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Comparison of Seizure Detection Performances of Features Based on Wavelet Transform and Empirical Mode Decomposition

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Abstract – Several features are used in order to evaluate the epileptic components of the Electroencephalogram (EEG) signals. The generated feature matrices are applied to different classifiers as input. It is aimed to detect different epileptic stage. In this study, performances of Wavelet Transform and Empirical Mode Decomposition methods which are used commonly to extract feature in epilepsy studies have been compared. EEG signals, which contain normal and seizure stages, have been divided into 5 sub-bands including different frequency components via both methods. Feature matrices have been obtained by calculating mean, standard deviation, entropy and power for each sub-band. The feature matrices have been classified by k-nearest neighbor algorithm and results have been compared for both feature extraction methods. Analysis has been implemented patient-specifically for 14 patients with epilepsy.

Keywords - *Seizure detection, feature extraction, wavelet transform, empirical mode decomposition.*

1. Introduction

Epilepsy of which characteristics are recurrent seizures causing involuntary movement in partially different parts of the body or the entire body, is defined as a chronic disorder of the brain experienced by many of the people in the world. There are about 50 million patients with epilepsy worldwide. The epilepsy cases in the developing countries are higher than the other countries because of the living conditions which expose people to the high risks that could lead to temporary brain damage. The cases of epilepsy are found in developing countries to about 80% [1].

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As for epilepsy research and diagnosis, EEG signals have an important role. EEG signals reflect electrical activities of cerebral cortex neurons in the brain. Thus, it is a major component in the diagnosis of epilepsy and the detection of epileptic attack. By the placement of necessary electrode to the different centers of a head, EEG signals are measured [2, 3].

Researchers have been analyzed to detect epileptic seizures EEG signals using different features. Non-linear features, time-domain features, frequency-domain features, time-frequency distribution and power spectrum features are commonly used in the epilepsy studies. Feature matrices obtained these features are given to classifier as input. At the end of classification it is aimed to detect the EEG signals into normal and seizure stages. Artificial neural networks, support vector machines, k- nearest neighbor algorithm, linear discriminant analysis and decision tree are widely used classifiers.

Vavadi et al. decomposed alpha, theta, gamma and delta sub-bands of EEG signals via wavelet transform. They calculated approximate entropy for original signal and its' sub-bands. They implemented T-test for classification [4]. Huasain and Rao performed seizure detection using Hilbert-Huang Transform and Empirical Mode Decomposition. They used 2nd, 3rd and 4th intrinsic mode functions to extract features of EEG signals. They achieved accuracy of 99, 8% in the classification process via neural network and back propagation algorithm [5].

Liu et al. proposed a novel seizure detection methods based on wavelet transform and high sensitivity. They implemented 5nd order wavelet transform for intracranial EEG and selected three sub-bands of all for feature extraction. Using relative energy, relative amplitude, coefficient of variation and fluctuation index features, they performed seizure detection with sensitivity of 94.46 % and specificity of 95.26 % via support vector machine classifier [6].

Das et al. investigated performances of empirical mode decomposition and wavelet transform during the separation of focal and non-focal samples. They used spectral entropy based features such as shannon entropy, log-energy entropy and renyi entropy. Support vector machines and k-Nearest neighbor Algorithm were performed for classification. They achieved with 89.4 % accuracy and 90.7 % sensitivity using both feature extraction methods and k-nearest neighbor classifier. They obtained higher accuracy of classification for wavelet transform [7].

Pachori and Bajaj represented intrinsic mode functions obtained by empirical mode decomposition to frequency domain via Hilbert-Huang Transform. They generated features based on surface area for circular shaped intrinsic mode functions. By calculating area values belong to the first four intrinsic mode functions, they detected normal and seizure stages. Normal and seizure stages were differentiated their feature extraction methods [8]. Juarez-Guerra et al. performed seizure detection based on wavelet transform and artificial neural networks. They used different filters and wavelet functions for feature extraction, and compared results. By using artificial neural network classifier, Chebyshev II filter and Haar function, they achieved seizure detection with accuracy of 99.26% [9].

Tafreshi et al. implemented seizure detection by using features based on wavelet transform and empirical mode decomposition. They used multilayer perceptron neural network classifier respectively for wavelet-based features, empirical mode-based features and both methods. They analyzed clustering levels via Self-Organizing Maps for each feature set. They reached the best classification accuracy of % 95.42 using both feature extraction methods together [10]. Shahnaz et al. carried out seizure detection by decomposing dominant intrinsic mode function via wavelet transform. They used to extract features only coefficients of Level 4 discrete wavelet transform. Thus it was aimed to reduce processing load. Finally, they used k nearest neighbor algorithm as classifier and compared classification results with prior studies [11].

In this study, the performances of Wavelet transform and Empirical mode decomposition methods, commonly used to analyze EEG signals in the feature extraction process, have been compared. Both feature sets have been classified separately via K-nearest neighbor Algorithm. Since epilepsy shows different characteristics depending on patient, analysis have been performed patient-specific for fourteen patients. As a result of comparison of the performances of the feature extraction methods it is aimed to help designer to reduce processing load in the real time seizure detection systems.

2. Method

In this paper, process consists of three steps. These steps are pre-processing, feature extraction and classification. In the first step, EEG signals have been divided 5 second period. Then these parts have been filtered using band-pass filter (0.5-32 Hz).

In the second step, Empirical mode decomposition and wavelet transform have been implemented for each filtered signals, by doing so EEG signals have been decomposed into five parts containing different frequency components. For each part mean, standard deviation, power and entropy have been calculated.

In the last step, feature set has been divided as training and testing data using cross-validation method. K-nearest neighbor algorithm has been used as classifier. The classification results belong to Wavelet Transform and Empirical Mode Decomposition methods have been compared. This process has been performed for each patient. The schema of the process is shown in Figure 1.

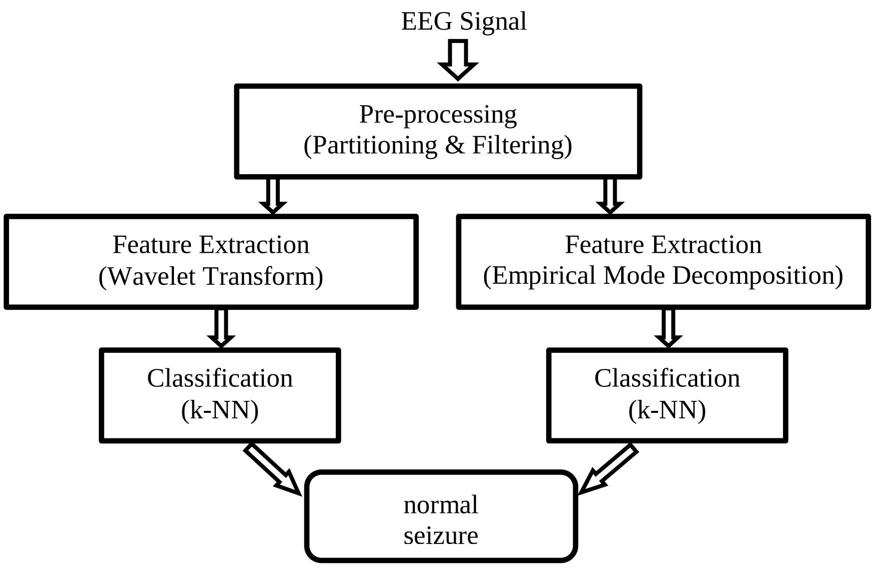

Figure1. The block schema of the process

2.1. Material

EEG signals belong to PhysioNet database [12]. EEG signals were obtained using scalp electrode and 10-20 electrode placement system, and were sampled in 256 Hz with 16-bit resolution. The beginning time of seizures and total seizure durations in database were indicated by the experts. In this study, EEG signals obtained from Channel P3-O1 have been analyzed. EEG signals include seizure and normal stages; have been divided into 5 second parts. The demographic information about the patients is given in Table 1.

Table 1. Demographic information

Patient	Gender	Age	Patient	Gender	Age
Patient 1	Female	11	Patient 8	Female	2
Patient 2	Female	14	Patient 9	Female	3
Patient 3	Male	22	Patient 10	Male	16
Patient 4	Female	7	Patient 11	Female	18
Patient 5	Male	3.5	Patient 12	Female	6
Patient 6	Female	10	Patient 13	Female	6
Patient 7	Male	3	Patient 14	Undefined	

2.2. Pre-processing

In this step, partitioning of EEG signals belongs to normal and seizure stages has been implemented. The seizure and normal stages have been divided into 5 second periods. Each sample has been filtered using band pass filter (0.5-32 Hz).

2.3. Feature Extraction

Wavelet Transform and Empirical Mode Decomposition have been used for feature extraction. EEG signals have been divided into five parts containing different frequency components. After that feature set (20 features) has been generated by calculating mean, standard deviation, power and entropy for each part. For sub-bands obtained via the methods of wavelet transform and empirical mode decomposition, with x_n=1,2,3…n as a time series and N as sample number, the features and their equations are demonstrated in Table 2.

Table 2. Features

Feature	Equation
mean	$M = \frac{1}{N}\sum_{n=1}^{N} x_n$
Standard Deviation	$SD = \sqrt{\frac{\sum_{n=1}^{N}(x_n - M)^2}{N-1}}$
Power	$P = \frac{1}{N}\sum_{i}^{N} \lvert x_i^2 \rvert$
Entropy	$E = -\sum_{i} p(x_i) log_2 p(x_i)$

2.3.1. Empirical Mode Decomposition

Empirical Mode Decomposition is commonly used a transform technique in the signal processing. It is an effective method for non-linear and non-stationary signals. Method represents time series signals as the sum of a finite number intrinsic mode function. The intrinsic mode functions contain the different frequency components of the original signal. At the end of decomposition, signal is divided into intrinsic mode functions and residue [13].

Two conditions must be provided to perform the empirical mode decomposition. First condition, the number of zero crossings and the number of local extrema in the entire signal must be equal to each other or different by at most one. Second condition, the mean value of the envelope defined by the local maxima and that defined by the local minima at any point, should be zero. By collecting intrinsic mode functions and residue, the original signal can be obtained without information loss and error [13-14]. The first four intrinsic mode functions and residue belong to filtered abnormal EEG signal are shown in Figure 2.

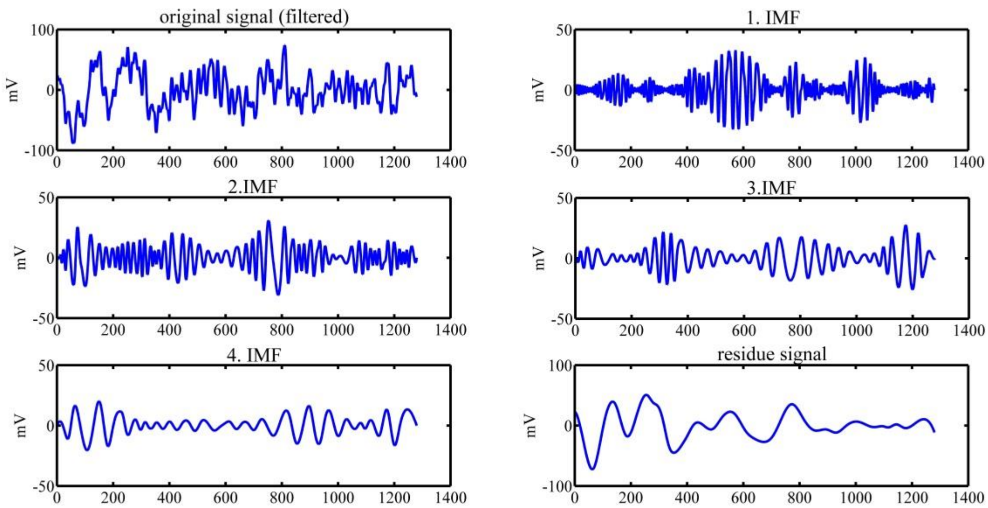

Figure 2. Empirical mode decomposition

2.3.2. Wavelet Transform

Wavelet transform is a successful technique to analyze non-stationary signals. It was designed to eliminate resolution problem in the Short Time Fourier Transform. Wavelet transform are applied in the same manner short time Fourier transform. It is carried out by adding the signal's multiplying by function. Wavelet transform does not only demonstrate the frequency information but also the location information. After getting wavelet transformation of a signal, it is possible to regenerate the original signal without any loss information [15-16].

Basically, wavelets have the filter characteristics in the frequency domain. Therefore, low and high pass filters are used in the discrete wavelet transform. For filtered EEG signal with seizure, approximation and detail components are shown in Figure 3. In this study, Level 4 wavelet transform has been performed using Daubechies 2 function.

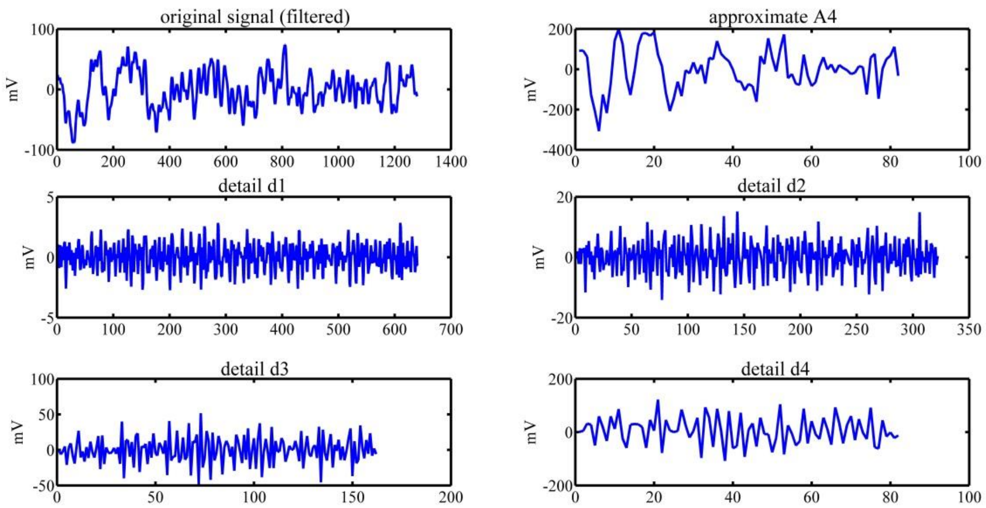

Figure 3. Wavelet transform

2.4. Classification

In this study, k-NN algorithm has been used in the classification stage. The feature set has been separated two parts as training set and testing set via cross-validation method for each patient. During the classification process, it has been aimed detecting of normal and seizure stages in the testing set.

K-NN, an instance-based on learning, is used widely as classifier. The similarity of testing and training data provide the basis for the implementation of this method. A majority of its neighbors is used in the classification process to classify a sample. Training data is represented in feature space. Each sample is a point in feature space. Thus, feature space has been used to store all training samples. When given an unlabeled sample to classifier, a k-nearest-neighbor algorithm searches the feature space for the *k* training samples that are closest to the unlabeled sample. These *k* samples are called the *k* "nearest neighbors" of the unlabeled samples. At the end of k-nearest-neighbor classification, the unlabeled sample is classified according to the majority votes of its k nearest neighbors [17-19].

3. Experimental Results

For both feature extraction methods, the confusion matrices are given in Table 4 and Table 5.

Table 4. The confusion matrices via empirical mode decomposition

label	normal		seizure	
predict	**normal**	**seizure**	**normal**	**seizure**
patient1	63	1	1	28
patient2	64	0	0	26
patient3	63	1	2	23
patient4	61	3	3	33
patient5	62	2	5	56
patient6	64	0	0	18
patient7	63	1	4	26
patient8	63	1	4	32
patient9	61	3	6	22
patient10	175	5	10	122
patient11	64	0	1	20
patient12	64	0	1	19
patient13	63	1	2	26
patient14	61	3	6	28

Table 5. The confusion matrices via wavelet transform

label	normal		seizure	
predict	**normal**	**seizure**	**normal**	**seizure**
patient1	64	0	1	28
patient2	64	0	0	26
patient3	63	1	2	23
patient4	64	0	1	35
patient5	61	3	5	55
patient6	64	0	0	18
patient7	64	0	0	29
patient8	64	0	5	31
patient9	64	0	7	21
patient10	172	8	7	125
patient11	64	0	0	21
patient12	64	0	1	19
patient13	62	2	0	28
patient14	62	2	4	30

Classification performances and AUC values for both methods are shown Table 6, Table 7 and Table 8.

Table 6. The classification performances for empirical mode decomposition

patient	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
sensitivity (%)	98,44	100,00	98,44	95,31	96,88	100,00	98,44	98,44	95,31	97,22	100,00	100,00	98,44	95,31
specificity (%)	96,55	100,00	92,00	91,67	91,80	100,00	86,67	88,89	78,57	92,42	95,24	95,00	92,86	82,35
accuracy (%)	97,85	100,00	96,63	94,00	94,40	100,00	94,68	95,00	90,22	95,19	98,82	98,81	96,74	90,82

Table 7. The classification performances for wavelet transform

patient	p1	p2	p3	p4	p5	p6	p7	p8	p9	p10	p11	p12	p13	p14
sensitivity (%)	100,00	100,00	98,44	100,00	95,31	100,00	100,00	100,00	100,00	95,56	100,00	100,00	96,88	96,88
specificity (%)	96,55	100,00	92,00	97,22	91,67	100,00	100,00	86,11	75,00	94,70	100,00	95,00	100,00	88,24
accuracy (%)	98,92	100,00	96,63	99,00	93,55	100,00	100,00	95,00	92,39	95,19	100,00	98,81	97,83	93,88

Table 8. AUC values

patient	EMD	WT
patient1	0,9749	0,9923
patient2	1	1
patient3	0,9638	0,9638
patient4	0,9349	0,9923
patient5	0,9454	0,9363
patient6	1	1
patient7	0,9516	1
patient8	0,9550	0,9638
patient9	0,8952	0,9507
patient10	0,9533	0,9504
patient11	0,9923	1
patient12	0,9923	0,9923
patient13	0,9661	0,9667
patient14	0,9068	0,9384

4. Discussion and Conclusion

Researchers suggest different feature extraction methods for seizure detection and prediction. Feature sets must be created to provide the highest level of discrimination between different epileptic stages. For this purpose, different features and feature sets are used together. In this study, performances of feature extraction methods based on Wavelet transform and Empirical mode decomposition have been compared in the seizure detection. For 14 patients with epilepsy, k-NN algorithm has been used patient-specifically in the classification process. The classification results based on wavelet transform outperform the empirical mode decomposition results. In 7 ones of all patients, wavelet transform has higher classification accuracy than empirical mode decomposition. Empirical mode decomposition has better classification accuracy for only patient 5. AUC values support classification accuracies. Consequently, experimental results show that wavelet transform features are more discriminating features than Empirical mode decomposition features to detection EEG signals into normal stages and seizure stages.

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