An Optimal EEG-based Emotion Recognition Algorithm Using Gabor Features

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Abstract: - Feature extraction and accurate classification of the emotion-related EEG-characteristics have a key role in success of emotion recognition systems. In this paper, an optimal EEG-based emotion recognition algorithm based on spectral features and neural network classifiers is proposed. In this algorithm, spectral, spatial and temporal features are selected from the emotion-related EEG signals by applying Gabor functions and wavelet transform. Then neural network classifiers such as improved particle swarm optimization (IPSO) and probabilistic neural network (PNN) are developed to determine an optimal nonlinear decision boundary between the extracted features from the six basic emotions (happiness, surprise, anger, fear, disgust and sadness). The best result is obtained when Gabor-based features and PNN classifier are used. In this condition, our algorithm can achieve average accuracy of 64.78% that can be used in brain-computer interfaces systems.

Key-Words: - electroencephalogram, emotion recognition, wavelet transform, Gabor functions, improved particle swarm optimization (IPSO), probabilistic neural network (PNN)

1 Introduction

Brain-computer interfaces (BCI) are systems that allow user to translate brain activities into sequences of commands for the computer in order to mentally control a computer application or Neuro prosthesis [1]. It provides ease of communication especially for physically challenged person [2]. Several methods are existing to detect brain activity such as magnetic resonance imaging (MRI) [3], magneto encephalography (MEG) [4], functional magnetic resonance imaging (FMRI) [5] and electroencephalogram [6]. But the EEG has rapid response time and is inexpensive method relative to other methods, so it is widely used to monitor brain activity in BCI research [7, 8]. The EEG signals are recorded as a weak potential by placing the electrodes on the scalp and analysis to establish a BCI system. The research is based on recording and analyzing EEG brain activity and recognizing EEG patterns associated with mental states [9]. For example, imagining a movement of the right hand is associated with a pattern of EEG activity in the left side of the motor cortex [10].

Various methods have been present to design a BCI system based on EEG signals such as event-related synchronization [11] and event-related desynchronization [12]. A number of EEG-based BCI systems have been developed recently in which patterns of EEG in different mental states can be discriminated for information transmission by feature extraction and classification algorithms [13]. Generally, in a BCI system EEG signals are pre-processed and the feature that best represent the details of the signal is extracted. Then the extracted features are used for training the classifier which discriminates the features [14]. One of these methods is emotion recognition that brain activity (EEG) of person is analysis based on various emotions such as happiness, surprise and anger. Currently, correct EEG-based recognition of artificially evoked emotion is only about 60%, but much research shows the suitability of EEG for this kind of task [15]. This field of research is still relatively new and there is still much to be done to improve on existing elements in BCI, but also to discover new possibilities.

To design an EEG-based emotion recognition system, effective feature selection and accurate classification are two important factors to improving the performance. The extracted features must be able to preserve the discriminant information from EEG signals into small unique values. Many different features have been thought up to be extracted from EEG signals. The most used transformation is Fourier analysis to be able to look at specific frequency bands [16]. The used classifier must be able set an optimal nonlinear decision boundary. Support vector machine (SVM) [17] and recently neural network (NN) [18] are used as classifier in works. For example, Petrantonakis [19] analyzed EEG signals and used neural networks to classify them in six emotions based on emotional valence and arousal, with a 61% success rate. Takahashi [20] used a setup of three dry electrodes on a head-band to classify five emotions based on multiple bio-potential signals (EEG, pulse and skin conductance). The success rate when classifying solely on the EEG using support vector machines was 41.7%.

In this paper, we propose an EEG-based emotion recognition algorithm based on spectral, spatial and temporal features and neural network classifiers. To obtain an optimal algorithm, the emotion-related EEG signals are decomposed by Gabor functions and wavelet transform. Then spectral and spatial features are extracted from sub-representations and sub-bands. To reduce the computational cost of the Gabor function, we introduce a simplified Gabor function that called GaborSD. It represents the EEG signals in several sub-representations by filtering them with the sum over scales and direction of Gabor function. Then several features are extracted from each sub-representation. Since the non-effective features increase computational cost and decrease the performance of algorithm, principal component analysis (PCA) is employed to select R effective features among of the several features, without supervisory. Furthermore, we develop the neural network classifiers such as improved particle swarm optimization (IPSO) and probabilistic neural network to create a non-linear decision boundary between the selected features. So, we obtain four algorithms. Each algorithm that has been minimum latency and maximum accuracy is specified as optimal algorithm.

The rest of the paper is organized as follows. The characteristics of the used emotion-related EEG dataset are described in section 2. The structure of algorithms including feature extraction and classification is presented in section 3. In section 4, the performances measures and results of the optimal algorithm on six basic emotions (happiness, surprise, anger, fear, disgust and sadness) are obtained and the best result is introduced as optimal algorithm. Finally, some conclusion is discussed in section 6.

2 Emotion-related EEG dataset

EEG recording were conducted using the g.MoBIlab (g.tec medical & electrical engineering, Guger technologies) portable biosignal acquisition system including of four EEG bipolar channels, passive electrodes, filters: 0.5-30 HZ, sensitivity: 100μv, data acquisition: A/D converter with 16-bit resolution and sampling frequency of 256HZ. The EEG signals from each subject were recorded during the projection phase. The EEG signals were acquired from FP1, FP2, F3, and F4 positions, according to the 10-20 system. The small number of EEG channels selected was as an effort to implement an emotion recognition method which would result in a more user-friendly environment in the future and to acquire signals from the brain areas according to the emotion expression in the brain, based on the asymmetry concept. The FP1 and FP2 positions were recorded as monopole channels (channels 1 and 2, respectively), whereas the F3 and F4 positions as a dipole (channel 3), resulting in a 3-EEG channel set. The averaged EEG signal in the time domain, corresponding to each one of the six basic emotions for channel 3 is shown in Fig. 1.

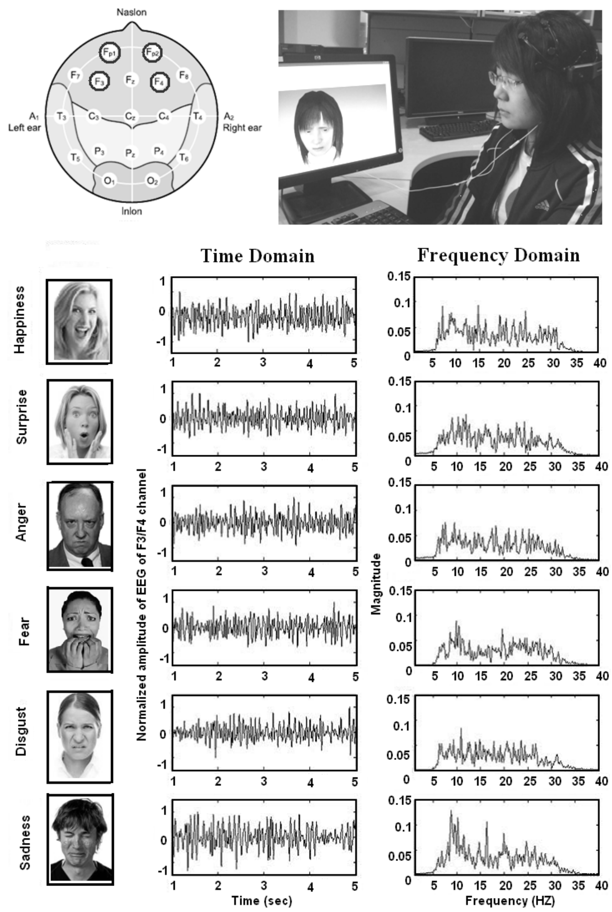

Fig. 1: EEG signal corresponding to each one of the six basic emotions for channel 3.

In this experiment, 10 healthy volunteers participated; all were right-handed subjects (6 males and 4 females) in the age group of 20-42 years. At first, a suitable interface was implemented for the automated projection of the emotion-related pictures and the self- assessment of the emotion picturized each time. Pictures of Facial Affect (POFA) by Ekman and Friesen [21], showing people expressing the six basic emotions (happiness, surprise, anger, fear, disgust and sadness), were subsequently previewed, separated by black and counting down frames to accomplish a relaxation phase before the projection of the new picture. More specifically, sixty pictures (10 pictures per emotion) were randomly projected for five seconds after a five-second black screen period, a five-second period in which countdown frames were demonstrated and a one-second projection of a cross shape in the middle of the screen to attract the sight of the subject. The same sixteen-second procedure was repeated for every one of the sixty pictures. An illustrated version of the experiment protocol is showed in Fig. 2. Table 1 show the number of five-second emotion-related EEG signals that is used for the training and test procedure of classifier.

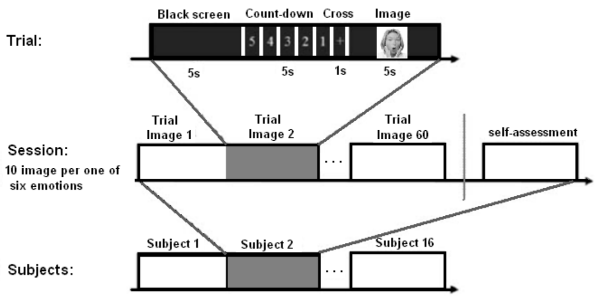

Fig. 2: Illustration of the experimental protocol for emotion elicitation

Table 1. The number of five-second emotion-related EEG signals that is used for the training and test of classifier.

sub ject	*sex*	*Number of training and test data*					
		happiness	*surprise*	*anger*	*fear*	*disgust*	*sadness*
1	M	7	6	8	7	6	7
2	F	8	6	7	6	8	7
3	F	8	7	6	8	7	8
4	M	7	8	8	7	7	7
5	M	7	6	8	8	7	8
6	M	7	8	6	7	8	7
7	M	8	7	8	6	8	8
8	F	7	7	7	6	7	8
9	M	7	6	6	8	8	7
10	F	6	7	7	7	8	7
Total		72	68	71	70	74	74

3 General structure of the EEG-based emotion recognition algorithms

The overall structure of an EEG-based emotion recognition algorithm is shown in Fig. 3. In this algorithm L-second epochs from emotion-related EEG-characteristics are decomposed to multiple frequency components by Gabor functions (GaborSD) or wavelet transform and represented in the spatial, spectral and temporal domain. Secondly, the spectrum energy of each sub-representation is calculated by Discrete Fourier Transform (DFT) to extract several features from each sub-representation or sub-bands. Then a three-layer MLP neural network with IPSO learning algorithm or PNN is trained on the extracted features from six emotions (happiness, surprise, anger, fear, disgust and sadness) for determining the optimal nonlinear decision boundary between different classes. So, four EEG-based emotion recognition algorithms are obtained including:

- EEG-based emotion recognition algorithm based on Gabor-features and IPSONN classifier (G-IPSONN algorithm)
- EEG-based emotion recognition algorithm based on Gabor-features and PNN classifier (G-PNN algorithm)
- EEG-based emotion recognition algorithm based on wavelet-features and IPSONN classifier (W-IPSONN algorithm)
- EEG-based emotion recognition algorithm based on wavelet-features and PNN classifier (W-PNN algorithm)

Each algorithm that has minimum average latency and maximum average accuracy is specified as optimal algorithm.

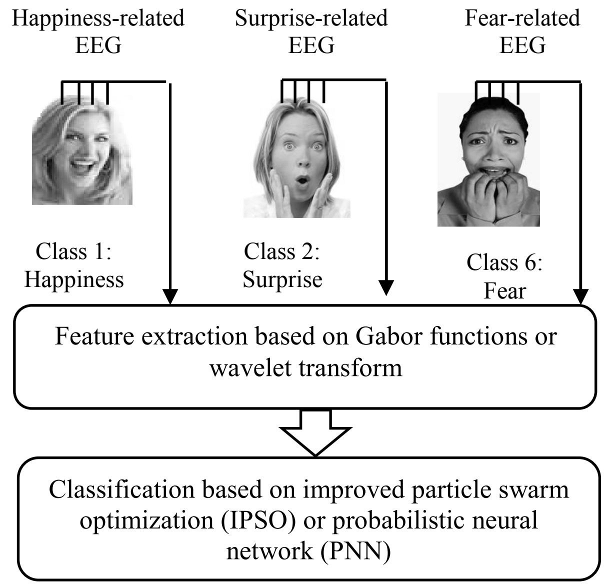

Fig. 3: Structure of an EEG-based emotion recognition algorithm

2.1 Wavelet-based features

Registration location of channels (electrodes) can be useful as a tool in creating the distinction between emotions. Furthermore, frequency contents of various emotions have different spectrum energy. The frequency components of EEG signals can be involved at five frequency bands, delta (2-4HZ), alpha (4-8HZ), beta (8-15HZ), theta (15-30HZ) and gamma (30-90HZ). In traditional approach, Discrete Fourier transform (DFT) is used to calculate the spectrum energy of each band for an EEG frame [22]. Since, the EEG signals have the nature of non-stationary, so DFT can not be a powerful tool to decompose the signals because it just provides the frequency resolution. Discrete wavelet transform (DWT) [23] can be used as a strong mathematical tool to disintegrate the EEG with time-frequency resolution. In this approach, EEG signals are decomposed by wavelet transform and represented in the spectral, spatial and temporal domain. For an EEG epoch sample $X_{c,t}$ at channel c and time t, wavelet coefficients (sub-bands), $x_{(c,f,t)}$ are calculated by the convolution with a wavelet function $M_{(t,f)}$ by:

$$x_{(c,f,t)} = \left\| M_{(t,f)} * X_{(c,t)} \right\| \qquad (1)$$

We choose the complex Morlet wavelet as mother wavelet function (2) because it has been successfully used in the analysis of the temporal-frequency of EEG signals [24].

$$\psi(t) = \frac{1}{\sqrt{\pi\sigma}} \exp(2i\pi\Omega t)\exp(-\frac{t^2}{\sigma}) \qquad (2)$$

In this paper, we use the both DWT and DFT to extract the features from the emotion-related EEG signals. In this strategy, L-second epochs are decomposed into five sub-bands by DWT and Morlet mother wavelet. Then spectrum energy of five frequency bands (Δ, α, β, θ, γ) is respectively calculated for five sub-bands (d5, d4, d3, d2, d1). This process is repeated for all of channels (N) and frames which is shown in Fig.4.

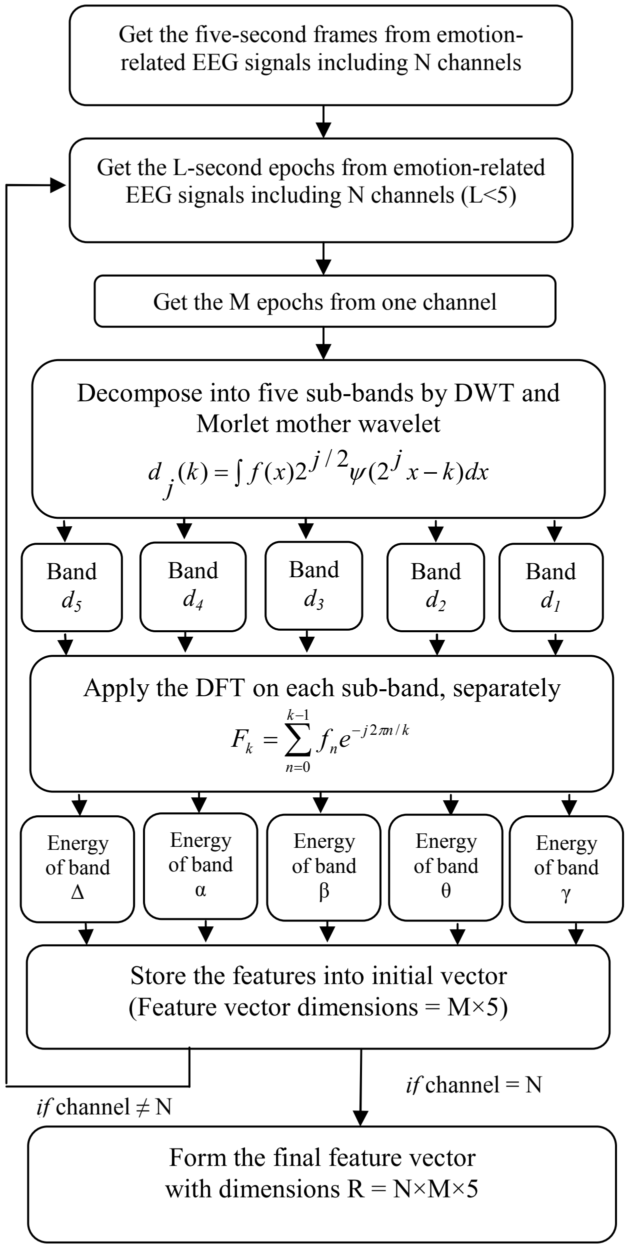

Fig. 4: The process of feature extraction based on DWT and DFT

2.2 Gabor-based features

Gabor's theory describes the signal as function of time and frequency content [25]. Gabor functions can be employed as a new representation for the processing information in the time and frequency domains [26]. The time-domain representation details the signal amplitude at each instant in time. While the frequency-domain representation uses infinitely-long pure sinusoids, described only by their frequency, amplitude and phase. A Gabor function is defined by:

$$g(t) = e^{-\alpha^2 (t-t_o)^2} .(\cos[2\pi f(t-t_o) + \phi] + i\sin[2\pi f(t-t_o) + \phi]) \qquad (3)$$

where α is the constant of the Gaussian modulating probability function and is inversely proportional to the width of the function, t_o defines the centre of the Gaussian function. f is the frequency of the oscillation, ϕ is the phase of the harmonic oscillation (relative to the center of the Gussian modulating function). In our application, we use Gabor functions with five different scales (t_o = 0,1,2,3,4) and eight different orientations ($\phi = \pi d/8$ for d = 0,1,2,3,4,5,6,7) and f = 2.

If $X_{c,w}$ be the L-second epoch at channel *c* and time *w*, the Gabor function representation is obtained by convolving the Gabor function with $X_{c,w}$. The result is a 3*th* order tensor in R^{N_1,N_2,N_3} which give the spatial, spectral and temporal domain. We use GaborSD for representations of $X_{c,w}$. It is the sum over scales and directions of Gabor function-based representation. The most important benefit of this new representation is low cost of computing. GaborSD is the magnitude part of the output generated by convolving an $X_{c,w}$ with the sum of all forty Gabor functions by:

$$GaborSD(c,f,t) = \left\| \sum_{t_o} \sum_{d} X_{c,w} * g(t) \right\| = \left\| X_{c,w} * \sum_{t_o} \sum_{d} g(t) \right\| \quad (4)$$

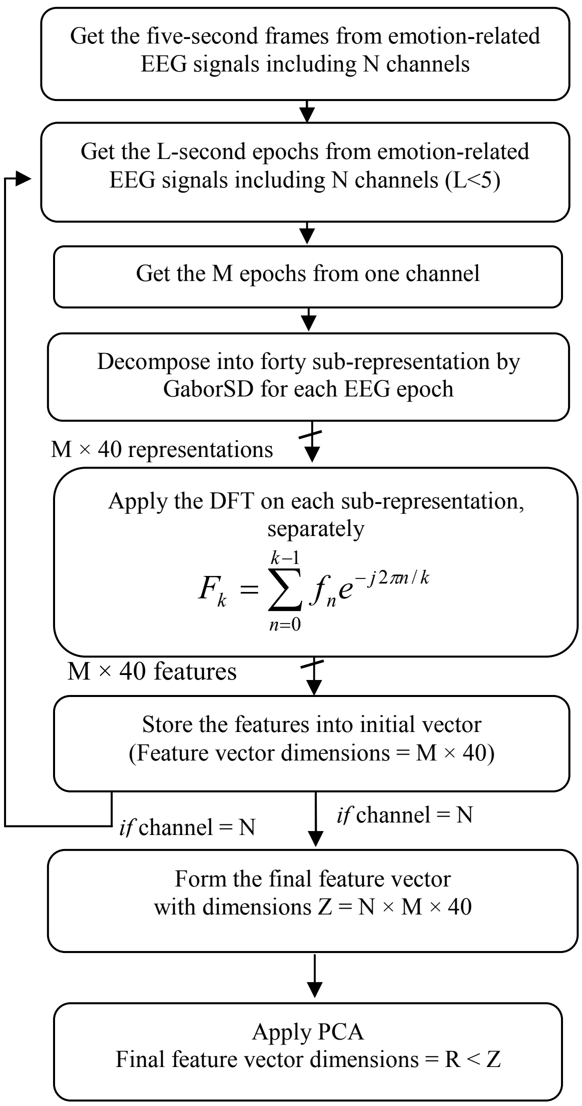

Fig. 5: The process of feature extraction based on GaborSD and PCA

GaborSD(c, f, t) is the output of the GaborSD method for representation. Therefor, forty sub-representation (sub-band) are calculated by GaborSD for each EEG epoch channel that are specified with its coefficients. In order to extract the features from the sub-representation of L-second EEG epochs, the spectrum energy of each sub-representation is calculated by applying Discrete Fourier Transform (DFT). The magnitude part of the generated outputs of DFT is identified as extracted features from EEG signals. Many of this features are non-effective and increase computational cost and decrease the performance of classification. On the other hand, when the number of features is too much, the effective feature selection is difficult, supervisory. Therefore, we employ PCA [27] to select six effective features. The selected features have two properties:

- dispersion of feature is small for training samples of within classes.
- dispersion of feature is large for training samples of between classes.

Fig. 5 shows the process of feature extraction and formation the feature vector. In this algorithm, PCA is transformed a feature vector with large dimension to a feature vector with lower dimension [28].

2.3 IPSONN Classifier

The nonlinear decision boundary (NDB) is best chose to classify the feature vectors as representative of emotion-related EEG signals. Thus, a nonlinear classifier can be employed to determine a NDB for each patient in order to improve the sensitivity of detector. Furthermore, a multilayer Perceptron (MLP) neural network can help to decrease the latency of detector. In this paper, we use a MLP classifier based on the improved particle swarm optimization (IPSO) [29] learning algorithm in order to adjust the parameter of the neural network (NN), efficiently. The IPSO method can search a better solution of the weights in a NN instead of other methods such as back propagation. It is including of the traditional particle swarm optimization (PSO) [30] algorithm and the modified evolutionary direction operator (MEDO). The PSO algorithm is based on the schooling of fish or flocking of birds and can quickly obtain the global solution. The MEDO [31] increases the capability of the PSO to find the optimal solution. The procedure of IPSO is shown in Fig. 6. The MEDO is used to prevent the premature convergence and accelerate the global search capacity. These can be useful for determine the optimal NDB between the extracted features of six classes.

The used MLP consisted of one input layer, one hidden layer and one output layer as shown in Fig.7. The normalized (between 0 and 1) feature vectors (with ten dimensions) are fed to the input layer and which distributed to each unit of the hidden layer. The first layer receives weights from the input. Each subsequent layer receives weights from the input and all previous layers. All layers have biases. The last layer is the network output. A logarithmic sigmoid function is used as the activation function in hidden layers while a linear function is used in the output layer. Additional connections improve the speed at which the network learns the desired relationship. The classifier is consisted of R = 5×N×M input neurons, R hidden neurons and six output neurons to indicate the emotions. The training and testing samples is normalized by adopting a binary normalization algorithm. Selection of the training and test data is performed randomly. The classifier is trained with 80% data samples and tested with 20% data samples for a test error tolerance of 0.1.

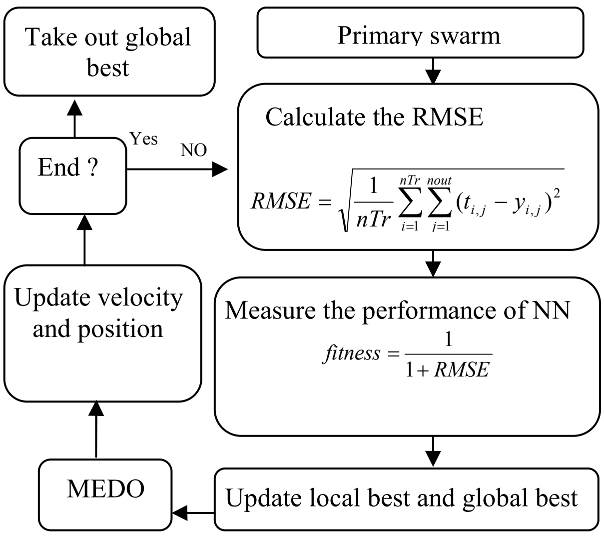

Fig. 6: The process of IPSO

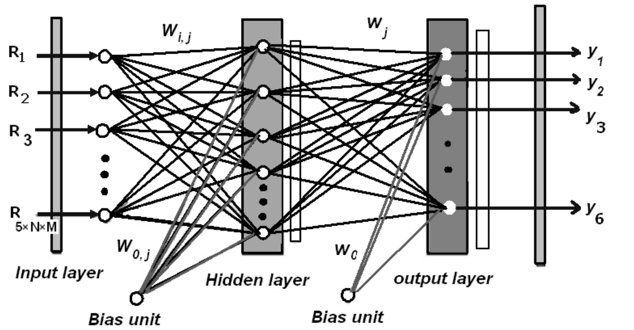

Fig. 7: The used IPSONN classifier. R=5×N×M (number of features)

2.3 PNN classifier

The probabilistic neural network (PNN) is introduced by Specht [32] and is characterized by fast training and convergence to Bayes-optimal decision surface. It estimates the Parzen [33] or a similar probability density function for each class based on the training samples and is capable of realizing or approximating the Bayes classifier:

$$c(x) = arg(\max_{1 \le j \le M}\{p_j f_j(x)\}) \quad (5)$$

where $x \in R^d$ is a d-dimensional feature vector, $c(x)$ denotes the estimated class of pattern x. p_j is the prior probability of class j, and the conditional probability density function of class j is f_j. The goal of the PNN is to estimate the values of f_j by:

$$\hat{f}_{n_j}(x) = \frac{1}{n_j}\sum_{i=1}^{n_j} K_{n_j}(x, X_i^{(i)}) \quad (6)$$

where $X = \{X_i, Y_i\}$ is the set of n observations, each $X_i \in x_i^d$ is a feature vector, and Y_i is a label indicating the class of pattern X_i. The sequence K_n is the Parzen kernel which is defined by:

$$K_n(x,u) = h_n^{-d} K(\frac{x-u}{h_n}) \quad (7)$$

where K is an appropriately selected function and h_n is a certain sequence of numbers. The function K can be presented by:

$$K(x) = \prod_{i=1}^{d} H(x^{(i)}) \quad (8)$$

Then, sequence is expressed by means:

$$K_n(x,u) = h_n^{-d}(2\pi)^{-1/2}\prod_{i=1}^{d} e(\frac{x^{(i)} - u^{(i)}}{h_n})^2 \quad (9)$$

The prior probabilities p_j are estimated by:

$$\hat{p}_j(x) = \frac{n_j}{n} \quad (10)$$

where n_j is the number of observations from class j.

We get the following discriminant function estimation by combining (5), (6) and (10).

$$\hat{d}_{j,n}(x) = \frac{1}{n_j}\sum_{i=1}^{n_j} k_{n_j}(x, X_i^{(j)}) \quad (11)$$

Assign input pattern x to class m in moment n if

$$\hat{d}_{m,n}(x)\hat{d}_{i,n}(x) > 0 \quad (12)$$

In this paper, we use a feed forward networks built with three layers. This network structure is shown in Fig.8. The input layer is fully connected to the hidden layer. Feature vectors are normalized and used as inputs of this network. The hidden layer has a node for each classification. Each hidden node calculates the dot product of the input vector with a test vector subtracts 1 from it and divides the result by the standard deviation squared. Three nodes in output are represented by unit vector happiness = [1 0 0 0 0 0], surprise = [0 1 0 0 0 0],..., sadness = [0 0 0 0 0 1].

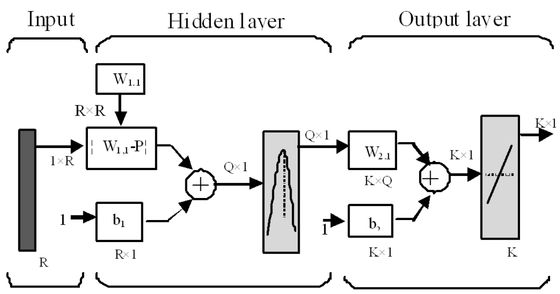

Fig. 8: PNN structure. R: number of features. Q: number of training samples, K: number of classes (K = 6). The three layers are input layer, radial basis layer and competitive layer.

Table 2. Effective parameters of the proposed algorithms and their values

Parameters	*Name*	*values*
L	Length of EEG epoch for feature extraction	1, 2.5, 5
R	Number of features is selected by using Gabor functions or wavelet transform approaches	15, 20, 25, 30

4 Experimental results

In this section, we evaluate the performance of four EEG-based emotion recognition algorithms. First, the performance measures and influence parameters are introduced. Finally, the results of algorithm with different values of the parameters are evaluated and compared with other algorithms.

4.1 Evaluation Measures

The performance of an EEG-based emotion recognition algorithm is frequently evaluated by means of classification accuracy as following: the percentage of emotions correctly identified which is calculated by:

$$\text{classification accuracy} = \frac{\text{Number of correct classified emotions}}{\text{Number of total emotions}} \tag{13}$$

We use the MATLAB to implement algorithms. To estimate the performance of systems and calculate the classification accuracy, the systems is trained with 80% of dataset. Table 2 shows the values of influence parameters at the performance, which is used to simulate the proposed algorithm. In each algorithm, we try to find the best values for EEG epoch length and number of selected features.

4.2 Performance of G-IPSONN algorithm

G-IPSONN algorithm uses the Gabor-based features and IPSONN classifier to recognition of emotions. To investigate the effect of parameter L, the parameter R = 25 is fixed and length of epochs has been changed for L = 1, 2.5 and 5. In this test, the classification accuracy has better results, when length of epochs has been decreased. The best results obtained for L = 2.5 seconds. In this condition, the average classification accuracy reached 57.20%. The results show that more details from features values has been shared to create the distinction between classes with decreasing the length of epochs. The result of this experiment is shown in Table 3.

To investigate the effect of R, the parameter L = 2.5 seconds is fixed and number of extracted features has been changed for R = 15, 20, 25 and 30. In this test, best result is obtained for R = 25. Thus, growing the number of features can increase the performance of G-IPSONN algorithm. The result of this test is shown in Table 4.

Table 3. Effect of change in length of epoch on performance of G-IPSONN algorithm (R=25)

Classification accuracy (%)	Length of epoch		
	L = 1	L = 2.5	L = 5
happiness	46.42	53.57	42.85
surprise	59.37	62.50	53.12
anger	65.51	68.36	58.62
fear	37.50	46.66	33.33
disgust	50.00	53.84	42.30
sadness	42.30	57.69	51.42
Average accuracy (%)	50.18	57.20	46.94

Table 4. Effect of change in number of selected features by GaborSD and PCA on performance of G-IPSONN algorithm (L = 2.5 second)

Classification accuracy (%)	Number of features			
	R = 15	R = 20	R = 25	R = 30
happiness	20.49	42.46	53.57	43.96
surprise	31.75	51.27	62.50	60.44
anger	45.27	54.36	68.96	58.07
fear	25.98	33.33	46.66	39.56
disgust	31.44	40.92	53.84	53.84
sadness	37.41	47.18	57.69	51.93
Average accuracy	32.05	38.25	57.20	51.30

4.3 Performance of W-IPSONN algorithm

Wavelet-based features and IPSONN classifier are used in W-IPSONN algorithm. To evaluate the effect of parameter L, the parameter R = 25 is fixed and length of epochs has been changed for L = 1, 2.5 and 5. In this test, the classification accuracy has better results, when length of epochs has been decreased. The best results are obtained for L = 1 second. In this condition, the average classification accuracy of 54.77% is reached. The results illustrate that more details from wavelet-based features values has been shared to create the distinction between classes with decreasing the length of epochs. The result of this experiment is shown in Table 5.

To evaluate the effect of R, the parameter L = 1 second is fixed and number of extracted features has been changed for R = 15, 20, 25 and 30. In this test, best result is obtained for R = 20. Thus, growing the number of features can increase the performance of W-IPSONN algorithm. The result of this test is shown in Table 6.

Table 5. Effect of different lengths of epoch on performance of W-IPSONN algorithm (R=25)

Classification accuracy (%)	Length of epoch		
	L = 1	L = 2.5	L = 5
happiness	51.93	45.41	40.75
surprise	60.75	58.96	51.97
anger	66.54	63.28	56.28
fear	43.12	39.14	34.37
disgust	51.47	49.70	41.56
sadness	54.86	40.66	50.31
Average accuracy (%)	54.77	49.35	45.87

Table 6. Effect of different numbers of selected features by DWT and DFT on performance of W-IPSONN algorithm (L = 2.5 second)

Classification accuracy (%)	Number of features			
	R = 15	R = 20	R = 25	R = 30
happiness	19.85	51.93	52.72	41.82
surprise	30.49	60.75	63.14	53.33
anger	41.58	66.54	65.66	56.91
fear	27.82	43.12	43.12	37.65
disgust	30.56	51.47	50.63	51.46
sadness	35.63	54.86	55.79	49.38
Average accuracy	30.98	54.77	46.73	48.42

4.4 Performance of G-PNN Algorithm

G-PNN algorithm uses the Gabor-based features and PNN classifier to recognition of emotions. To investigate, the effect of parameter L, the parameter R = 25 is fixed and length of epochs has been changed for L = 1, 2.5 and 5. In this test, the classification accuracy has better results, when length of epochs has been decreased. The best results are obtained for L = 2.5 seconds. In this condition, the average classification accuracy of 64.78% is reached. The results show that more details from features values has been shared to create the distinction between classes with L = 2.5 seconds. The result of this experiment is shown in Table 7.

To investigate the effect of R, the parameter L = 2.5 seconds is fixed and number of extracted features has been changed for R = 15, 20, 25 and 30. In this test, the best result is obtained for R = 25. Thus, growing the number of features can increase the performance of G-PNN algorithm. The result of this test is shown in Table 8.

Table 7. Effect of different lengths of epoch on performance of G-PNN algorithm (R=25)

Classification accuracy (%)	Length of epoch		
	L = 1	L = 2.5	L = 5
happiness	49.24	58.76	43.59
surprise	61.74	67.05	55.24
anger	67.16	73.64	62.85
fear	39.07	56.79	38.14
disgust	51.04	69.47	46.07
sadness	44.37	62.97	53.26
Average accuracy (%)	52.25	64.78	49.85

Table 8. Effect of different numbers of selected features by DWT and DFT on performance of G-PNN algorithm (L = 2.5 second)

Classification accuracy (%)	Number of features			
	R = 15	R = 20	R = 25	R = 30
happiness	21.93	45.67	58.76	45.61
surprise	30.58	52.73	67.05	63.72
anger	47.73	56.62	73.64	60.18
fear	29.38	37.14	56.79	44.63
disgust	32.71	45.28	69.42	58.49
sadness	45.11	56.82	62.97	56.38
Average accuracy	34.57	49.04	64.78	54.83

4.5 Performance of W-PNN algorithm

W-PNN algorithm uses the wavelet-based features and PNN classifier to recognition emotions. To evaluate the effect of parameter L, the parameter R = 25 is fixed and length of epochs has been changed for L = 1, 2.5 and 5. In this test, the classification accuracy has better results, when length of epochs has been decreased. The best results are obtained for L = 2.5 seconds. In this condition, the average classification accuracy of 59.99% is reached. The results show that more details from features values has been shared to create the distinction between classes with L = 1. The result of this experiment is shown in Table 9.

To evaluate the effect of R, the parameter L = 2.5 seconds is fixed and number of extracted features has been changed for R = 15, 20, 25 and 30. In this test, best result is obtained for R = 25. Thus, growing the number of features can increase the performance of W-PNN algorithm. The result of this test is shown in Table 10.

Table 9. Effect of different lengths of epoch on performance of W-PNN algorithm (R=25)

Classification accuracy (%)	Length of epoch		
	L = 1	L = 2.5	L = 5
happiness	54.74	48.15	43.59
surprise	61.20	60.72	54.27
anger	66.39	64.16	60.23
fear	45.76	38.07	34.76
disgust	54.17	51.63	43.05
sadness	59.73	43.91	54.63
Average accuracy (%)	59.99	51.10	48.42

Table 10. Effect of different numbers of selected features by DWT and DFT on performance of W-PNN algorithm (L = 2.5 second)

Classification accuracy (%)	Number of features			
	R = 15	R = 20	R = 25	R = 30
happiness	29.48	48.58	54.74	41.95
surprise	31.76	53.26	61.20	60.43
anger	45.28	56.37	66.39	58.87
fear	26.88	38.83	45.76	39.50
disgust	32.44	40.72	54.17	53.04
sadness	38.41	47.25	59.73	51.73
Average accuracy	34.20	47.50	59.99	50.92

5 Discussion and comparison with other algorithms

In this section, we obtain a perfect comparison between our proposed algorithm and other presented algorithms in the literature. For example, Pertrantonakis et al. [19] presented a method for the evaluation of emotion states that are elicited within EEG-based emotion recognition (EEG-ER) scenario and localized emotion-related activity. Petrantonakis's approach was based on the information shared between specific EEG locations in the brain, using multidimensional directed information (MDI) [34] analysis. The asymmetry concept that rules the experience of negative or positive emotions was both verified and exploited to evaluate the degree of a subject experiences or a certain affective state. Furthermore, the development of the windowed MDI on IMFs provided a promising technique for the time-frequency segmentation of EEG signals in regard with the subjective brain emotional activity, contributing towards both more reliable emotion elicitation techniques and robust feature extraction methods. Petrantonakis reported an average accuracy of 61% from 16 subjects visually stimulated with pictures. It was not successful in recognition of emotions with EEG containing a mixture of frequencies or those with low-amplitude high-frequency activity. Khosrowabadi et al. [35] presented an EEG-based emotion recognition system. Multi-information and magnitude squared coherence was applied to investigate the interconnectivity between 8 scalp regions. A study was performed to collect 8 channels of EEG data from 26 healthy right-handed subjects in experiencing 4 emotional states while exposed to audio-visual emotional stimuli. After feature extraction, 5-fold cross-validation was then performed using the KNN and SVM classifiers. The frequency band of 2-30 HZ of EEG signal was evaluated for valence and arousal discrimination. Investigation of emotions using 2-second EEG signal with sampling rate of 250 HZ has been shown as a meaningful window length. Khosrowabadi reported an average accuracy of 58.2%. Schaaff et al. [36] investigated a method to facilitate emotion recognition from EEG signals. Schaaff developed a headband to measure EEG signals on the forehead and collected data from five subjects. To induce emotions, 90 pictures from the International Affective Picture System (IAPS) belonging to the three categories pleasant, neutral and unpleasant were used. A system based on SVM classifiers was developed for emotion recognition. With this system an average accuracy rate of 47.11% was be achieved on subject dependent recognition.

Ishino et al. [37] proposed a system for estimating the feelings of joy, anger, sorrow and relaxation by using neural network, which was obtained accuracy rate of 54.5% for joy, 67.7% for anger, 59% for sorrow and 62.9% for relaxation. Berkman et al. [38] used a single-layer neural network to predict three categories of emotions including positive, negative and neutral with accuracy rate of 43%. Chanel et al. [39] showed that arousal assessment of emotion can be obtained with a maximum accuracy rate of 58% for three emotion classes estimated by the naive Bayes classifier. Also, previous work involved MLP and SVM to recognize music-induced emotion response with accuracy rate of 69.69% and 92.73%, respectively. Murugappan et al. [40] proposed an emotion recognition system from EEG signals. The audio-visual induction-based acquisition protocol had been designed for acquiring the EEG signals under four emotions (disgust, happy, surprise and fear) for participants. Totally, 6 healthy subjects with an age group of 21-27 using 63 biosensors were used for registering the EEG signal for various emotions. After preprocessing, the signals, two different lifting-based wavelet transforms (LBWT) were employed to extract the three statistical features for classifying human emotions. In this algorithm, Fuzzy C-Means (FCM) clustering was used to classify the emotions. Murugappan reported an average accuracy rate of 57% from six subjects and four emotions. Considering the above research works, all of them targeted on emotional categorization of two or four classes. Unlike, the felt-emotion categories, the expressed-emotion can be described in a total of 67 adjectives. However, when the number of the categories of predicted felt-emotion increases, it would be an inevitable issue as how to maintain or even improve the performance. Accordingly, we suggest an optimal EEG-based emotion recognition algorithm to handle the multi-class classification problem. In our algorithms, the growing the number of features increases the classification accuracy. Furthermore, when PNN classifier is used to classify the Gabor-based features, the algorithm has maximum accuracy rate. Because, it has several advantages relative to the IPSONN classifier:

- Training samples can be added or removed without extensive retraining.
- This algorithm guarantees to converge to an optimal classifier as the size of the representative training set increases (Bayes' optimal decision surface)
- An inherently parallel structure (making parallel implementation a natural progression) is constructed.
- The probability density function for each class is estimated based on the training samples.
- The implementation of our algorithm is relatively simple.
- This algorithm is robustness to noise and has self-learning ability.

The selected features by Gabor functions and PCA also have two properties: dispersion of features is small for training samples of within classes and dispersion of features is large for training samples of two classes. Therefore, the G-PNN algorithm can used as a optimal EEG-based emotion recognition algorithm with average accuracy rate of 64.78%. Table 11 shows a comparison between our algorithm and other presented algorithms in the literature.

Table 11. The comparison between our algorithm and other algorithms in the literature

Algorithms	**No. subject**	**No. emotions**	**Accuracy rate (%)**	**The used features and classifier**
Petrantonakis [19]	16	Six	61.45	MDI-IMF based features and KNN classifier
Khosrowabadi [35]	26	Four	58.26	5-fold cross-validation And KNN-SVM
Schaaff [36]	5	Three	47.31	SVM
Murugappan [40]	6	Four	57.63	Statical features and FCM clustering
Our algorithm	10	Six	64.78	Gabor-PCA based features and PNN classifier

6 Conclusion

We presented an EEG-based emotion recognition algorithm. In this algorithm, the emotion-related EEG signals were decomposed by Gabor functions (GaborSD) and were represented in spectral, spatial and temporal domains. Then R effective features were obtained from each representation by applying DFT and PCA. Finally a PNN classifier was used to determine an optimal nonlinear decision boundary. The used PNN classifier had an inherently parallel structure and prevented the premature convergence which can increase the sensitivity of algorithm. The proposed algorithm was implemented to classify six basic emotions. In order to obtain the best results, we changed some effective parameters such as length of epochs (L) and number of features (R). In the experimental result, the average classification accuracy of 64.78% is reached for L = 2.5 seconds and R = 25 features.

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