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Original Article

Combination of Empirical Mode Decomposition Components of HRV Signals for Discriminating Emotional States

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Abstract

Introduction
Automatic human emotion recognition is one of the most interesting topics in the field of affective computing. However, development of a reliable approach with a reasonable recognition rate is a challenging task. The main objective of the present study was to propose a robust method for discrimination of emotional responses thorough examination of heart rate variability (HRV). In the present study, considering the non-stationary and non-linear characteristics of HRV, empirical mode decomposition technique was utilized as a feature extraction approach.
Materials and Methods
In order to induce the emotional states, images indicating four emotional states, i.e., happiness, peacefulness, sadness, and fearfulness were presented. Simultaneously, HRV was recorded in 47 college students. The signals were decomposed into some intrinsic mode functions (IMFs). For each IMF and different IMF combinations, 17 standard and non-linear parameters were extracted. Wilcoxon test was conducted to assess the difference between IMF parameters in different emotional states. Afterwards, a probabilistic neural network was used to classify the features into emotional classes.
Results
Based on the findings, maximum classification rates were achieved when all IMFs were fed into the classifier. Under such circumstances, the proposed algorithm could discriminate the affective states with sensitivity, specificity, and correct classification rate of 99.01%, 100%, and 99.09%, respectively. In contrast, the lowest discrimination rates were attained by IMF1 frequency and its combinations.
Conclusion
The high performance of the present approach indicated that the proposed method is applicable for automatic emotion recognition.

Keywords: Classification, Emotion, Heart rate, Signal processing

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1. Introduction

So far, extensive research has been performed to design, evaluate, and execute human-computer interfaces in order to facilitate a more human-like interaction. Recently, affective computing has become a challenging subject for facilitating emotion recognition, expression, and regulation via computers.

Since emotions may be perceived through different modalities, some efforts have been made to develop a reliable approach for automatic affect recognition by analyzing gestures and facial, vocal, and physiological parameters. Among these parameters, physiological characteristics cannot be simply faked. Therefore, more attention is being paid to emotion recognition through physiological data processing.

Picard et al. analyzed the statistical features of five physiological signals [1]. By integrating feature selection methods in Fisher's projections, the highest recognition rate (81%) was attained. Despite promising achievements, the most significant weakness of the proposed system was the evaluation of only one participant.

In this regard, Kim et al. adopted a support vector machine (SVM) as a classifier for the discrimination of emotions in 50 subjects [2]. By applying linear and spectral features, maximum correct rates of 78.4% and 61.8% were reported for the recognition of three and four affective states, respectively. In addition, further attempts have been made to examine the feasibility of artificial neural networks (ANN) in emotion recognition [3-5]. However, the best performance for distinguishing two classes of emotional states was approximately 96.6%.

Moreover, a comparative study was performed on machine learning methods, including K-nearest neighbor (KNN), regression tree, Bayesian network, and SVM to resolve the problem of emotion recognition [6]. Based on the findings, SVM could offer the best classification accuracy (85.81%) for discriminating five emotional states.

In the following years, some efforts were made to develop new approaches, based on the standard features [7-17]. However, despite the limited number of emotion categories, no improvement was achieved for the correct accuracy rate of the proposed systems. The efficiency of time-frequency (wavelet) methods on affect recognition has been also investigated in previous studies [18, 19].

By applying a wavelet-based approach, the hybrid particle swarm optimization, as a feature selection method, along with Fisher's linear discriminant, a recognition rate of 92.6% was achieved. In the following studies, non-linear features were incorporated in the feature extraction procedure. In this regard, Hilbert-Huang transform (HHT) and SVM were applied to discriminate four affective states [20]. The results showed that the proposed method outperformed traditional statistical techniques with the highest accuracy rate of 76%.

Valenza et al. evaluated the role of various non-linear indices in affective recognition, including deterministic chaos, recurrence quantification parameters, detrended fluctuation analysis, approximate entropy, and dominant Lyapunov exponents [21-23]. The findings indicated that use of non-linear features in combination with a quadratic discriminant classifier could lead to a dramatic increase in the percentage of accurate recognition (recognition accuracy > 90%) [23].

To categorize the emotional information in electrocardiogram (ECG) signals, Jerritta et al. appraised the Hurst parameter as a non-linear feature [24, 25]. By using KNN and fuzzy KNN, maximum accuracy of 92.87% was attained for discrimination of six emotional types. By applying HHT and discrete Fourier transform, 52% performance was achieved [26].

In a previous study, embedded dimensions, time delay, correlation dimension, approximate entropy, and Lyapunov exponents of galvanic skin response were analyzed to distinguish emotions [27]. By using SVM, the highest correct classification rate was 80.31%. Recently, addition of some lagged Poincaré indices to various standard and non-linear features resulted in a recognition accuracy of 84.72% on the valence dimension and 84.26% accuracy on the arousal dimension [28].

Table 1. Previous achievements on emotion recognition applying physiological parameters.

Study	No. emotion classes	Signal	Features	Classifier and Classification rate
[1]	8	EMG, BVP (& corresponding HR), SC, RSP	Statistical features	SFFS + Fisher (81%)
[2]	3 & 4	ECG, SC, ST	Linear and spectral indices	SVM (3 classes: 78.4%, 4 classes: 61.8%)
[4]	2	EMG, SC, BVP, ECG, RSP, ST	Linear features	ANN (Valence 90%, Arousal 96%)
[5]	4	ECG, SC	Linear and spectral indices	ANN (80.2%)
[3]	3	BVP, SC	Linear features	ANN (74.5%)
[6]	5	ECG, BVP,SC,EMG	Linear and spectral indices	KNN, RT, BN, SVM (86%)
[15]	4	RSP	Linear and spectral indices	PCA, SDA (65.3%)
[12]	3	ECG, BVP, SC, ST	Linear and spectral indices	CCA (85.3%)
[17]	2	SC, BVP, PD, ST	Linear and spectral indices	SVM (~%90)
[16]	2	ECG, BVP, SC	Linear and spectral indices	SVM, ANN (~70%)
[13]	3	ECG, ICG, PPG, PCG, SC, EMG	Time, frequency, Time-frequency based	SVM (83%)
[11]	4	ECG, EMG, RSP, SC	Statistical measures	SVM & ANFIS (79.3%-76.7%)
[20]	4	ECG, EMG, SC and RSP	EMD	SVM (76%)
[19]	2	ECG	Wavelet	Fisher (~92.6%)
[7]	3	BVP, ECG, SC, RSP, PW	Linear indices	SVR (~90%)
[18]	2	ECG	Wavelet	Fisher and KNN (~89%)
[10]	5	BVP, ECG,SC,RSP	Linear indices	ANN, SVM, Random Forests, a Neuro-Fuzzy System). (84.3%)
[14]	1 - 4	ECG, EMG, SC, RSP	Statistical features	GA, KNN (97%- 74.5%)
[23]	5	ECG, RSP, SC	Various standard and nonlinear methods	QDC (> 90%)
[21]	2	HRV	LE, AE	Kruskal–Wallis test
[24]	6	ECG	Hurst	KNN and Fuzzy KNN (70.23%)
[25]	6	ECG	Hurst, HOS	KNN and Fuzzy KNN (92.87%)
[8]	-	EDA (Tonic and Phasic)	Linear indices	Wilcoxon test
[22]	4	HR	Spectrum, Bispectrum, LE	SVM (circumplex model of affect: 79.29%, 79.15% on the valence, and 83.55% on the arousal)
[27]	4	SC	LE, CD, AE, ED, TD	SVM (80.31%)
[26]	5	ECG	HHT, DFT	LDA, KNN (52%)
[28]	4 in arousal/ 2 in valence	HRV	Various standard and nonlinear methods	QDC (84.72% on the valence dimension, and 84.26% on the arousal dimension)
[9]	3	ECG, SC, BVP, ST	Linear and spectral indices	DFA, LDA, CART, SVM, SOM, BN (84.7%)

Abbreviations: (*for Signals*) BVP: Blood-Volume Pressure, ECG: Electrocardiogram, EMG: Electromyogram, HR: Heart Rate, HRV: Heart Rate Variability, ICG: Impedance Cardiogram, PCG: Phonocardiogram, PD: Pupil Diameter, PPG: Photoplethysmogram, PW: Pulse, RSP: Respiratory Activity, SC: Skin Conductivity, ST: Skin Temperature. (*for Features*) AE: Approximate Entropy, CD: Correlation Dimension, DFT: Discrete Fourier Transform, ED: Embedded Dimensional, EMD: Empirical Mode Decomposition, HHT: Hilbert–Huang Transform, HOS: Higher Order Statistics, LE: Lyapunov Exponents, TD: Time Delay. (*for Classification*) BN: Bayesian Network, CART: Classification and Regression Trees, CCA: Canonical Correlation Analysis, DFA: Discriminant Function Analysis, GA: Genetic Algorithm, KNN: K-Nearest Neighbor, LDA: Linear Discriminant Analysis, QDC: Quadratic Discriminant Classifier, RT: Regression Tree, SDA: Stepwise Discriminant Analyses, SFFS: Sequential Floating Forward Search, SOM: Self-Organizing Map, SVM: Support Vector Machine, SVR: Support Vector Regression.

Table 1 provides a concise look at recent findings on emotion recognition approaches, using biosignal indices, such as blood pressure, heart rate, ECG findings, electromyogram (EMG) results, skin conductance, and temperature. Feature extraction and classification techniques are also highlighted in Table 1.

Among the conducted studies, application of time-domain and spectrum-based techniques is very common. However, these techniques are appropriate for linear and stationary signals and cannot completely provide biosignal information. Most physiological signals have a dynamic nature and show complex and chaotic behaviors. Therefore, non-linear approaches may be preferred for characterizing the dynamic properties of biological signals. In a previous study, empirical mode decomposion (EMD) technique was proposed to deal with random and chaotic behaviors of such time series [29].

Some applications of EMD in biomedical signal processing include the assessment of mental tasks [30-32], depth of anesthesia from EEG [33], ECG signal denoising [34-37], congestive heart failure [38], screening of obstructive sleep apnea with ECG [39], personal identification [40], fatigue assessment by EMG signal analysis [41], and epileptic seizure prediction [42].

EMD method can be applicable to non-stationary and non-linear signals. Therefore, in this method, extraction of useful features from HRV signals is more plausible, compared to traditional methods. EMD may result in a better frequency and temporal resolution in comparison with Fourier analysis [32]. Additionally, EMD is regarded as a data-driven procedure in comparison with wavelet analysis. By using EMD, a signal is decomposed into intrinsic mode functions (IMFs) in a natural manner without any prior knowledge about the data series [43].

In addition, IMFs are uncorrelated among themselves due to being orthogonal [29]. Similar to a dyadic filter bank [44], not only the bandwidth of each IMF is limited, but also each IMF can be applied as an adaptive spectral band. The advantage of EMD in separating high- and low-frequency components of RR interval time series has been demonstrated in the literature [45].

In several studies, EMD has been applied in emotion recognition systems [6, 20, 26]. EMD can represent different oscillation modes of a signal, i.e., fast oscillation modes demonstrated by lower-order IMFs and slow oscillations verified by higher-order IMFs. In addition, It has been hypothesized that IMF combinations can show different oscillatory modes of data. Therefore, these combinations could be applied for a better description of the signal dynamics and help provide a better characterization of HRV signals in different affective states.

For the first time, in the present study, we assessed the IMF combinations regarding emotion recognition. The purpose of this study was to determine the efficacy of EMD in combination with other indices in discriminating emotions. In this article, first, the process of data acquisition is briefly described. Second, the applied methodology is introduced, which consists of feature extraction and classification. Next, the experimental results are reported, and conclusions are presented.

2. Materials and Methods

After collecting ECG data, the signals were pre-processed. Alternating current (AC) power-line noise (50 Hz) was removed, and the signals were segmented according to the blocks of emotional load. HRV was estimated from ECG signals. By applying EMD, each segment of the signal was decomposed into its IMF components.

Afterwards, some standard and non-linear features were extracted from each IMF and IMF combination as an indicator of emotional reaction; finally, a classifier was applied on the extracted features. Different processing stages and methods applied in the present study are demonstrated in Figure 1.

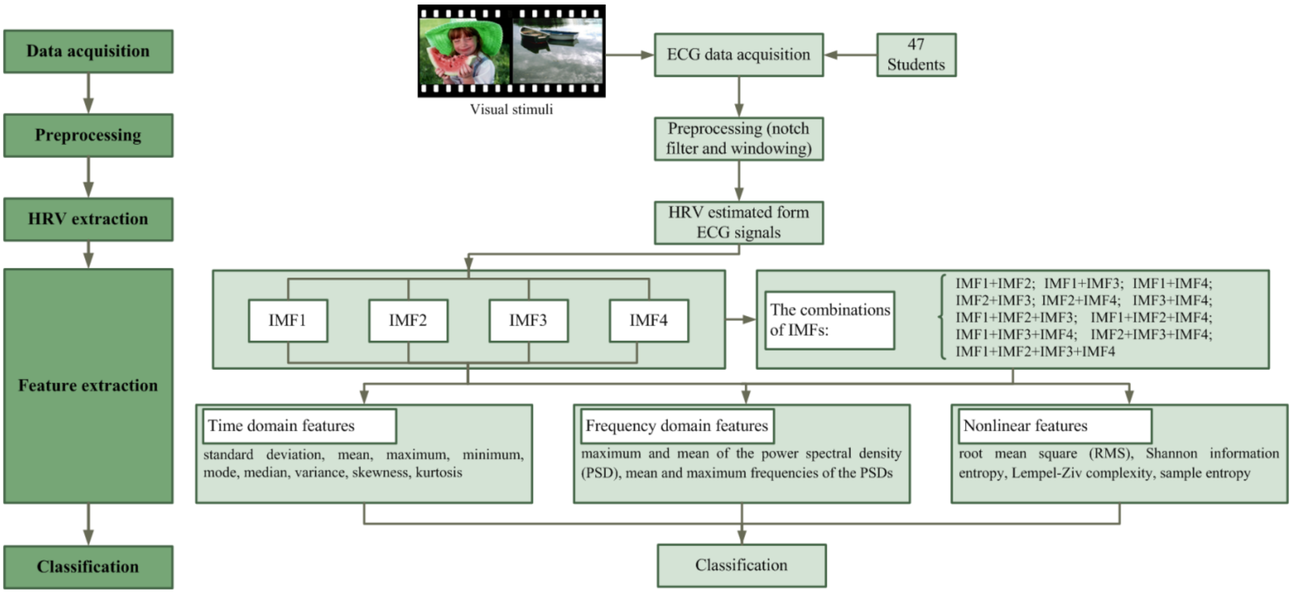

Figure 1. The proposed methodology applied in the present study

2.1. Data collection

ECG data were collected from 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). To elicit emotions in the participants, images from the International Affective Picture System (IAPS) were used [46].

Based on the dimensional structure of the emotional space, IAPS images corresponding to relaxed, happy, sad, and fearful states were selected. In total, 35 images were selected per emotional category (total of 140 images). Each subset was selected by considering empirical thresholds on valence and arousal scores [47].

Upon arrival in the laboratory, all subjects were asked to read and sign a consent form to participate in the experiment. The participants were also instructed to remain still during data recording and avoid movements of fingers, hands, and legs. As the participants sat in front of the laptop screen (15.5 inch, VAIO E Series), their physiological responses (i.e., ECG signals) were recorded from lead I. The entire procedure took 15 min, and images were represented after 2 min rest.

After performing the initial baseline measurements, 28 blocks of pictorial stimuli were presented on the laptop screen at random to avoid habituation in the participants; furthermore, the blocks were balanced between the subjects. Each block consisted of five images from the same emotional class, displayed for 15 sec with 10 sec of blank screen display at the end of each block. The blank screen was followed by a white plus (for 3 sec) to prompt the participants to concentrate on the center of the screen and be prepared for the next block.

As emotions are dependent on past experiences of the subjects, they were asked to self-assess their emotional states. All the signals were recorded in the Computational Neuroscience Laboratory, using 16-channel PowerLab (ADInstruments) at a sampling rate of 400 Hz. A digital notch filter was applied to the data at 50 Hz to remove any artifacts caused by the AC line noise.

2.2. Feature extraction

2.2.1. *Empirical mode decomposition*

EMD is an innovative algorithm of data processing in non-stationary and non-linear time series [29]. This technique is applied in order to decompose a complex time series to a limited number of IMFs. Two conditions must be satisfied in an IMF: 1) number of zero crossings and extrema must either be equal or differ by one, and 2) the mean value of the envelope defined by the local maxima and the envelope defined by the local minima should be zero.

IMF was extracted from the data, using the mean values of upper and lower envelopes, while applying the cubic spline method to connect the extrema. As mentioned earlier, the number of IMFs extracted from a complex time series is limited, and the residue signal remains with a monotonous pattern. In other words, by applying the EMD technique, a segment of HRV signal, x(t), can be separated into n-IMFs: C_1, C_2, …, C_n and a residue signal r_n. Therefore, the reconstructed x(t) signal could be shaped, using a linear combination (1):

$$X(t) = \sum_{n=1}^{N} C_n + r_n \tag{1}$$

where X(t) is the original signal, C_n in the n^{th} IMF, and the residue after n-decomposing operations is represented by r_n.

The systematic method to extract IMFs is presented in Figure 2. This method is described by the following steps:

1) Extraction of the local minimum and maximum x(t);

2) Connection of all sequential local minima to derive the lower envelope, $e_{min}(t)$, using a cubic spline. The same procedure was performed for every sequential local maxima to drive the upper envelope, $e_{max}(t)$;

3) Calculation of the mean value of the envelope by averaging the lower and upper envelopes, $m(t)=[e_{min}(t)- e_{max}(t)]/2$;

4) Computation of the transient local oscillation h(t)=x(t)-m(t). If h(t) is an IMF, n=n+1, C_n=h(t), we moved on to step (5); otherwise, if x(t)=h(t), cycle 1-4 was repeated; and 5) Calculation of the residue r(t)=x(t)-c(t). If the computed residue (r(t)) was a monotonic function, the procedure was ended; otherwise, with x(t)=r(t), we moved on to step (1) and repeated the process.

The first IMF (IMF1) was related to the highest local frequency, whereas the residue included the lowest frequency.

2.2.2. *Estimated parameters*

Four IMFs and the residue for each HRV segment were extracted by applying the EMD technique. Figure 3 demonstrates a typical EMD decomposition for the HRV data during rest. Then, 17 parameters were estimated for each IMF. These parameters were carefully selected from the literature [30, 32, 33, 36, 48, 49]. The proposed parameters are as follows:

- Mean,

$$\overline{IMF} = \frac{1}{N}\sum_{i=1}^{N} IMF_i \tag{2}$$

where N is the number of the samples.

- Standard deviation,

$$SD(IMF) = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(IMF_i - \overline{IMF})^2} \tag{3}$$

- Maximum, the largest value of IMF,
- Minimum, the smallest value of IMF,
- Mode, the most frequent value of IMF,
- Median, the median value of IMF,
- Variance,

$$Var(IMF) = SD^2(IMF) \tag{4}$$

- Moments, the central moment of order k,

$$M_k(IMF) = \frac{1}{N}\sum_{i=1}^{N}(IMF_i - \overline{IMF})^k$$

where k is 2, 3, and 4, respectively.

- The maximum and mean values of the power spectral density (PSD) of each IMF, where PSD of the signal is estimated, using fast Fourier transform algorithm.
- The mean and maximum frequencies of PSDs,
- Root mean square (RMS),

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} IMF_i^{\,2}} \tag{6}$$

- Lempel-Ziv complexity [50],
  After transforming the numerical data into a symbolic sequence, the sequence should be parsed to get distinct words, encoded with the length of L(n). Lempel-Ziv (L-Z) complexity is defined as follows:

$$L - Z = \frac{L(n)}{n} \tag{7}$$

- The Shannon information entropy (ShEn) and sample entropy (SaEn), which are usually considered as a measure of complexity, unpredictability, and irregularity.

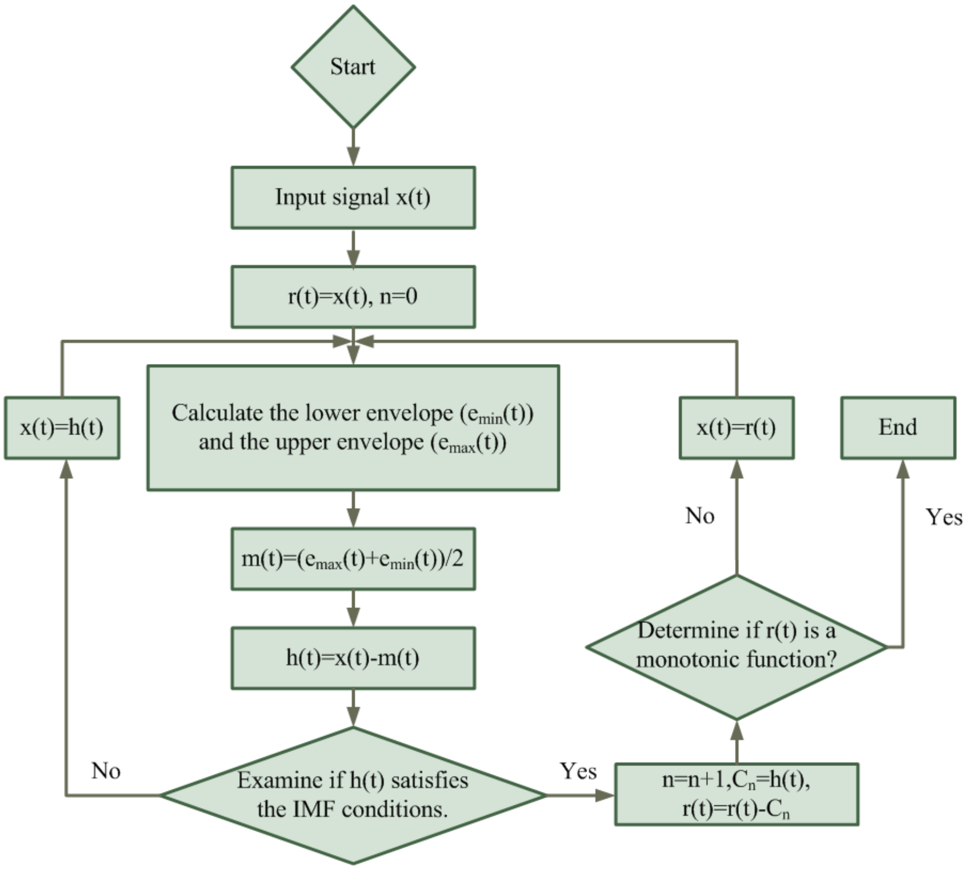

Figure 2. The algorithm of empirical mode decomposition (EMD) analysis

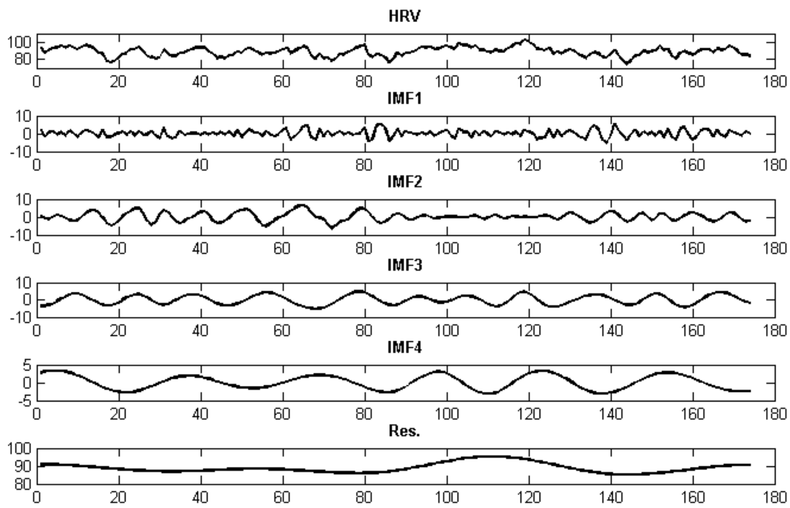

Figure 3. A typical empirical mode decomposition (EMD) for heart rate variability (HRV) signal during rest. From top to bottom: HRV signal, IMF1, IMF2, IMF3, IMF4, and the residue

So far, different types of entropies have been introduced. In this article, ShEn and SaEn were utilized [51]. ShEn appraised the average minimum amount of bits desired to encode a sequence of symbols, based on the occurrence of symbols:

$$ShEn = -\sum_{i=0}^{N-1} p_i \log_2 p_i \tag{8}$$

Where p_i is the probability of a symbol.

In SaEn, after selecting two parameters (*m* and *r*), the computation of SaEn could be realized. Here, $B^m(r)$ had to be computed (with the embedding dimension *m* and tolerance coefficient of 1). This measure was finally obtained as follows:

$$SampEn(m,r,N) = -\ln \frac{B_{m+1}(r)}{B_m(r)} \quad (9)$$

where

$$B_m(r) = \frac{N-m-l}{N-m} \sum_{i=1}^{N-m} B_i(r) \quad (10)$$

2.2.3. Classification

In previous research, probabilistic neural network (PNN) has shown proper performance in classification problems [52]. As soon as an input is fed into the PNN classifier, the first layer calculates the distance between the input and training input vectors and offers a vector, the elements of which show closeness between the input data and training vector points. In the present study, by adding some measures, a competitive layer was used to produce the output vector.

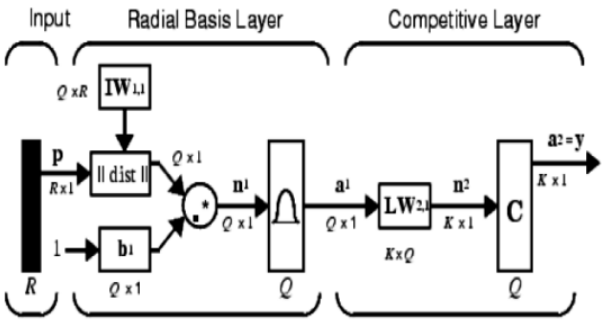

Figure 4. The architecture of the probabilistic neural network (PNN)[1]

A competitive layer picked the maximum probabilities and produced a 1 to that class and 0 for the others. Figure 4 provides the schematic PNN architecture. In the training process of PNN, measurement of the smoothing parameter (sigma, σ) was a fundamental step. In this network, an optimal σ was derived by trial and error.

3. Results

To evaluate the ability of features in discriminating different emotions, several classification techniques, including PNN with various structures and KNN, were appraised. As PNN outperformed KNN, the PNN results were subsequently reported. The classifier randomly selected two-thirds of the feature vector as the training set and the rest of the vector was chosen as the test, which is known as conventional validation. The classification accuracy was measured as follows:

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (13)$$

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

The classifier performance was also tested by means of sensitivity (true positive rate) and specificity (true negative rate), based on Equations (14) and (15), respectively:

$$Sensitivity = \frac{TP}{TP+FN} \quad (14)$$

$$Specificity = \frac{TN}{TN+FP} \quad (15)$$

Based on the dimensional structure of the emotional space, the accuracy of the classifier was examined with the following considerations:

1) Four categories of emotions (happy, sad, fearful, and peaceful), as well as a rest category (a total of five classes), were considered (5C).

2) Positive arousing emotions (happy and fearful) were classified in a category, while negative arousing emotions (peaceful and sad) were assumed to be a unique class. As a result, the number of classes was reduced to three, including positive arousal (stimulating), negative arousal (relaxing), and the rest (3A).

3) In a similar manner, three classes for valence, i.e., pleasant (peacefulness and happiness), unpleasant (fearfulness and sadness), and the rest state, were selected (3V).

The classification rates of the proposed method are shown in Table 2. In addition, sensitivity and specificity of the classifier are provided in Table 2.

1. http://www.mathworks.com/access/helpdesk/help/toolbox/nnet.

Table 2. Classification rates for different combinations of IMFs using conventional validation.

	Emotion Classes	Classification Accuracy (%)				Sensitivity	Specificity
		σ =0.2	σ =0.1	σ =0.05	σ=0.01	σ=0.01	
IMF1	5C	26.63	30.21	34.10	49.06	47.72	84.95
	3A	44.80	46.63	50.15	59.39	19.45	99.09
	3V	44.19	46.26	49.48	59.64	21.28	98.71
IMF2	5C	39.21	61.52	84.62	98.48	99.7	99.01
	3A	52.52	67.90	86.93	98.78	97.26	100
	3V	51.79	66.93	86.38	98.66	98.18	99.7
IMF3	5C	31.12	43.95	64.92	95.62	95.14	99.09
	3A	46.50	55.62	71.12	96.11	90.88	99.85
	3V	46.69	55.14	71.55	95.93	91.49	99.7
IMF4	5C	31.67	49.06	77.02	98.36	98.78	99.24
	3A	47.48	57.87	79.45	98.60	98.48	99.47
	3V	46.57	58.78	80.12	98.54	97.87	99.62
IMF1+ IMF2	5C	26.81	31.12	36.9	66.81	66.87	89.21
	3A	44.13	47.17	53.37	72.58	44.07	99.54
	3V	44.44	46.69	51.19	74.10	43.47	99.16
IMF1+ IMF3	5C	25.84	29.36	33.43	55.62	55.93	86.7
	3A	43.77	45.65	49.42	63.89	24.92	99.39
	3V	43.47	45.90	49.30	64.44	25.53	99.47
IMF1+ IMF4	5C	25.78	28.69	34.22	52.89	53.5	86.02
	3A	42.67	47.66	49.73	61.76	23.4	99.47
	3V	43.34	45.53	49.30	62.13	23.71	99.62
IMF2+ IMF3	5C	32.89	46.26	69.12	97.33	97.57	98.86
	3A	48.57	55.74	73.13	97.87	94.83	100
	3V	46.93	57.93	74.29	97.45	94.22	99.85
IMF2+ IMF4	5C	33.86	52.64	76.17	97.99	99.09	98.40
	3A	48.69	61.09	78.66	98.30	96.35	99.62
	3V	47.90	61.76	79.15	98.30	96.05	99.62
IMF3+ IMF4	5C	27.11	38.72	59.76	95.32	95.47	99.01
	3A	45.96	50.64	66.57	95.93	92.40	99.70
	3V	45.11	51.31	66.26	95.93	89.67	99.92
IMF1+ IMF2+ IMF3	5C	25.65	30.82	35.74	67.60	75.38	86.02
	3A	43.95	46.32	51.06	72.58	45.59	98.78
	3V	43.40	45.65	50.94	73.86	45.59	99.09
IMF1+ IMF2+ IMF4	5C	26.57	29.91	36.29	66.57	72.34	87.01
	3A	43.89	46.20	50.88	72.10	42.55	99.54
	3V	43.53	46.87	50.94	73.31	44.68	99.32
IMF1+ IMF3+ IMF4	5C	25.84	29.54	33.43	56.78	61.09	85.33
	3A	43.28	46.14	49.60	64.62	28.57	99.47
	3V	42.80	46.38	48.09	64.62	29.79	99.09
IMF2+ IMF3+ IMF4	5C	30.21	42.25	64.01	96.66	97.57	97.87
	3A	46.87	53.62	69.24	97.26	93.92	99.54
	3V	46.99	54.10	70.88	96.66	93.31	99.39
IMF1+ IMF2+ IMF3+ IMF4	5C	25.90	29.48	34.47	67.17	71.73	87.16
	3A	43.83	46.14	49.54	71.85	39.51	99.47
	3V	43.40	46.20	51.25	72.64	40.73	99.47
IMF1, IMF2, IMF3, IMF4, Res.	5C	77.75	88.88	94.47	99.09	100	99.01
	3A	81.16	89.85	95.2	99.33	99.7	99.47
	3V	80.67	89.18	94.71	99.33	99.09	99.70

Note: : the best, : the second best (97 < Accuracy (%) < 99), : the third best (95 < Accuracy (%) < 97) classification rates.

According to the results, the best classification rates (>99%) were achieved for σ= 0.01, when all IMFs (IMF1, IMF2, IMF3, IMF4, and residue), without being combined, were simultaneously applied to the classifier. The classification resulted in 100%, 99.7%, and 99.09% sensitivity and 99.01%, 99.47%, and 99.7% specificity for 5C, 3A, and 3V, respectively.

By considering the parameters of each IMF, the recognition rates of IMF2, IMF4, and IMF3 were nearly 98.64%, 98.5%, and 95.89% for all the categories of emotions, respectively. In addition, it was found that the extracted features from IMF1 frequency were unsuitable for resolving the problem of emotion recognition.

The combination of IMF1 with other IMFs (i.e., IMF1+IMF2; IMF1+IMF3; IMF1+IMF4; IMF1+IMF2+IMF3; IMF1+IMF2+IMF4; IMF1+IMF3+IMF4; and IMF1+IMF2+IMF3+IMF4) might decrease the classification accuracy. The findings confirmed that the lowest recognition rate was attributed to the combination of IMF1 with other IMFs (Table 2).

Based on the results, it can be concluded that not only the lower-frequency components of HRV do not play a significant role in emotion recognition, but also they reduce the classification rates. According to the results presented in Table 2, the accuracy rates for five categories of emotions were closely similar to those in three classes. Therefore, it seems that the number of emotion types does not have any significant effect on the classifier performance.

To limit problems such as over-fitting, the classifier's performance was tested by means of k-fold technique, which is known as a cross-validation approach. In this case, the data were randomly divided into k equal-sized partitions. A single partition was assigned as the validation data for testing the model, while the remaining k-1 partitions were used as the training data; this process was repeated k times.

The average of computed values in k-fold technique was considered as a single estimation. In the present study, k value was considered to be 5. The obtained results are reported in Table 3. Acceptable performances were also achieved in emotion recognition, using the cross-validation test.

4. Discussion

Over the past decades, automatic emotion recognition has become a challenging issue in human-computer interfaces. Therefore, this study aimed to propose an efficient method for discriminating emotional responses through physiological signals.

The data acquisition protocol and emotion elicitation technique were described in detail. In total, 16 IMF combinations were evaluated, using four significant IMFs. For each IMF, 17 parameters, including standard and non-linear features, were extracted. To evaluate the ability of features in discriminating emotions, PNN was applied as a classification method. The best correct rate (99.33%) was achieved when all IMFs were fed into the classifier without being combined. On the other hand, the combination of IMF1 with other IMFs resulted in the worst rate of emotion recognition.

Compared to previously published studies, a higher recognition rate was attained in the present study (Table 1). Zong and Chetouani analyzed ECG, EMG, skin conductivity, and respiratory changes with EMD and SVM and reported a classification rate of 76% [20]. Furthermore, analysis of the standard features of some autonomic signals with support vector regression resulted in an accuracy of up to 90% [7]. Also, Niu et al. obtained the highest rate of recognition (97%), using a genetic algorithm on the statistical features of ECG, EMG, skin conductivity, and respiratory changes [14].

In a previous study, by applying KNN along with higher-order statistics and Hurst parameters of ECG signals, a classification accuracy of 93% was achieved [25]. Also, in another article, spectral representation, higher-order spectral representation, and Lyapunov exponent of HR signals were used as the inputs of SVM, resulting in an average accuracy of 80% [22]. Moreover, by using EMD and discrete Fourier transform, maximum accuracy of 52% was accomplished with linear discriminant analysis and KNN [26].

The number of emotions considered in emotion recognition is an important issue. Previously, a maximum classification rate of ~93% was attained for the classification of six types of emotions from ECG signals [25]. In the present study, five and three emotional states were classified with the maximum recognition rates of 99.09% and 99.33%, respectively. Therefore, increasing the number of emotion categories does not have any significant effect on the classifier performance.

In line with previous research, the reliability of ECG signals in discriminating emotional states was confirmed in the current study [25]. Furthermore, the effectiveness of the proposed method was approved by the high accuracy rates of PNN. As the recognition rates of the present approach outperformed previously reported techniques (Table 1), this approach was shown to be highly successful in overcoming the problem of emotion recognition.

The major shortcoming of EMD is its computational cost. The algorithm iteratively selects local maxima and minima for each empirical mode, which is a computationally intensive procedure. Despite the high performance of the suggested algorithm, this amount of computational load encumbers its real-time application, such as embedment into wearable sensors.

5. Conclusion

Automatic emotion recognition using the information extracted from biomedical signals has fascinated researchers in the recent past. Quite a lot of algorithms addressing bio-signals have been offered in the literature. In the current study, four emotional states, including happiness, peacefulness, sadness, and fearfulness were characterized by standard and non-linear parameters of the IMFs and different IMF combinations of HRV signals. Moreover, by comparing the results obtained by the PNN, the influence of the different IMF combination choices in emotion recognition rate has been appraised. The results showed that the proposed EMD based approach efficiently categorized the features into the emotional classes. The high performance of the classifier revealed the usefulness of the EMD based method for screening emotion of mankind.

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