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Discrete Wavelet Transform Coefficients for Emotion Recognition from EEG Signals

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Abstract— **In this paper, we propose to use DWT coefficients as features for emotion recognition from EEG signals. Previous feature extraction methods used power spectra density values dervied from Fourier Transform or sub-band energy and entropy derived from Wavelet Transform. These feature extracion methods eliminate temporal information which are essential for analyzing EEG signals. The DWT coefficients represent the degree of correlation between the analyzed signal and the wavelet function at different instances of time; therefore, DWT coefficients contain temporal information of the analyzed signal. The proposed feature extraction method fully utilizes the simultaneous time-frequency analysis of DWT by preserving the temporal information in the DWT coefficients. In this paper, we also study the effects of using different wavelet functions (Coiflets, Daubechies and Symlets) on the performance of the emotion recognition system. The input EEG signals were obtained from two electrodes according to 10-20 system: F_{p1} and F_{p2}. Visual stimuli from International Affective Picture System (IAPS) were used to induce two emotions: happy and sad. Two classifiers were used: Extreme Learning Machine (ELM) and Support Vector Machine (SVM). Experimental results confirmed that the proposed DWT coefficients method showed improvement of performance compared to previous methods.**

I. Introduction

As technology becomes an integral part of human lives, extensive research has been conducted to improve Human-Machine Interaction (HMI). In the case of human interaction, research has shown that emotion plays a crucial role in the perception and interpretation of information [1]. It is clear that current technologies must be equipped with emotion recognition capability in order to make HMI as effective as human interaction.

Numerous approaches have been tested for quantifying and analyzing human emotions: facial images [2], speech signals [3] and autonomous nervous signals [4]. Though these approaches showed promising performances, there are major drawbacks in the implementation. For facial images and speech signals, the subjects need to explicitly express the emotion, which may not be possible for disabled individuals. This also allows the subjects to suppress the actual emotion. For autonomous nervous signals, they are heavily contaminated by factors which are not emotion related. The actual implementation would also restrict free movement of hands and body. In contrast, EEG signals showed strong correlation with the actual emotion and they are also accessible for disabled individuals. Moreover, since the EEG electrodes are applied in the scalp, actual implementation would allow free movement of hands and body. These facts support that EEG signal is an appropriate approach for quantifying and analyzing human emotion.

Numerous EEG feature extraction methods for emotion recognition have been reported [5]. The most widely used method is spectra analysis using Fourier Transform [6]. Despite its popularity, this method is not suitable, because this method does not allow simultaneous time-frequency analysis, which is essential for non-stationary signal analysis [7]. In modern signal processing techniques, Short Time Fourier Transform (STFT) and Discrete Wavelet Transform (DWT) are widely used for non-stationary signal analysis [8]. However, the time-frequency resolution obtained from DWT extract more useful information from non-stationary signal compared to Fourier Transform or STFT [8][7].

DWT have been proven effective for the analysis of EMG and ECG signals. Despite its effectiveness on these non-stationary signals, there have not been much effort in applying DWT for emotion recognition from EEG signals. Murugappan in [9] used sub-band energy and entropy derived from DWT as features. However, using these features would eliminate the temporal information obtained from DWT analysis, which are essential in analyzing non-stationary signals.

In this paper, we propose to directly use the DWT coefficients as features for emotion recognition from EEG signals. The DWT coefficients represent the degree of correlation between the analyzed signal and the wavelet function at different instances of time. Therefore, DWT coefficients carry useful temporal information about the transient activity of the analyzed signal [10]. In contrast to previous methods, our proposed feature fully utilizes the simultaneous time-frequency analysis of DWT by preserving the temporal information in the DWT coefficients. It was observed that the choice of wavelet function in DWT greatly affects the resulting DWT coefficients. Hence, we also study the effects of using different wavelet functions on the performance of emotion recognition from EEG signals.

The performance of the proposed DWT coefficients method is compared with two previous feature extraction methods: 1) power spectra density and 2) DWT based sub-band energy and entropy. The input EEG signals were obtained using two electrode placements: F_{p1} and F_{p2}.The

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performance of the feature extraction methods were evaluated using two classifiers: Extreme Learning Machine [11] and Support Vector Machine [12].

The rest of the paper is organized as follows. Section II presents the EEG signal acquisition methodology. Section III discusses the emotion recognition experiment from EEG signals. Previous relevant works are presented in Section IV. Section V thoroughly discusses the proposed method. Section VI discusses the classification algorithm used. Lastly, results and discussion are presented in Section VII.

II. EEG Signal Acquisition

This section describes the EEG signal acquisition methodology for the emotion recognition experiment. There were 5 subjects in the experiment; all were healthy right-handed male in the age group of 24-25. In this experiment, 2 emotions were used: happy and sad. These emotions were induced using visual stimuli obtained from International Affective Picture System (IAPS) [13]. There were 15 images for each emotions and they were chosen based on the valence mean values; high values for happy emotion and low values for sad emotion. The experiment was divided into 3 sets, where 10 pictures were shown for each set. Each pictures was shown to the subjects for 4 seconds. It was observed that only the 2.5 – 3.5 seconds timeframe contain useful EEG signal information, hence in the experiment, EEG signals outside this timeframe was removed.

The recording of EEG signals was performed using g.USBAmp and g.EEGCap with a sampling period of 256 Hz. Two electrodes were chosen based on the 10-20 electrode placement system: F_{p1} and F_{p2}, with F_z and C_z as reference point and ground, respectively. Numerical study showed that features from the alpha band wave resulted in better system performance. To extract the alpha band wave, a Butterworth filter with a bandwidth of 5-15Hz was applied on the EEG signals. A 50 Hz Notch filter was also used to remove power line interference.

III. Emotion Recognition from EEG Signals

Fig. 1 summarizes the steps involved in the emotion recognition experiment from EEG signals. The first step was the acquisition of EEG signal, $x(t)$. As the recording was performed using two electrodes, there were two corresponding input EEG signals. In the experiment, each input signals was used and tested separately. Next, feature extraction method was used to extract salient features which have discriminatory power over the different emotions. The feature vectors are denoted as $\vec{F}$, with the feature size equals to N. Lastly, the feature vectors were used as the input to the classification algorithm which would create the mappings between the feature vectors and the actual emotional label of the EEG signals.

IV. Relevant Previous Works

For comparison purposes, two relevant previous works on feature extraction method for emotion recognition from EEG signals are presented:

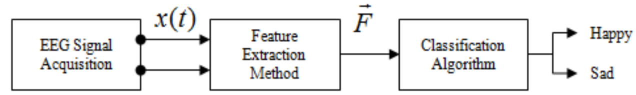

Figure 1. Flow chart of emotion recognition system from EEG signals

1) Power Spectra Density: Fourier analysis is a popular feature extraction method for emotion recognition from EEG signals. Schaaff in [6] used the power spectra density as the feature vectors for classification. Let $X(\omega)$ be the Fourier Transform of the EEG signal, $x(t)$, then the feature vector, $\vec{F}$, is defined as:

$$\vec{F} = \{X(\omega_1)X^*(\omega_1),...,X(\omega_N)X^*(\omega_N)\} \tag{1}$$

The alpha band wave bandwidth is taken as 5 to 15 Hz. With sampling frequency of 256 Hz and sample duration of 1 second, the size of the feature vector, N, is equal to 10.

The problem with using Fourier Transform is the assumption that the analyzed signals are stationary in nature. However, it is well known that EEG signals are non-stationary in nature. This would restrict Fourier Transform based method to extract salient features from EEG signals for emotion recognition purposes.

2) Wavelet Sub-Band Energy and Entropy: DWT has been proven to be effective in analyzing non-stationary signals. Murugappan in [9] used sub-band energy and entropy derived from DWT as the features for emotion recognition. The DWT coefficients are defined as follows:

$$C_{x(t)}(l,n) = \int_{-\infty}^{\infty} x(t)\psi_{l,n}(t)dt \tag{2}$$

$$\psi_{l,n}(t) = 2^{-(l+1)}\psi(2^{-(l+1)}(t-2^{-l}n)) \tag{3}$$

The EEG signal, $x(t)$, is correlated with a wavelet function $\psi_{l,n}(t)$. The variable l and n are the scale and translation variables of the wavelet function, respectively. These variables are chosen based on dyadic scale, as in (3), to ensure orthogonality, so that reconstruction of original signal can be performed [10].

The scale variable provides analysis in frequency domain: compressed version of the wavelet function corresponds to the high frequency components of the original signal while the stretched version corresponds to the low frequency components; and the translation variable provides analysis in the time domain. The outputs of the DWT algorithm are “detail” coefficients, which correspond to high frequency detail signals, and “approximation” coefficients, which correspond to coarse approximation of original signal in time domain.

The frequency responses for the decomposed signals for a system with a 256 Hz sampling rate are shown in Table 1 [14]. Since the frequency range of interest is in the alpha band wave of the EEG signals, only detail coefficients level 4 is relevant.

TABLE I
FREQUENCY CHARACTERISTIC OF DWT SIGNALS DECOMPOSITION

Decomposition Level	EEG Frequency Band	Frequency Bandwidth (Hz)
D1	Noises and Upper Gamma	64 – 128
D2	Lower Gamma	32 – 64
D3	Upper Beta	16 – 32
D4	Lower Beta and Alpha	8 – 16
A4	Delta and Theta	0 – 8

After performing DWT, the sub-band energy and entropy are calculated as follows:

$$ENG_l = \sum_n \left| C_{x(t)}(l,n) \right|^2 \tag{4}$$

$$ENT_l = \sum_n \left| C_{x(t)}(l,n) \right|^2 \log\left[\left| C_{x(t)}(l,n) \right|^2 \right] \tag{5}$$

With, $l = 4$, corresponding to detail coefficients level 4. Then, the feature vector, $\vec{F}$, can be defined as:

$$\vec{F} = \{ENG_l, ENT_l\} \tag{6}$$

Using sub-band energy and entropy eliminates useful temporal information obtained from the DWT due to the summation ofver the DWT coefficients. This temporal information is essential in the analysis of non-stationary signals.

It has to be noted that the number of electrodes placement used in this experiment is only a small subset of the ones used in [9]. However, it is of interest in this experiment to measure the performance of emotion recognition with minimal number of electrode placements.

V. PROPOSED FEATURE EXTRACTION METHOD

The coefficients of DWT for a particular decomposition level represent the degree of correlation between the EEG signal, $x(t)$ and the wavelet function, $\psi_{l,n}(t)$ at different instances of time. These coefficients carry useful information about the transient activity of the EEG signals. Therefore, we propose to use these DWT coefficients as features for the emotion recognition experiment. The proposed feature extraction method fully utilizes the time-frequency analysis of the DWT by preserving the temporal information contained in the coefficients.

In this paper, we also study the effect of using different wavelet functions on the performance of the emotion recognition system. The waveforms of the wavelet function should be as similar to the transient activity to be detected in the EEG signals. However, since the optimal waveform for is unknown, various types of wavelet function were considered: Daubechies ('db4') Order 1 to 20, Symlets ('sym') Order 1 to 20 and Coiflets ('coif') order 1 to 5. The performance of the different types of wavelet functions would indicate their suitability to detect transient activity in EEG signals, which correspond to either happy or sad emotion.

TABLE II
EMOTION CLASSIFICATION ACCURACY (%) OF THE PROPOSED DISCRETE WAVELET COEFFICIENTS FEATURES

Classifier	Wavelet Function	Classification Accuracy (%)			
		Before PCA		After PCA	
		Fp1	Fp2	Fp1	Fp2
Extreme Learning Machine	Symlets 6	75.33	76.67	84.67	83.33
	Daubechies	80.00	80.00	84.67	80.00
	Symlets 19	81.33	81.33	79.33	83.33
	Coiflets 1	76.67	78.00	82.00	76.67
Support Vector Machine	Symlets 6	78.00	80.00	81.33	80.00
	Daubechies	78.00	78.00	82.00	80.00
	Symlets 19	77.33	81.33	78.67	78.67
	Coiflets 1	79.33	78.67	78.67	76.00

The DWT coefficients, $C_{x(t)}(l,n)$, were obtained using (2) with $l = 4$, corresponding to detail coefficients from decomposition level 4. The number of coefficients varies between 25-45 depending on the type and order of the wavelet functions. These raw DWT coefficients would still contain redundancies, because they also contain other information that may not be emotion related. To reduce these redundancies, we propose to use Principal Component Analysis (PCA) [15]. By applying PCA, coefficients with minimal variation between training samples will be eliminated while coefficients with significant variation will be emphasized.

The feature vector, $\vec{F}$, can then be defined as follows:

$$\vec{F} = \{f_1, f_2, \ldots, f_N\} \tag{7}$$

where f_i are the principal components obtained by performing PCA on the DWT coefficients. In the experiment, the number of principal components used as the features, N, was varied from 1 to $n-1$, where n is the number of training samples. The optimal number principal component was chosen as the one that resulted in the highest classification accuracy.

VI. CLASSIFICATION ALGORITHMS

In this paper, the performance of two classifiers are considered: Extreme Learning Machine (ELM) and Support Vector Machine (SVM). Based on the assumption that individuals respond differently to emotional stimuli, the classifiers were trained separately for different subjects. The EEG signals obtained from the two electrodes, F_{p1} and F_{p2}, were used separately.

To fully utilize the EEG signals, the classifiers were trained using three-fold cross validation method. Firstly, the 30 feature vectors derived from the EEG signals were divided into 3 sets with equal number of happy and sad samples. Secondly, the classifiers were trained using 2 sets and tested using 1 set. Lastly, the first and second steps were repeated two more times using different combinations of the training and testing sets.

TABLE III
EMOTION CLASSIFICATION ACCURACY (%) OF PROPOSED DWT COEFFICIENTS METHOD AND PREVIOUS METHODS

Features	Fp1			Fp2		
	Happy	Sad	Average	Happy	Sad	Average
Extreme Learning Machine Classifier						
DWT Coefficients (Proposed)	80.00	89.33	84.67	84.00	82.67	83.33
Power Spectra Density	69.33	85.33	77.33	65.33	85.33	75.33
Wavelet Sub-Band Energy and Entropy	72.00	82.67	77.33	77.33	76.00	76.67
Support Vector Machine Classifier						
DWT Coefficients (Proposed)	76.00	86.67	81.33	78.67	82.67	80.00
Power Spectra Density	69.33	80.00	74.67	68.00	78.67	73.33
Wavelet Sub-Band Energy and Entropy	66.67	78.67	72.67	69.33	82.67	76.00

The classification accuracy was calculated using (8). The classification accuracy for each subject was obtained by averaging over the three-fold cross validation. The final classification accuracy was obtained by averaging over the different subjects.

$$Accuracy\,(\%) = \frac{\#\ Correct\ Classsific\,ations}{\#\,Test\ Samples} \times 100\,(\%) \quad (8)$$

VII. RESULTS AND DISCUSSION

The effect of applying PCA and using different types of wavelet functions is summarized in Table 2. Experimental results showed that PCA improved the classification accuracy of the system in general. The features derived from the EEG signal using DWT contained other information which may not be emotion related. These information would not vary signficantly between sad and happy EEG signals, thus applying PCA would remove such information.

There were four wavelet functions that showed the best performances: Symlets order 6 and 19, Daubechies order 4 and Coiflets order 1. Experimental results showed large variation in emotion classification performance for other types of wavelet functions. These results indicate the critical importance of choosing the right type of wavelet function for emotion recognition from EEG signals. Symlets order 6 was chosen as the best wavelet function as it generally showed better performance than other wavelet functions. This may indicate that the waveform of Symlets order 6 is similar to the transient activities in the EEG signals that correspond to sad or happy emotions.

The performance comparison of the proposed DWT coefficients method, using Symlets order 6, with two other previous methods is summarized in Table 3. The proposed method showed the best classification performance, reaching 84.00% (F_{p2}) and 89.33% (F_{p1}), for happy and sad emotions, respectively. The proposed method also showed the best average performance of 84.67%. It can be observed that the best performance was obtained irrespective of the type of classifier used. The experimental results also showed that ELM almost constantly outperformed SVM and sad emotion generally had higher accuracy of classification.

It can be concluded that the proposed feature extraction method showed very promising performance and is a very attractive method as it outperformed previous methods used in emotion recognition from EEG signals. The experimental results confirmed that our proposed method can be implemented in emotion recognition systems from EEG signals to improve its performance and reliability.

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