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Multilevel Wavelet Packet Entropy and Support Vector Machine for Epileptic EEG Classification

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***Abstract*—Electroencephalogram (EEG) is a bioelectric signal produced by brain activity. The abnormalities that occur in the brain, such as epilepsy, can be seen through a particular pattern on the EEG signal. A recurrent unprovoked seizure occurs in epilepsy patients as a result of excessive brain cell activity. EEG is a non-linear and non-stationary signal, so a visual interpretation is difficult to conduct. One method to measure EEG characteristics is the entropy that quantifies the signal complexity. Several studies have been conducted to classify epileptic EEG signal using entropy as the feature set. Previous studies has shown a promising result for epileptic EEG signal classification. However, to achieve effectiveness for the classification process, we propose a new method to reduce the number of features with a competitive accuracy. In this research, we propose a wavelet-based entropy method named multilevel wavelet packet entropy (MWPE) for automatic EEG signal analysis. MWPE is calculated from the wavelet packet entropy (WPE) which performed at some decomposition level. WPE was calculated from wavelet packet decomposition (WPD) which give more informations in every signal subbands compared to discrete wavelet transform (DWT). Using MWPE, we got informations about the distribution of subband energy in every level of signal decomposition. MWPE and support vector machine (SVM) are used as the feature extraction and classifier respectively. The result showed that the method is able to classify three classes of the EEG data set (normal, interictal, seizure). The best accuracy is 94.3% which achieved by using a 1-5 decomposition level with biorthogonal 2.8 wavelet, and cubic or quadratic SVM. MWPE provides high accuracy with relatively few features.**

***Index Terms*—wavelet packet entropy, multilevel wavelet packet entropy, epileptic EEG, support vector machine**

I. Introduction

Biological signals are complex signal resulting from complex physiological processes in the body [1]. The signal can bring valuable information which can be used to analyze one's health condition. The biological signal can be an electrical signal that describes electrical activity in cells or tissues of the body. One of biological signal comes with great attention is electrical brain activity named Electroencephalogram (EEG). EEG signal analysis can provide information related to brain activity such as emotional state, audiovisual response and even abnormalities of the brain. Epilepsy is a disorder that occurs in the nerve of the brain. This abnormality can be seen through a certain pattern of an EEG signal. Visual analysis of non-linear and non-stationary EEG signal patterns is difficult to perform. The complex signal analysis is required to obtain the information characteristics of the EEG signal.

Wavelet entropy is widely used for complex signal analysis such as for biological signals. Wavelet entropy (WE) is entropy calculation using a sub-band of discrete wavelet transform (DWT) on the signal. Research by Rosso et al. [2], wavelet entropy was used for brain signals analysis at short durations. Compared to spectral entropy (SE), WE were able to detect a non-stationer signal better than spectral analysis. WE is calculated from the subband of discrete wavelet transform (DWT), while WPE is obtained from the subband of wavelet packet decomposition (WPD). Entropy in the WPD subband was used by Safara et.al for the murmur analysis of heart sound [3]. Not all subband was used for entropy calculation, but it needs to be calculated based on the frequency range, noise frequency, and energy threshold [3].

Variation from WE is the different entropy calculations on wavelet subbands. Sample entropy calculation in the DWT subband for EEG signal analysis was presented by Sharma et al. [4]. Cen and Li used Tsallis wavelet entropy for power signal analysis [5]. Normalized Shannon wavelet entropy was calculated on the wavelet coefficient for EEG epileptic analysis was reported by Rosenblatt et al. [6].

Another method based on WE is the wavelet packet entropy (WPE). Some variations of WPE were proposed by some researchers. Safara et al. [7], proposed a method to calculated entropy using crest energy on each subband of the WPD result while in study by Chen et al. [8] the Shannon method was used. The number of features generated was 2^j, where j is the signal decomposition level. In another study by Rizal et al., multilevel wavelet packet entropy (MWPE) was proposed for pulmonary voice analysis [9]. If WPE done by Chen et al. [8] calculates Shannon entropy on each WPD subband, then Rizal et al. [9] generate WPE from Shannon entropy calculations from the relative energy of each subband as WE calculation done by Rosso et.al [2] so that each decomposition level will produce an entropy value. Since WPE was calculated on multilevel then when N level was used the decomposition will produce N entropy value as characteristic of a signal. From the experiment, the result reported 97.98% accuracy using Daubechies 8 at the level of decomposition four [9]. The results were obtained in

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five classes of voice data.

Proper extraction methods are essential in processing and analyzing EEG signals due to their complex nature. The goal is to get significant differences in the value of the characteristics of one class to another to simplify the process of classification. Kannathal et al. [10] used four entropies features and provides more than 90% of accuracy, but it was only done to classify two classes of epileptic EEG. Chua et al. [11] were able to get better accuracy and fewer features to detect three classes of epileptic EEG. However, Acharya et al. [12] obtained a better result compared with those two previous research. They were able to obtain 99,7% of accuracy for three classes of epileptic EEG signal. To get this high accuracy, they used more features than the previous research. The previous research has shown a promising result for epileptic EEG signal classification. However, to achieve effectiveness for the classification process, we propose a new method to reduce the number of features with a competitive accuracy.

In this study, we proposed methods for analysis of EEG epileptic signals using wavelet-based entropy. This method is then called multilevel wavelet packet entropy (MWPE). MWPE is calculated from the entropy packet wavelet (WPE) performed at some decomposition level. In this research, MWPE used as a feature extraction and support vector machine (SVM) is used for EEG signal classification. SVM is a powerful algorithm to solve nonlinear classification problems and the selection of appropriate parameters and kernels are the key to the performance. Several non-linear research about epileptic EEG signals done by Acharya et al [13]–[15], Chua et. al [11], [16] use SVM for the classification and it shows a good result. The results showed that the method used was able to distinguish three classes of EEG signal data (normal, interictal, seizure) with an accuracy of up to 94.3%. The highest accuracy was achieved using a 1 to 5 decomposition level with biorthogonal 2.8 wavelets and cubic or quadratic SVM classification. MWPE provides high accuracy with relatively few features.

II. Material and Methods

This study focuses on the classification of EEG signals for normal, interictal, and seizure conditions. 300 EEG data sets consisting of 3 classes are tested on the proposed system as shown in Fig. 1. Raw EEG data is normalized so that the amplitude level is in the range of 0 to 1 to reduce computational complexity. The normalized signal is decomposed using a wavelet with several different levels and basis and then calculated the entropy value and becomes the feature dataset of each class. The final process is signal classification using linear, quadratic, cubic, fine gaussian, gaussian medium and cuarse gaussian SVM.

A. EEG Data

The EEG epileptic data were obtained from the Klinik fur Epileptologie, Universitat Bonn EEG dataset [17]. The frequency sampling of the data is 173.61 Hz, and the EEG device frequency width is from 0.5 to 85 Hz [17]. The length of each data is 4098 samples. We used three classes of data; each class consists of 100 data. The first class is an EEG signal when the patient has a seizure; the second is an EEG signal when the epilepsy patient does not have a seizure (inter-ictal) and the last normal EEG data.

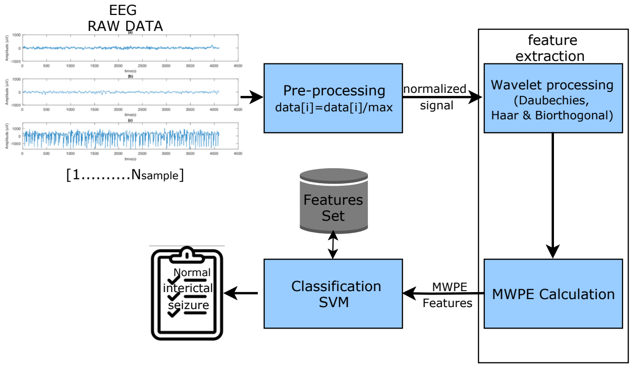

Fig. 1: Proposed system.

B. Wavelet Packet Entropy

Entropy is a measuremet of signal complexity [12]. One method of measuring entropy is WE that uses subband from DWT [2]. The development of WE is WPE that uses subband results from WPD [7]. WPE is often used for the analysis of biological signals such as heart sound and lung sound [7] [9]. The WPE linkage process as described in (1).

$$d_{j,n}(k) = 2^{j/2} \int_{-\infty}^{+\infty} S(t)\Psi_n(2^{-j}t - k)dt \quad ;0 \leq n \leq 2^N - 1. \tag{1}$$

$S(t)$ is the original signal, j is the scale, n and k are bands and surge parameters respectively. From (1) we calculate the energy of each subband using (2):

$$E_{j,n} = \sum k \left| d_{j,n}(k) \right|^2. \tag{2}$$

j, n, k represent the scale, band, and surge parameter, respectively. The total energy from the WPD is defined as:

$$E_{tot} = \sum n E_{j,n}. \tag{3}$$

Relative energy for each subband in scale j expressed in (4):

$$p_{j,n} = \frac{E_{j,n}}{E_{tot}}. \tag{4}$$

Wavelet packet entropy is described as:

$$WPE_N = -\sum p_{j,n} \ln p_{j,n}. \tag{5}$$

the notation N in WPE_N is used to express the decompostition level used in the WPD. In previous research, we used one WPE value as a feature for signal analysis. In this work, N number of WPE used for feature extraction of EEG signal to improve the accuracy as has been done for pulmonary sound classification [9]. The characteristics used in this study as in (6) with the number of $N = 5$.

$$MWPE = [WPE_1, WPE_2, ..., WPE_N]. \tag{6}$$

III. Classifier and Validation

Support Vector Machines (SVM) being developed for the first time by Vapnik in 1995 and this is gaining popularity due to good empirical performance and many attractive features. The main goals of SVMs development are to solve the classification problem, but in the next step, they also extended to solve the domain of regression problems [18]. The basic concept of SVM is a combination of computational theories that have existed decades earlier, such as hyperplane margins, the kernel was introduced by Aronszajn in 1950, as well as other supporting concepts [18].

SVM is a linear classifier, and next developed to work on nonlinear problems. Explanation of the SVM concept can be express simply as a search of the best hyperplane that being a separator from two classes. Hyperplane in a dimensionless vector space is an affinity subspace of dimension d-1 that divides the vector space into two parts, each corresponding to a different class. To find the best separator hyperplane between of the two classes can be done by measuring the hyperplane's margins and find out for the maximum point. The margin is the distance between the hyperplane and the nearest pattern in every single class. The closest position of the pattern is called a support vector [19].

A. Linear SVM

Acording to Vapnik, if we have a lineary grouped data set such defined in (7), then it can be seperated using a hyperplane. A j-dimensional vector contained in each a_i has R quantity of feature. Hyperplane is a logic separator which can devide group of data based on their class. Good hyperplane is located equaly between two classes. Generaly the hyperplane is described in (8).

$$D = \left\{ (\vec{a_i}, \vec{b_i}) \mid \vec{a_i} \, \epsilon \, i^j, \vec{b_i} \, \epsilon \, \{-1, 1\} \right\}_{i=1}^{n} \tag{7}$$

$$\vec{w}.\vec{a} - x = 0. \tag{8}$$

The best hyperplane is obtained by maximizing its margin with the data sample while the margin between two hyperplanes needs to be minimized. In case the data is not linear, the hyperplane calculation needs to be adjusted using (9)

$$\frac{1}{2} \|\vec{w}\|^2 + T \sum_{i=1}^{k} \varepsilon_i. \tag{9}$$

T is the trade-off parameter between the classes separation and the training set error. While the set of slack variable is defined as ε. Finding the maximum margin can be done by maximizing the distance value between the hyperplane and its nearest point. This can be formulated as a Quadratic Programming (QP) problem [18], which is to find the minimum point of (10), taking into account the constraint of (11).

$$min \left| \langle w, x^i \rangle + b \right| = 1 \tag{10}$$

$$y^i [\langle w, x^i \rangle + b] \geq 1, i = 1, 2, ..., l. \tag{11}$$

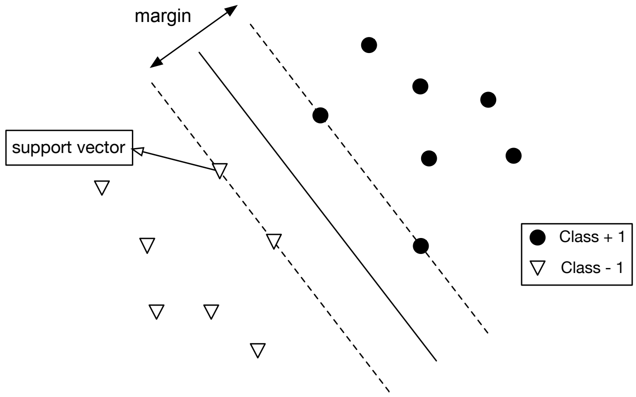

Fig. 2: Best hyperplane on SVM classifier.

B. Nonlinear SVM

A kernel trick can be used to do classification for a non-linear survace. The use of kernel trick on SVM approach is called as nonlinear SVM classifier. Two types of nonlinear SVM used in this research are polynomial function which are and radical basis fuction. Quadratic and Cubic SVM is the representation for polynomial function while radical basis function is represented by fine, medium and coarse gaussian SVM. SVM is a supervised learning method, so we use N-fold cross-validation (NF-CV) to divide the training and the testing data. The EEG signal dataset is divided into N data set. $N-1$ data sets are used as training data and one data set as testing data. This process is repeated N times until every single data set has been used as testing data. In this research, we use $N = 5$ so that every data set consist of 20 data from each class.

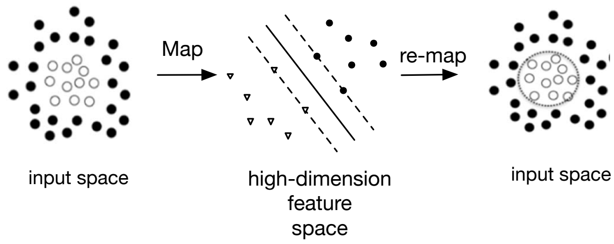

Fig. 3: Nonlinear SVM feature space.

IV. Result and Discussion

Figure. 4 shows the EEG signals in a normal person (healthy), epilepsy patients when no seizure occurs (interictal), and when a seizure occurs (ictal). Visually it is seen that normal EEG signals and interictal signals have a slightly different pattern. The amplitude of both EEG signals tends to be low with low fluctuations. Meanwhile, when seizures occur, amplitude tends to increase and have high fluctuations. With the MWPE method, the three conditions on the signal are then differentiated quantitatively. Fig. 5 and Fig. 6 show MWPE using Haar and Bior2.8 as the mother wavelet. It appears that the larger the decomposition level, the difference in the WPE

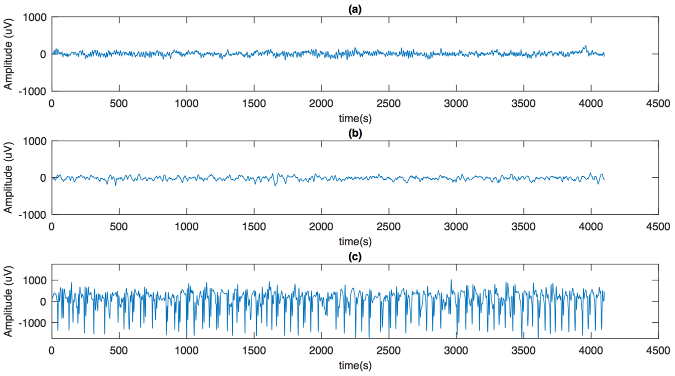

Fig. 4: (a) Normal (b) interictal (c) Seizure

value on the three EEG signals is definite. This shows that the frequency distribution of each wavelet sub-band in the three data classes is different. The high WPE value indicates that the signal energy is spread more evenly over the entire sub-band while if the energy of the signal is concentrated in one sub-band only then the WPE value will be low [3]. The WPE value of the seizure is higher than the other two conditions indicating that there is higher activity on the EEG signal. This corresponds to the shape of the EEG signal when be observed visually. Meanwhile, in interictal conditions, WPE values are lower than normal WPE. It shows that in EEG epilepsy signal in seizure condition does not decrease signal complexity as reported in the study by Costa et al. [20].

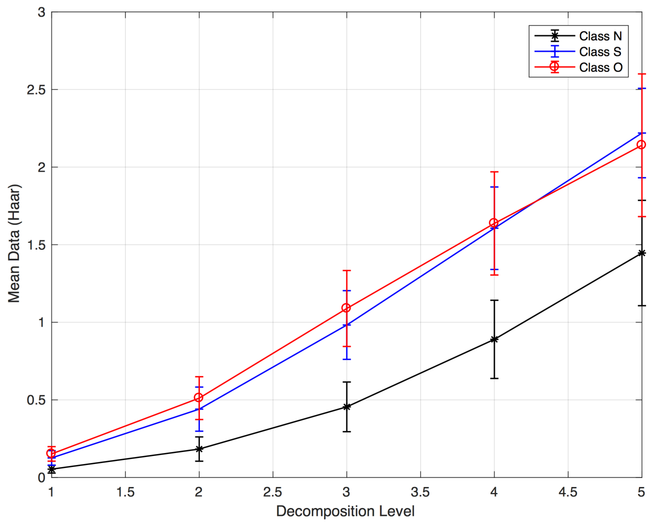

Fig. 5: WPE using Haar wavelet for decomposition level N 1-5

SVM with different kernels used as a classifier in this research. The kernels that used are linear SVM, quadratic SVM, cubic SVM, fine Gaussian SVM, medium Gaussian SVM, and coarse Gaussian. The resulting accuracy for each SVM and mother wavelet kernel is shown in Table 1. The highest

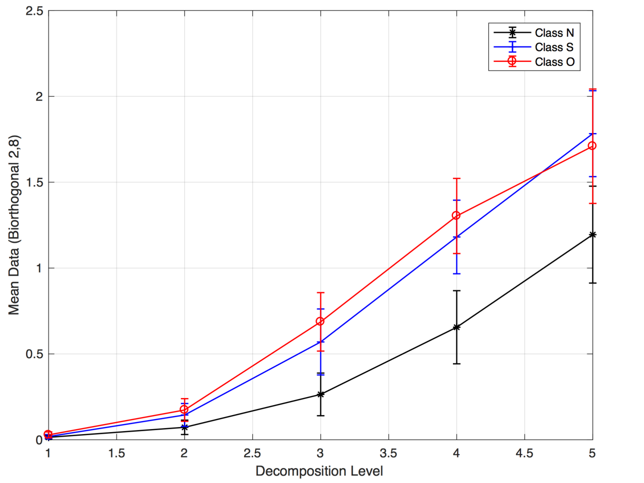

Fig. 6: (WPE using Biorthogonal 2.8 wavelet for decomposition level N 1-5

accuracy of 94.94% is generated by quadratic SVM and cubic SVM with Bior2.8.

Cubic SVM Classifier has a medium type of flexibility model which suitable for data with complex interoperability. From the feature values, the classified data has an apparent distinction between classes. Based on the condition, linear SVM classifier and nonlinear SVM using the polynomial function, such as a quadratic and cubic, have better result compared with Gaussian function SVM which categorized as radial basis function classifier.

TABLE I: Acuracy (%) of classification using 6 types of SVM classifier and mother wavelet

SVM Classifier	**Mother Wavelet**				
	DB 2	***DB8***	***Bior 1.5***	***Bior 2.8***	***Haar***
Linear SVM	91	91	90	93.3	85.3
Quadratic SVM	91.3	92.7	89.3	94.3	91
Qubic SVM	89.7	89.3	87.3	94.3	92
Fine Gauss SVM	89.7	92	81.7	89.3	81.3
Medium Gauss SVM	83	90	81.7	89.3	81.3
Cuarse Gauss SVM	76.3	75.3	75.7	81	74.7

Several points determine WPE; the first is the mother wavelet selection, next is the decomposition level and the subband selection. The mother wavelet selection is related to the frequency response of the associated wavelet filter. For example, Haar and Daubechies 8 wavelet have a different frequency response so that the resulting WPE also different for the same decomposition level. The decomposition level is selected based on the distribution of information in the data. If the signal is spread at low frequencies, e.g. in $fs/8$, then WPE at level $N = 1$ will be close to zero [3]. This condition shows the low signal complexity. Meanwhile, higher decomposition level produces higher values as in Fig. 5 and Fig. 6. The figures show that higher decomposition level produces WPE values, this happens because the signal energy are scattered

TABLE II: Comparison with previous research using entropy

Author	Features (No. of features)	Classifier	Accuracy (%)	Data classes
Kannathal et.al [10]	Entropies (4)	ANFIS	92.2	Normal, Epileptic
Chua et.al [11]	Entropy, Bispectrum (3)	GMM, SVM	93.1, 92.7	Normal, Ictal, Interictal
Wang et.al [22]	Wavelet Packet Entropy (4)	K-NN	99.4	Normal, Epileptic
Acharya et.al [23]	Entropies, HOS, Highuci FD, Hurst (7)	Fuzzy	99.7	Normal, Ictal, Interictal
Proposed method	MWPE (5)	SVM	94.3	Normal, Ictal, Interictal

over the higher subband. In WPE standard, all subbands at the highest decomposition level are used for WPE calculation. If it is necessary, the subband used for WPE calculation can be selected according to the information inside the data. The subband selection scheme of WPD can be seen in [3] for heart sound cases or [21] for lung voice cases.

Table 2 presents a comparison of some previous studies for EEG epileptic classification using entropy. The entire data uses the same EEG signal database [17]. Kannathal et al. [10] uses some entropy such as Shannon entropy, Renyi entropy, Spectral entropy, Kolmogorov-Sinai entropy, and approximate entropy (ApEn) as a feature and adaptive neuro-fuzzy inference system (ANFIS) as a classifier. The research reported 92.2% of accuracy to distinguish normal EEG and Epilepsy signals. Chua et al. [11] reported better results with more data classes. The characteristics used are entropy and bispectrum. Gaussian mixture model (GMM) as classifier produces 93.1% accuracy while support vector machine (SVM) produces 92.7% accuracy. Wavelet packet entropy with the best basis wavelet selection was reported by Wang et al., achieved the highest accuracy up to 99.4% for normal and epileptic EEG signal classification [22]. The study used entropy to calculate the best base wavelet was used for statistical feature calculation. The difference with the research is on subband selection and entropy calculation. Better results are shown in the study by Acharya et al. [23]. The characteristics used in the study are sample entropy (SampEn), ApEn, Higuchi fractal dimension (HFD), and Hurst exponent.

Compared to previous research, MWPE provides fairly competitive results with a small number of features. Kannathal et. al used four entropies as features to produce accuracy of 92.2%. Chua et al used three bispectral based features and produce accuracy of 93.1% [11]. Acharya et al used seven non-linear features to obtain accuracy of 99.7% [12]. Meanwhile our proposed method used five features to produce accuracy of 94.3%. MPWE is still open for further exploration such as the selection of best basis wavelets and other entropy calculation methods. MWPE also proved produce highly accuracy for another biological signal such as lung sound classification [9]. In previous study, MPWE achieved accuracy of 97.98% for five classes of lung sound [9].

V. Conclusion

This research describes EEG epileptic signal classification using MWPE and SVM. Using MWPE level 5 with mother wavelet Bior2.8 and Quadratic / Cubic SVM as a classifier generated the highest accuracy of 94.3%. Classification is done using 5fold-CV. These results indicate that the information in EEG signals can be described by their sub-bands. Using MWPE can be shown that with a proper mother wavelet and level of decomposition can be separated normal, inter-ictal and seizure EEG signals. The determination of the optimal decomposition level and the most appropriate mother wavelet become the next interest research topic.

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