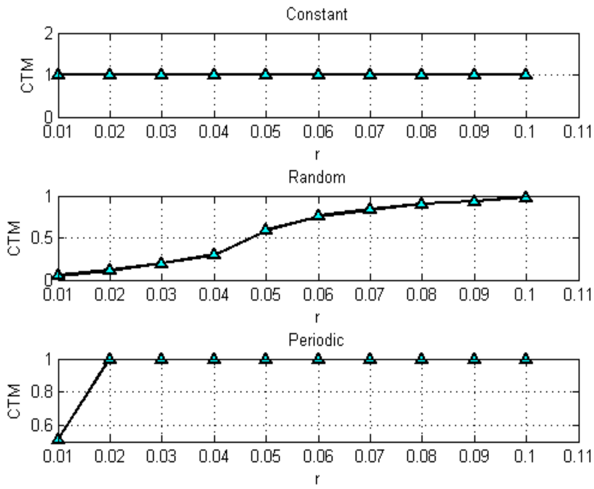


Figure 7. Considering different radii, CTM values for (top) constant, (middle) random, and (bottom) periodic time series are presented.

In the current work, this approach was employed on the WT coefficients of ECGs. A typical second-order difference plot for approximate coefficients at the level of eight is displayed in figure 8a. Considering different radii (r = 1-15), the corresponding CTMs are plotted in figure 8b. These findings are more similar to the random time series than those of the others.

For all the emotion categories, CTM and the corresponding D values were calculated. The mean density of the CTM values of all the emotion categories is presented in figure 9.

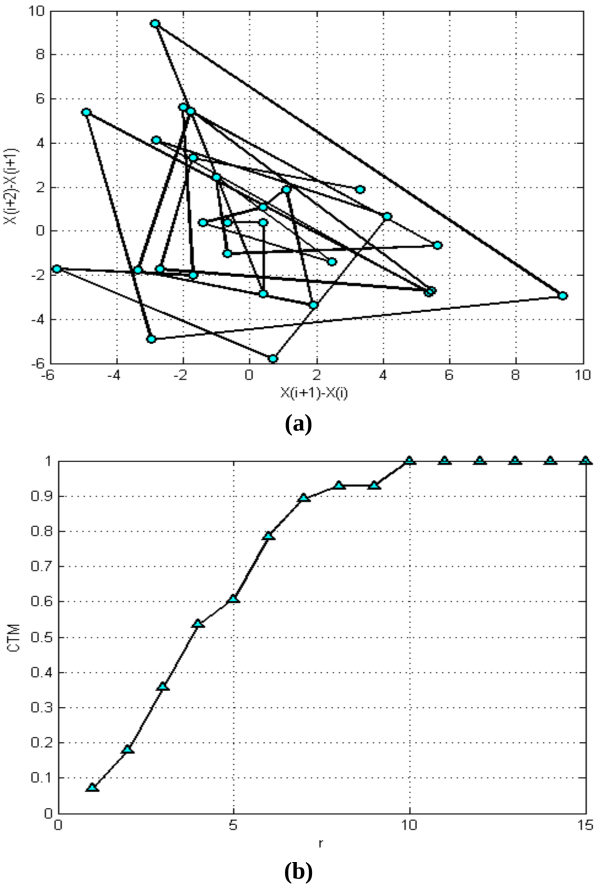


Figure 8. (a) Second-order difference plot for A8 of ECG during rest. (b) Corresponding CTMs for different radii.

For some emotion classes (happy-relax and sad-fear), the CTM distributions were the same (Figure 9). In addition, the density of the CTM values for the rest was different from those of the affective states. Significant differences between the emotions and the rest were evaluated by means of the Mann-Whitney U-test.

To investigate the efficiency of the proposed second-order difference plot indices, some statistical measures of the wavelet coefficients were also extracted. The statistical measures were mean, standard deviation, maximum, minimum, median, mode, and second-, third-, and fourth-moments. Table 1 demonstrates the results obtained.

As shown in table 1, there were no significant differences between the rest and the emotional states for the statistical measures. However, the second-order difference plot measures for the last level of wavelet coefficients (level 8; A8 and D8) could successfully differentiate between the emotional states and the rest. In addition, significant differences between the CTM values in the rest and the affective states were observed in D3.

Next, the LS-SVM classifier was employed to measure the classification performance based on the extracted features. 75% of the feature vector was randomly considered as the training set, and the remaining 25% of the vector was chosen as the test.

To evaluate the classifier performance, the accuracy, sensitivity (true positive rate), and specificity (true negative rate) were calculated. The classification accuracy was measured using (4):

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \quad (4)$$

where, TP designates true positives, TN shows true negatives, FP denotes false positives, and FN represents false negatives.

The sensitivity and specificity of the classifier were also verified based on (5) and (6), respectively:

$$Sensitivity = \frac{TP}{TP + FN} \quad (5)$$

$$Specificity = \frac{TN}{TN + FP} \quad (6)$$

In addition, a Receiver Operating Characteristic (ROC) curve was provided to graphically evaluate the classifier performance.

Figure 10 represents the ROC curves for the proposed methodology. In addition, the classification accuracy, sensitivity, and specificity are provided in figure 10.

The classification results reveal that CTM in combination with the wavelet coefficients outperformed the other index in the classification of each emotional state and the rest. Higher performances (~80%) were achieved for the fear and relaxed affective states.

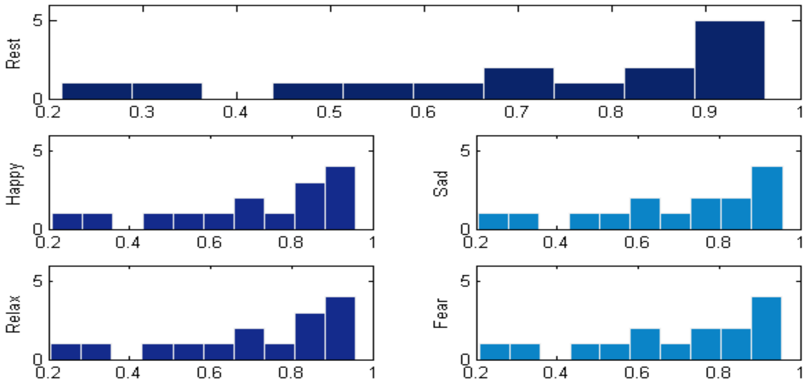


Figure 9. Histogram of mean CTM values for all emotion classes.

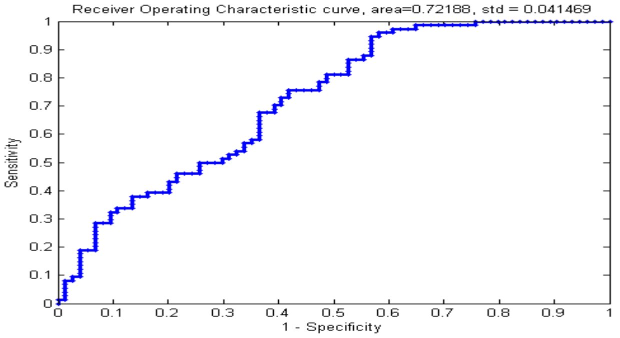
Table 1. Comparison between different linear and non-linear indices in emotions and rest for different DWT coefficients.

Feature	DWT Coefficients	Rest *vs.* Happy	Rest *vs.* Relax	Rest *vs.* Sad	Rest *vs.* Fear
Mean	A8	0.4896	0.4676	0.0638	0.2124
	D8	0.6565	0.4441	0.4426	0.9244
	D7	0.8852	0.6848	0.5437	0.7357
	D6	0.4418	0.3427	0.136	0.9603
	D5	0.1365	0.2685	0.0585	0.0666
	D4	0.5922	0.7633	0.49	0.9979
	D3	0.8237	0.3598	0.7582	0.732
	D2	0.752	0.5396	0.5823	0.7633
	D1	0.9596	0.7773	0.3258	0.8538
STD	A8	0.4282	0.4188	0.2346	0.3035
	D8	0.5266	0.6771	0.3162	0.4888
	D7	0.4432	0.4611	0.3466	0.4324
	D6	0.6697	0.6056	0.5919	0.7349
	D5	0.7586	0.5501	0.6551	0.5475
	D4	0.6655	0.6056	0.4897	0.5659
	D3	0.4279	0.2297	0.339	0.3702
	D2	0.3964	0.3543	0.3197	0.3174
	D1	0.4347	0.3535	0.2635	0.2181
Maximum	A8	0.1546	0.0966	0.0829	0.1605
	D8	0.1204	0.0415*	0.0073*	0.0978
	D7	0.166	0.1856	0.114	0.1168
	D6	0.1642	0.3116	0.1657	0.3268
	D5	0.249	0.3199	0.4979	0.1834
	D4	0.3782	0.3618	0.3088	0.2295
	D3	0.2695	0.0216*	0.1336	0.1415
	D2	0.3879	0.1854	0.4149	0.2962
	D1	0.3906	0.1658	0.1137	0.1629
Minimum	A8	0.053	0.0101*	0.0007*	0.0013*
	D8	0.1759	0.152	0.064	0.2261
	D7	0.2492	0.0838	0.1135	0.2249
	D6	0.835	0.1406	0.3483	0.5692
	D5	0.731	0.545	0.397	0.2763
	D4	0.9596	0.5046	0.5909	0.5833
	D3	0.0502	0.0263*	0.0616	0.0399*
	D2	0.0359*	0.0148*	0.0935	0.0378*
	D1	0.1832	0.01*	0.0858	0.0207*
Median	A8	0.9512	0.5192	0.3472	0.6978
	D8	0.271	0.1038	0.1408	0.2162
	D7	0.981	0.3383	0.6722	0.9691
	D6	0.788	0.6248	0.1818	0.6191
	D5	0.4504	0.1793	0.1612	0.1226
	D4	0.3666	0.3093	0.3393	0.7958
	D3	0.3176	0.1348	0.2439	0.4021
	D2	0.2407	0.7194	0.8312	0.7205
	D1	0.6365	0.8125	0.1977	0.986
Mode	A8	0.053	0.0101*	0.0007*	0.0013*
	D8	0.1759	0.152	0.064	0.2261
	D7	0.2492	0.0838	0.1135	0.2249
	D6	0.835	0.1406	0.3483	0.5692
	D5	0.731	0.545	0.397	0.2763
	D4	0.9596	0.5046	0.5909	0.5833
	D3	0.0502	0.0263*	0.0616	0.0399*
	D2	0.0359*	0.0148*	0.0935	0.0378*
	D1	0.1832	0.01*	0.0858	0.0207*

(Continued Table 1). Comparison between different linear and non-linear indices in emotions and rest for different DWT coefficients.

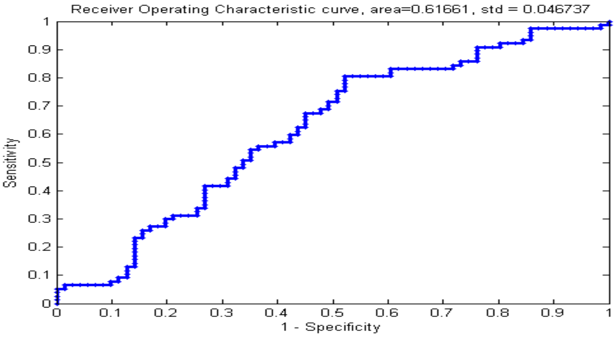
Feature	DWT Coefficients	Rest *vs.* Happy	Rest *vs.* Relax	Rest *vs.* Sad	Rest *vs.* Fear
1st Moment	A8	0.429	0.4152	0.2344	0.3008
	D8	0.5157	0.6645	0.3088	0.4836
	D7	0.4404	0.4446	0.3436	0.4285
	D6	0.6708	0.6086	0.5916	0.7331
	D5	0.7622	0.5565	0.6558	0.544
	D4	0.6631	0.6016	0.4851	0.5585
	D3	0.4237	0.2269	0.3383	0.3628
	D2	0.3946	0.351	0.3167	0.3158
	D1	0.4316	0.3441	0.2592	0.2149
2nd Moment	A8	0.5026	0.6957	0.3795	0.4511
	D8	0.4903	0.0671	0.5204	0.1304
	D7	0.4579	0.1434	0.8163	0.0259*
	D6	0.2192	0.8681	0.8219	0.6729
	D5	0.8662	0.7212	0.9046	0.4467
	D4	0.8871	0.8237	0.3528	0.4305
	D3	0.5135	0.8159	0.5741	0.5111
	D2	0.6722	0.8196	0.2284	0.5285
	D1	0.4951	0.9979	0.2007	0.9309
3rd Moment	A8	0.2714	0.2316	0.1296	0.1553
	D8	0.4204	0.4848	0.1635	0.3155
	D7	0.3991	0.3414	0.2542	0.3628
	D6	0.5272	0.5074	0.3959	0.6464
	D5	0.6873	0.5731	0.6187	0.4421
	D4	0.5569	0.4435	0.4097	0.3954
	D3	0.2708	0.1099	0.1939	0.2131
	D2	0.3118	0.2276	0.2656	0.2748
	D1	0.3588	0.2091	0.1706	0.1318
CTM	A8	0.3016	0.0282*	0.0092*	0.0084*
	D8	0.0273*	0.0036*	0.0006*	0.0088*
	D7	0.3428	0.1541	0.139	0.0265*
	D6	0.0678	0.1769	0.0071*	0.1415
	D5	0.0185*	0.063	0.1057	0.0769
	D4	0.2007	0.253	0.0768	0.137
	D3	0.0391*	0.0448*	0.0429*	0.0401*
	D2	0.0215*	0.0067*	0.0512	0.0207*
	D1	0.381	0.0361*	0.0757	0.0927
D	A8	0.0222*	0.0069*	0.0135*	0.0105*
	D8	0.045*	0.0505*	0.0095*	0.0094*
	D7	0.0849	0.1676	0.0155*	0.1007
	D6	0.1881	0.2234	0.1138	0.0968
	D5	0.0327*	0.1489	0.0779	0.0623
	D4	0.1033	0.0956	0.2095	0.0519
	D3	0.0749	0.199	0.0883	0.174
	D2	0.0634	0.083	0.0128*	0.0707
	D1	0.043*	0.11	0.0226*	0.052

* $p<0.05$



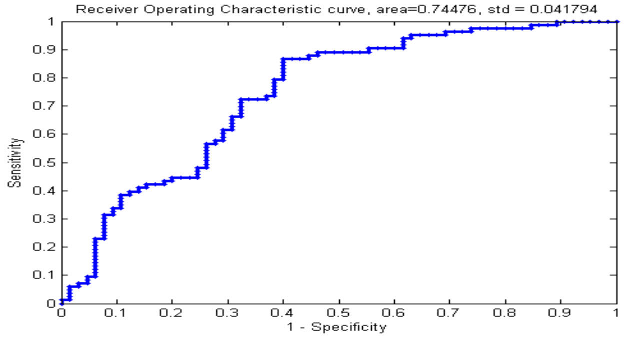
ACC = 61.09%, Spec = 60.76%, Sen = 61.43%

(a)



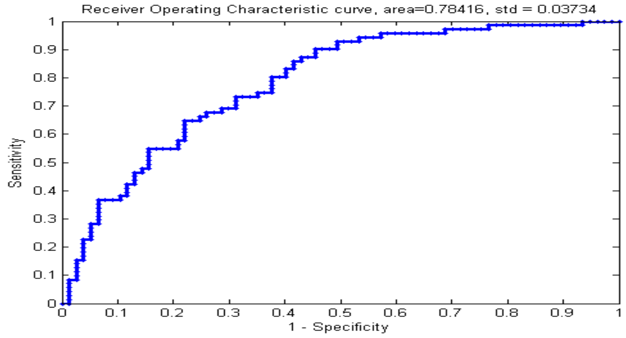
ACC = 55.83%, Spec = 55.73%, Sen = 55.93%

(b)



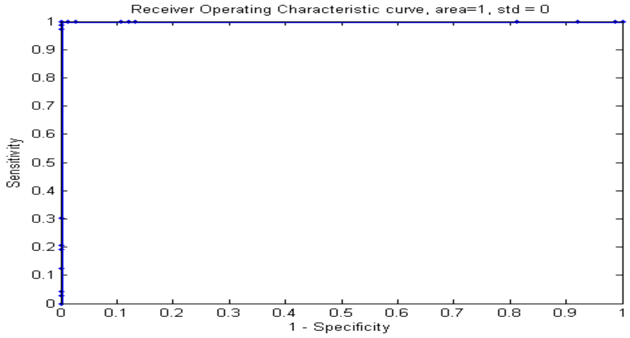
ACC = 62.1%, Spec = 63.39%, Sen = 61.09%

(c)



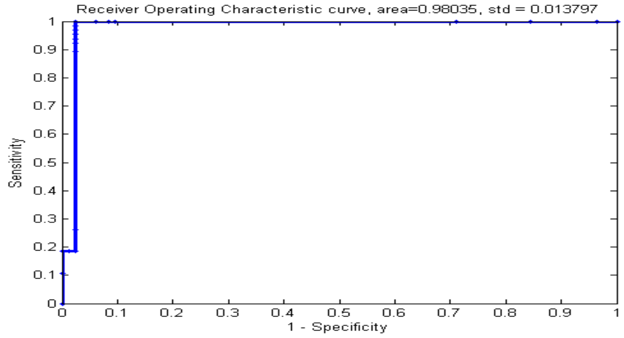
ACC = 64.17%, Spec = 63.29%, Sen = 65.12%

(d)



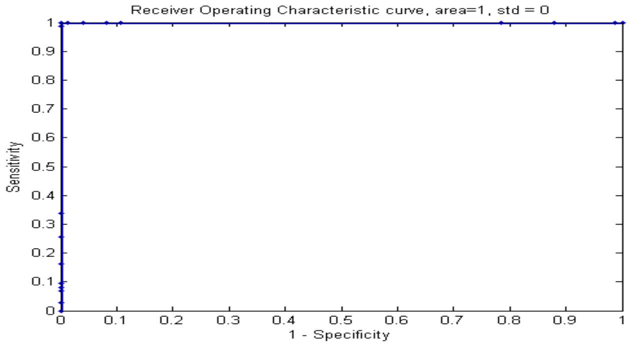
ACC = 74.29%, Spec = 77.11%, Sen = 71.39%

(e)



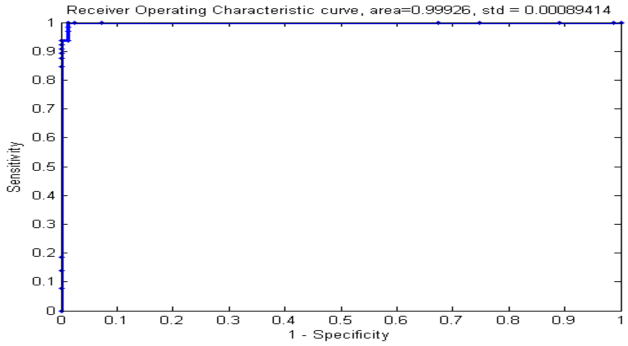
ACC = 78.02%, Spec = 79.01%, Sen = 76.76%

(f)



ACC = 70.95%, Spec = 77.11%, Sen = 64.79%

(g)



ACC = 80.24%, Spec = 77.77%, Sen = 83.38%

(h)

Figure 10. LS-SVM performance on: second-order difference plot measure (D) of last level of wavelet coefficient (A8) in discrimination between rest and (a) happy, (b) relax, (c) sad, (d) fear; CTM of last level of wavelet coefficient (A8) in discrimination between rest and (e) happy, (f) relax, (g) sad, (h) fear; Note- ACC: Accuracy; Spec: Specificity; Sen: Sensitivity.

4. Discussion

In the past, both the WT and non-linear approaches have been used in the problem of affect interpretation and recognition [14,15,24,31-37]. In the current study, a methodology was presented based on the WT and non-linear indices to evaluate the emotional ECGs. The non-linear technique was carried out using a second-order difference plot. The ECG signals were pre-processed to eliminate the line noise power and segmented according to the emotional loads. For each segment, the WT coefficients (db4 at level 8) were extracted. Then two features of a second-order difference plot were calculated for each WT coefficient. These indices were D and CTM. The Mann-Whitney U-Test was performed to show the significant differences between classes. Finally, LS-SVM was implemented to differentiate between each emotional class and the rest.

The higher variability of the signal (random) results in a higher dispersion of the points in the second-order difference plot (Figure 6). In contrast, the low variable signal (constant) makes the points congregated toward the center of the plot. Comparing figure 8 with figures 7 and 6, it was revealed that the ECG signals tended to have a random pattern.

The results obtained (Figure 8) also showed that the CTM density was comparable in happy/relax and sad-/fear, which was not the same for the rest. It can be concluded that this pattern can be interpreted based on the valence dimension of emotion. For affective states assigned to the positive valence, the CTM distributions were equivalent. Similar results were achieved for the negative valence. However, this scheme is distinctive for the positive and negative emotions, and also the rest. In addition, the second-order difference plot indices extracted from the last level of the WT coefficients show significant differences between the rest and the emotion classes (Table 1). The *p*-value results also indicate that there is no significant difference between the categories for linear indices of DWT. In contrast, the non-linear indices including CTM and D show significant differences between the rest and each emotion class. Therefore, a combination of non-linear analysis and DWT is more useful to apprehend the emotional changes than that of linear indices.

Classification rates also designate the superiority of CTM over D in discrimination between the rest and the emotional states. Among the affective states, higher recognition rates were assigned to fear and relax (Figure 10).

In the past, different ECG analyses have been performed in the problem of emotion recognition. Bong et al. [38] have extracted time-based features of ECG and have mapped them into K-nearest neighbor (KNN) and SVM to emotional stress classification. The best recognition rate of 77.69% was reported. In the study performed by Basu et al. [39], six time domain features have been calculated from physiological signals. By evaluating different classification algorithms including Quadratic Discriminant Classifier (QDC), kNN, Naive Bayes, and Linear Discriminant Analysis (LDA), a maximum accuracy of 75% was realized. Time, frequency, and statistical analysis of ECG were recruited to offer a wearable emotion detection device [40]. However, the correct rate of 50% was provided by the proposed system. By employing the empirical mode decomposition, as a non-linear signal processing approach, and discrete Fourier transform, no improvement on accuracy rates (~52%) was achieved with linear discriminant analysis and KNN [33]. However, combining information from standard and non-linear ECG analysis estimated through lagged Poincare plots improved the recognition rates up to 84% [41]. Their results confirm that the ECG signals are a powerful tool for emotion recognition, especially with the use of non-linear dynamics. Although the reported rates are slightly higher than the results of the current study, there are two major differences between the studies. First, their experiment was performed on fewer number of subjects. Secondly, they only focused on the arousal dimension [41], while in this study, both the arousal and valence-based emotion dimensions were considered. In conclusion, the current study emphasizes the importance of non-linear dynamics for affect recognition. The efficiency of non-linear techniques has attracted many researchers in the field of emotion recognition. However, they applied other bio-signals rather than ECG.

Dynamical evaluation of ECG, respiration, skin conductance, and temperature were combined with some traditional linear approaches to monitor five affective states [42]. An accuracy of about 60% was reported for classifying 5 discrete emotion categories. Recently, Valencia et al. [43] have incorporated recurrence quantification measures (RQA) as a non-linear approach to classify two valence categories and three arousal categories using the multimodal emotion recognition scheme. Other examples can be found in [14-15,34,35,44-48].

In the future studies, improvements in the classification rates will be evaluated using the feature selection approaches.

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References

[1] Jansen, K., Varon, C., Van Huffel, S., & Lagae, L. (2013). Peri-ictal ECG changes in childhood epilepsy: Implications for detection systems. Epilepsy & Behavior, vol. 29, no. 1, pp. 72-76.

[2] Khalaf, A. F., Owis, M. I., & Yassine, I. A. (2015). A novel technique for cardiac arrhythmia classification using spectral correlation and support vector machines. Expert Systems with Applications, vol. 42, no. 21, pp. 8361-8368.

[3] Thomas, M., Kr Das, M., & Ari, S. (2015). Automatic ECG arrhythmia classification using dual tree complex wavelet based features. AEU - International Journal of Electronics and Communications, vol. 69, no. 4, pp. 715-721.

[4] Vafaie, M. H., Ataei, M., & Koofigar, H. R. (2014). Heart diseases prediction based on ECG signals' classification using a genetic-fuzzy system and

dynamical model of ECG signals; Biomedical Signal Processing and Control, vol. 14, pp. 291-296.

[5] Varon, C., Jansen, K., Lagae, L., & Van Huffel, S. (2015). Can ECG monitoring identify seizures? Journal of Electrocardiology, vol. 48, no. 6, pp. 1069-1074.

[6] Ebrahimzadeh, A., Ahmadi M., & Safarnejad, M. (2016). Classification of ECG signals using Hermit functions and MLP neural networks. Journal of AI and Data Mining, vol. 4, no. 1, pp. 55-65.

[7] Akselrod, S., Gordon, D., Ubel, F. A., Shannon, D.C., Berger, A. C., & Cohen, R. J. (1981). Power spectrum analysis of heart rate fluctuation: A quantitative probe of beat-to-beat cardiovascular control. Science, vol. 213, no. 4504, pp. 220-222.

[8] Grasso, R., Schena, F., Gulli, G, & Cevese, A. (1997). Does low-frequency variability of heart period reflect a specific parasympathetic mechanism? J Auton Nerv Syst, vol. 63, no. 1-2, pp. 30-38.

[9] Pagani, M., Lombardi, F., Guzzetti, S., Rimoldi, O., Furlan, R., Pizzinelli, P., Sandrone, G., Malfatto, G., Dell'Orto, S., Piccaluga, E., et al. (1986). Power spectral analysis of heart rate and arterial pressure variabilities as a marker of sympatho-vagal interaction in man and conscious dog. Circ Res, vol. 59, no. 2, pp. 178-193.

[10] Goshvarpour, A., Goshvarpour, A., & Rahati, S. (2011). Analysis of lagged Poincaré plots in heart rate signals during meditation. Digital Signal Processing, vol. 21, no. 2, pp. 208-214.

[11] Ranganathan, G., Rangarajan, R., & Bindhu, V. (2012). Estimation of heart rate signals for mental stress assessment using neuro fuzzy technique. Applied Soft Computing, vol. 12, no. 8, pp. 1978-1984.

[12] Kreibig, S. (2010). Autonomic nervous system activity in emotion: a review. Biological Psychology, vol. 84, no. 3, pp. 394-421.

[13] Costa, T., Galati, D., & Rognoni, E. (2009). The Hurst exponent of cardiac response to positive and negative emotional film stimuli using wavelet. Autonomic Neuroscience: Basic and Clinical, vol. 151, no. 2, pp. 183–185.

[14] Valenza, G., Lanata, A., & Scilingo, E. (2012). The role of nonlinear dynamics in affective valence and arousal recognition. IEEE Transactions on Affective Computing, vol. 3, no. 2, pp. 237-249.

[15] Valenza, G., Allegrini, P., Lanata, A., & Scilingo, E. (2012). Dominant Lyapunov exponent and approximate entropy in heart rate variability during emotional visual elicitation. Frontiers in Neuroengineering, vol. 5, no. 3, pp. 1-7.

[16] Park, S., & Kim, K. (2011). Physiological reactivity and facial expression to emotion-inducing films in patients with schizophrenia. Archives of Psychiatric Nursing, vol. 25, no. 6, pp. e37-e47.

[17] Drusch, K., Stroth, S., Kamp, D., Frommann, N., & Wolwer, W. (2014). Effects of training of affect recognition on the recognition and visual exploration of emotional faces in schizophrenia. Schizophrenia Research, vol. 159, no. 2-3, pp. 485-490.

[18] Hazlett, R. (2006). Measuring emotional valence during interactive experiences: Boys at video game play, CHI ’06: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM Press, New York, NY, USA. pp. 1023-1026.

[19] Yannakakisa, G., & Hallam, J. (2008). Entertainment modeling through physiology in physical play. International Journal of Human-Computer Studies, vol. 66, no. 10, pp. 741-755.

[20] Rafiee, J., Rafiee, M. A., Prause, N., & Schoen, M.P. (2011). Wavelet basis functions in biomedical signal processing. Expert System with Applications, vol. 38, no. 5, pp. 6190–6201.

[21] Henry, B. I., Lovell, N. H., & Camacho, F. (2001). Nonlinear dynamics time series analysis. In M. Akay (Ed.), Nonlinear Biomedical Signal Processing (pp. 1–39). Institute of Electrical and Electronics Engineers, Inc.

[22] Cohen, M.E., Hudson, D. L., & Deedwania, P. C. (1996). Applying continuous chaoticmodeling to cardiac signal analysis. IEEE Engineering in Medicine and Biology Magazine, vol. 15, no. 5, pp. 97–102.

[23] Lang, P. J., Bradley, M. M., & Cuthbert, B. N. (2005). International affective picture system (IAPS): Digitized photographs, instruction manual and affective ratings (Technical Report A-6). University of Florida: Gainesville, FL.

[24] Goshvarpour, A., Abbasi, A., & Goshvarpour, A. (2015). Affective visual stimuli: Characterization of the picture sequences impacts by means of nonlinear approaches. Basic and Clinical Neuroscience, vol. 6, no. 4, pp. 209-221.

[25] Daubechies, I. (1990). The wavelet transform, time frequency localization and signal analysis. IEEE Transactions on Information Theory, vol. 36, no. 5, pp. 961-1005.

[26] Ratnakar, M., Sunil, K. S., & Nitisha, J. (2009). Signal filtering using discrete wavelet transform, International Journal of Recent Trends in Engineering, vol. 2, no. 3, pp. 96-98.

[27] Hu, Y. H., & Hwang, J. N. (Eds.) (2002). Handbook of neural network signal processing. Electrical engineering and applied signal processing (Series), CRC PRESS, pp 384.

[28] Suykens, J. A. K., Van Gestel, T., De Brabanter, J., De Moor, B., & Vandewalle, J. (2002). Least squares support vector machines. World Scientific, Singapore.

[29] Suykens, J. A. K., & Vandewalle, J. (1999). Least squares support vector machine classifiers. Neural Processing Letters, vol. 9, no. 3, pp. 293–300.

[30] Zhou, J., Shi, J., & Li, G. (2011). Fine tuning support vector machines for short-term wind speed forecasting. Energy Conversion and Management, vol. 52, no. 4, pp. 1990–1998.

[31] Jerritta, S., Murugappan, M., Wan, K., & Yaacob, S. (2013). Emotion detection from QRS complex of ECG signals using hurst exponent for different age groups, Humaine Association Conference on Affective Computing and Intelligent Interaction (ACII), Geneva, Switzerland. pp. 849-854.

[32] Jerritta, S., Murugappan, M., Wan, K., & Yaacob, S. (2013). Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst. BioMedical Engineering OnLine, vol. 12, 44.

[33] Jerritta, S., Murugappan, M., Wan, K., & Yaacob, S. (2014). Electrocardiogram-based emotion recognition system using empirical mode decomposition and discrete Fourier transform. Expert Systems, vol. 31, no. 2, pp. 110-120.

[34] Nardelli, M., Valenza, G., Greco, A., Lanata, A., & Scilingo, E. (2015). Recognizing emotions induced by affective sounds through heart rate variability. IEEE Transactions on Affective Computing, vol. 6, no. 4, pp. 385-394.

[35] Valenza, G., Citi, L., Lanata, A., Scilingi, E., & Barbieri, R. (2014). Revealing real-time emotional responses: a personalized assessment based on heartbeat dynamics. Scientific Reports, vol. 4, 4998.

[36] Xu, Y., Liu, G., Hao, M., Wen, W., & Huang, X. (2010). Analysis of affective ECG signals toward emotion recognition. Journal of Electronics (China), vol. 27, no. 1, pp. 8-14.

[37] Xu, Y., & Liu, G.-Y. (2009). A method of emotion recognition based on ECG signal, International Conference on Computational Intelligence and Natural Computing. IEEE. pp. 202-205.

[38] Bong, S. Z., Murugappan, M., & Yaacob, S. (2012). Analysis of Electrocardiogram (ECG) Signals for human emotional stress classification, First International Conference on Trends in Intelligent Robotics, Automation, and Manufacturing. Kuala Lumpur, Malaysia, 28-30Nov., pp. 198-205.

[39] Basu, S., Bag, A., Mahadevappa, M., Mukherjee, J., & Guha, R. (2015). Affect detection in normal groups with the help of biological markers. India Conference (INDICON). 17-20 Dec. IEEE.

[40] Guo, H. W., Huang, Y. S., Chien J. C., & Shieh, J. S. (2015). Short-term analysis of heart rate variability for emotion recognition via a wearable ECG device. International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS). 28-30 Nov., IEEE.

[41] Nardelli, M., Valenza, G., & Greco, A. (2015). Arousal recognition system based on heartbeat dynamics during auditory elicitation. 37th Annual International Conference of the Engineering in Medicine and Biology Society (EMBC). 25-29 Aug., IEEE.

[42] Kukolja, D., Popović, S., Horvat, M., Kovač, B., & Ćosić, K. (2014). Comparative analysis of emotion estimation methods based on physiological measurements for real-time applications. International Journal of Human-Computer Studies, vol. 72, no. 10-11, pp. 717-727.

[43] Valencia, C. T., Lopez, M. A., & Gutierrez, A. O. (2017). SVM-based feature selection methods for emotion recognition from multimodal data. Journal on Multimodal User Interfaces, vol. 11, no. 1, pp. 9-23.

[44] Kim, J., & Andre, E. (2008). Emotion recognition based on physiological changes in music listening. IEEE Transactions on Pattern Analysis and Machine Intelligence. vol. 30, no. 12, pp. 2067-2083.

[45] Goshvarpour, A., Abbasi, A., & Goshvarpour, A. (2016). Dynamical analysis of emotional states from electroencephalogram signals. Biomedical Engineering Applications, Basis and Communications, vol. 28, no. 2, pp. 1650015 [12 pages].

[46] Roque, A., Valenti, V., Guida, H., Campos, M., Knap, A., Vanderlei, L., Ferreira, L., Ferreira, C., & Abreu, L. (2013). The effects of auditory stimulation with music on heart rate variability in healthy women. Clinics, vol. 68, no. 7, pp. 960-967.

[47] Silva, S., Guida, H., Santos, A., Vanderlei, L., Ferreira, L., de Abreu, L., Sousa, F., & Valenti, V. (2014). Auditory stimulation with music influences the geometric indices of heart rate variability in men. International Archives of Medicine, vol. 7, no. 27, pp. 1-7.

[48] Wang, L., Liu, G., & Yang, Z. (2014). The emotion recognition for grief based on nonlinear features of GSR. Journal of Computational Information Systems, vol. 10, no. 4, pp.1639-1649.

نشریه هوش مصنوعی و داده کاوی

بازشناسی احساسات مبتنی بر تبدیل موجک و طرح تفاضلی مرتبه دوم الکتروکاردیوگرام

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چکیده:

احساسات به عنوان یک حالت سایکوفیزیولوژیکی، نقش مهمی در ارتباطات و زندگی روزمره بشری ایفا می‌کند. مطالعه سیگنال‌های فیزیولوژیکی در احساسات موضوع بسیاری از کارهای تحقیقاتی اخیر بوده است. در این مطالعه، رویکرد مبتنی بر ویژگی‌های ترکیبی برای ارزیابی حالات احساسی اتخاذ شده است. بدین منظور، سیگنال‌های الکتروکاردیوگرام ۴۷ دانشجو با اعمال تحریک تصاویر احساسی ثبت شد. تصاویر احساسی از سیستم بین المللی تصاویر عاطفی انتخاب و به چهار کلاس احساسی مختلف اختصاص یافت. پس از استخراج ضرایب تقریب و جزئی از تبدیل موجک (دابیچیز ۴ در سطح ۸)، دو اندازه از طرح تفاضلی مرتبه دوم (CTM و D) برای هر ضریب موجک محاسبه شد. سپس، از ماشین بردار پشتیبان حداقل مربعات (LS-SVM) برای تمایز بین حالات احساسی از حالت استراحت استفاده شد. تحلیل‌های آماری نشان می‌دهد که چگالی CTM در حالت استراحت قابل تمایز از دسته‌های احساسی است. به علاوه، اندازه‌های طرح تفاضلی مرتبه دوم در سطح آخر ضرایب موجک، تفاوت معناداری را بین استراحت و حالات عاطفی نشان می‌دهند. با بکارگیری LS-SVM، ماکزیمم نرخ طبقه‌بندی ۸۰/۲۴ ٪ برای تفکیک استراحت از ترس حاصل شد. نتایج این مطالعه، بیانگر مفید بودن ترکیب موجک با روشی غیرخطی در توصیف حالات احساسی است.

کلمات کلیدی: ویژگی‌های ترکیبی، الکتروکاردیوگرام، احساسات، طرح تفاضلی مرتبه دوم، تبدیل موجک.