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FEATURE SELECTION FOR EPILEPSY DETECTION USING EEG

Mandeep Singh[1] and Sunpreet Kaur[2]

Abstract: EEG signal when decomposed into frequency subbands, gives us several statistical features in each band. Some of these features that may be employed for detection of epilepsy are explored in this paper.

1. INTRODUCTION

Epilepsy is a neurological disorder due to excessive neuronal activity in the brain characterized by recurrent brain malfunction. Epilepsy can be assessed by the EEG i.e. the electrical activity of brain. It is highly non-linear and non-stationary, and therefore is difficult to characterize and interpret. The signals are normally presented in the time domain, but many new EEG machines are capable of applying simple signal processing tools such as the Fourier transform to perform frequency analysis. There have been many algorithms developed so far for processing EEG signals. The operations include, but are not limited to, time-domain analysis, frequency-domain analysis, and spatial-domain analysis. For past many years there are various features that have been extracted by the researchers for the purpose of classification of EEG signal to be epileptic or not on the basis of the those features[1-4].

2. PROBLEM DEFINITION

For identifying the epileptic and non-epileptic EEG, it is required to examine subject for selected features extracted from the subbands of EEG. It is probable that some of the features may have non-overlapping range. Those features are needed to be identified for detection of epilepsy.

3. METHODOLOGY

The subband decomposition of the EEG signal explicitly explained by Mandeep Singh and Sunpreet Kaur [5] is applied on the sets of epileptic and non-epileptic data of 50 subjects each. Each set is composed of 4096 samples at sampling frequency of 173.6 Hz. In this study, the discrete wavelet transform is used as a primary computational tool for extracting features of the epileptic EEG signals at different resolutions. Decomposition of Epileptic and Non-Epileptic data into Delta, Theta, Alpha, Beta, Gamma subbands are shown in figure 1 and Figure 2 resp. It is apparent from figures that the amplitude of gross epileptic signal is considerably higher than non-epileptic one. Also the amplitudes of subbands are significantly high in case of epileptic data, especially in gamma subband.

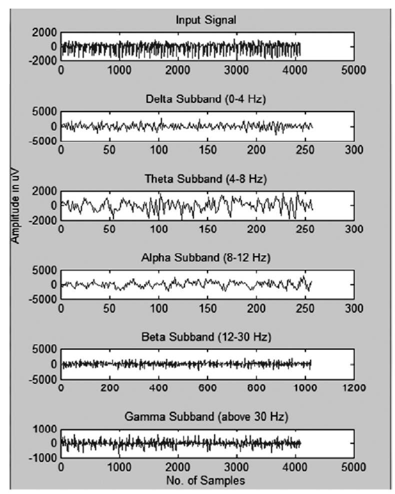

Figure 1: Epileptic EEG Signal with Delta, Theta, Alpha, Beta and Gamma Subband Decomposition

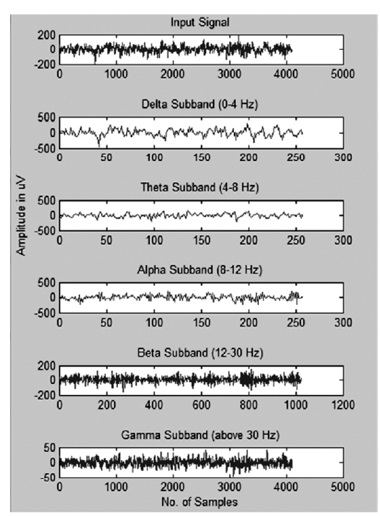

Figure 2: Non-epileptic EEG Signal with Delta, Theta, Alpha, Beta and Gamma Subband Decomposition

[1,2] Department of Electrical & Instrumentation Engineering, Thapar University, Patiala, India
[1] *E-mail: mandy_tiet@yahoo.com*
[2] *E-mail: sunpreet.kaur25@gmail.com*

Some of the parameters derived for epilepsy detection are defined here under:

1. Variance: Variance is defined as a measure of the dispersion of a set of data points around their mean value. Assume some random variable *X* that have the sample values of each EEG subband signal. Let the sample value of *X* is $X_i = \{X_1, X_2, ... X_n\}$. Where *i* represent a sample set from the subbands delta, theta, alpha, beta, and gamma. The variance can thus be expressed as

$$y^2 = \frac{\Sigma(X-\mu)^2}{n} \tag{1}$$

where μ is the mean value of the set *X* and n is the number of samples in the EEG dataset.

2. Energy: The energy of the signal is defined as the sum of squared modulus of the sample values of any signal. The wavelet based energy of each decomposed subbands such as delta, theta, alpha beta and gamma can be calculated using the formula

$$E = \sum_{n=0}^{N-1} |X|^2 \tag{2}$$

where *X* is the samples values in each subbands and *N* is the total number of samples.

3. Power Spectral Density (PSD): The PSD is the amount of power per unit frequency as a function of frequency. Periodogram is commonly used for computing PSD. This is computed by squared modulus of the Fourier transform of the time series of the signal.

$$\max(\omega) = \frac{1}{n}|X(\omega)|^2 \tag{3}$$

The Maximum and minimum values are estimated from the PSD of each EEG subbands can be considered as feature for classification.

4. Entropy: Entropy is a numerical measure of the randomness of a signal. Entropy can act as a feature and used to analyze psychological time series data such as EEG data.

$$(e) = -\sum_{1}^{n} X^2 \log(X^2) \tag{4}$$

Entropy is the statistical descriptor of the variability within the EEG signal and can be a strong feature for epilepsy detection.

The above statistical features are extracted from each subband *i.e.* Delta, Theta, Alpha, Beta, Gamma of each set to represent the time-frequency distribution of the EEG signals and are nomenclatured as

1. Variance of the coefficients in each subband (*y*1, *y*2, *y*3, *y*4, *y*5)
2. Energy of the wavelet coefficients in each subband (*E*1, *E*2, *E*3, *E*4, *E*5)
3. Power Spectral Density (max) and Power Spectral Density (min) of each subband (max1, max2, max3, max4, max5, min1, min2, min3, min4, min5)
4. Entropy of wavelet coefficients in each subband (*e*1, *e*2, *e*3, *e*4, *e*5)

4. RESULTS AND CONCLUSION

Of these 25 parameters analysed for 50 non-epileptic and 50 epileptic cases taken from database [5], it is found that in 10 parameters the upper limit in non-epileptic group is lower than the lower limit of epileptic group. This is illustrated in the Table 1. These features can be significantly used for detection of epilepsy.

Table 1
Non-overlapping Parameter Ranges of EEG Signal

		Y1	Y2	Y3	Y4	Max2	Max3	Min2	Min3	e2	e3
Epileptic	Upper limit	1733910	1040070	1396296	574335	4945068	7628536	1924	1769	-1263466	-1043503
	Lower limit	74800	22722	7319	2965	59120	40246	55	30	-11673332	-8134397
Non-epileptic	Upper limit	32743	8524	5432	2627	23969	32464	33	27	-30319327	-12441917
	Lower limit	2676	1467	1043	442	2391	1780	0.0266	0.0178	-2419993620	-2885722822

5. FUTURE WORK

Although there is a significant gap between the lower limit of epileptic and upper limit of non-epileptic group. Yet some tolerance needs to be built in to improve the efficiency of detection. It is proposed that a scoring system be designed to achieve this effect.

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