Seizure Type Detection in Epileptic EEG Signal using Empirical Mode Decomposition and Support Vector Machine

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***Abstract*—Epilepsy is a serious neurological disorder that needs more attention by society. The International League Against Epilepsy (ILAE) mentioned that the term epilepsy referred to the number of seizure occurred in patients. Electroencephalogram signal is a common epilepsy diagnostic tools used by the neurologist. Research about the detection and classification of the epileptic signal from the EEG signal has massively conducted. In this research, we detect and classify four types of seizures which are focal non-specific seizure (FNSZ), generalized non-specific seizure (GNSZ), simple partial seizure (SPSZ), and tonic-clonic seizure (TNSZ). The EEG signal used was taken from Temple University Hospital EEG Seizure Corpus (TUSZ) version 1.2.0. The EEG signal decomposed with empirical mode decomposition (EMD) to extract five levels of intrinsic mode functions (IMFs). Feature extraction is done by calculating the mean, variance, skewness, kurtosis, standard deviation, and interquartile range. Support Vector Machine (SVM) used for classification with five-fold cross-validation. The best accuracy obtained is 95% by using quadratic SVM kernel.**

***Index Terms*—Seizure Type, EEG, EMD, SVM**

I. Introduction

Epilepsy is a neurological disorder which became a severe problem to humanity [1]. There were 80% of epilepsy cases mostly found in the developing countries and third world countries [2]. The spreads in the countries happened because most of the people in the countries were not well educated about what and the danger may be caused by epilepsy [2], [3]. The number of people with epilepsy counted was around 0,6-0,8% of the world population [4], which more than 50 million people [2]. Two million of them found in America [5]. In a developing country like Indonesia, the number of people with epilepsy cannot be predicted precisely. This condition happened due to the lack of awareness from the people with epilepsy and their families. Moreover, they even often get a negative stigma from society [6].

The term epilepsy referred to the number of seizure that occurred in patients. A seizure can inflict certain parts of the body to do an uncontrolled movement. Furthermore, the movement spreads to all parts of the body, and sometimes that can make the patients fainting [3]. There is a chance up to 66% that seizure symptoms can be cured by consuming a regular medication, and around 8% of the possibilities that seizure can be cured by doing surgery. Unfortunately, there is still a 25% of possibilities that seizure unable to cured [7]–[9]. For that 25% of people with epilepsy, their biggest problem that they need to face is that they can not predict when will the seizure occurs [9]. This problem became the major handicap, and the most significant source of worry for them and their family [10].

Electroencephalography (EEG) signal is a current measurement of the brain which flows during the excitation process in the synapses [11]. There are two primary methods for EEG recording, the first one is scalp EEG recording (sEEG), and the second one is intracranial EEG (iEEG) [10]. sEEG recording obtained by placing the electrodes into the scalp of the head using the recommendation from The International Federation of Societies for Electroencephalography and Clinical Neurophysiology called the 10-20. iEEG signal obtained by placing electrodes inside the scalp called multicontact foramen ovale (FO) electrodes [11]. Knowing how the signal obtained, the sEEG is generally very vulnerable to noise compared to iEEG. EEG mostly used as the preferred diagnostic tool for analyzing brain behavior, because of its simplicity, economical, non-invasiveness, and easy to use [12]. Studies have shown that EEG has been used frequently to help diagnose a lot of neurological diseases such as Mild Cognitive Impairement [13], [14], Alzheimer [15], [16], and to detect seizure [17]–[22]. The primary key for the success of EEG-based seizure detection lies on how good the system can extract the features of the EEG signal so that it can characterize the seizure well [23].

Measurement of EEG features can be done using one channel (univariate) or multiple channels (multivariate) [24]. In this research, we classify four types of seizure from the EEG signal. We use empirical mode decomposition (EMD) to decompose the EEG signal into several numbers of intrinsic mode functions (IMF). EMD was first introduced by Huang [25], which the idea is to analyze nonlinear and non-stationary data. The data is decomposed into a finite number of IMF by using Hilbert transforms [25]. EMD commonly used for EEG signal analysis, such as brain death determination [26], removal of blink noise [27], [28], apnea discrimination [29] and seizure detection [30]–[32]. The IMF then extracted to find the features of the

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TABLE I: Seizure Types and Manifestation

Name	Location	Manivestation	Description
Focal Non-Specific Seizure (FNSZ)	Hemispheric / Focal	Electrographic	Focal seizures that can't be specified by the type
Generalized Non-Specific Seizure (GNSZ)	Generalized	Electrographic	Generalized seizure that can not be further classified
Simple Partial Seizure (SPSZ)	All	Electroclinical	Partial seizure occured during consciousness
Tonic Clonic Seizure (TNSZ)	All	Electroclinical	Stiffening of body during seizure which cause the EEG effects disappears

signal to be processed for seizure detection [33]. The statistic measurement was used to find the EEG signal feature. The obtained features then fed to Support Vector Machine (SVM) as the classifier. The EEG dataset used in this research taken from Temple University Hospital EEG Seizure Corpus (TUSZ) v.1.2.0. This dataset is a subset from the TUH EEG Corpus which contains session confirmed as seizure events that have been annotated manually by a neurologist to show the seizure events [34]–[36].

The remaining section for this paper is formatted as Section II is the explanation of the dataset used, EMD method, statistical feature extraction, and SVM. Section III is the result experimental result, and finally in Section IV is the conclusion.

II. Material and Method

A. Temple University Hospital Seizure Corpus

The electroencephalography corpus from Temple University Hospital (TUH EEG Corpus) is one of the largest open dataset available for public [35]. The data consist of more than 25,000 EEG recording, which comes from more than 14,000 patients. Each data accompanied by a neurologist's interpretation, demographic information of the patients, and medical history [35], [37]. EEG signal recording was done by using several models of Natus Medical Incorporated's Nicolet™ EEG, which done since 2002. The RAW signal has several types fo channels recordings between 20 to 128 channels, and the sampling frequency used is 250 Hz. All of the EEG data in this dataset are saved by using EDF file format which has 24 unique fields containing recorded signal condition and the patient's information [37].

The TUH EEG Corpus has four subsets that designed to support specific EEG analysis research. The subsets are the TUH EEG Seizure Corpus (TUSZ), the TUH EEG Abnormal EEG Corpus, TUH EEG Slowing Corpus, and TUH EEG Epilepsy Corpus [34]. This research used the TUSZ version 1.2.0, which has seven types of seizures. The seizure types used in this research are focal non-specific seizure, generalized non-specific seizure, simple partial seizure, and tonic-clonic seizure.

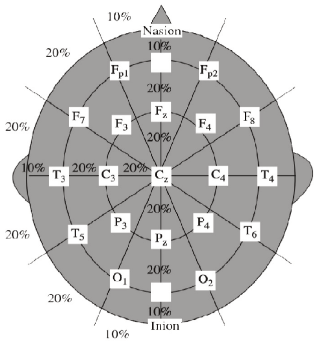

Fig. 1: Channel Configuration [11]

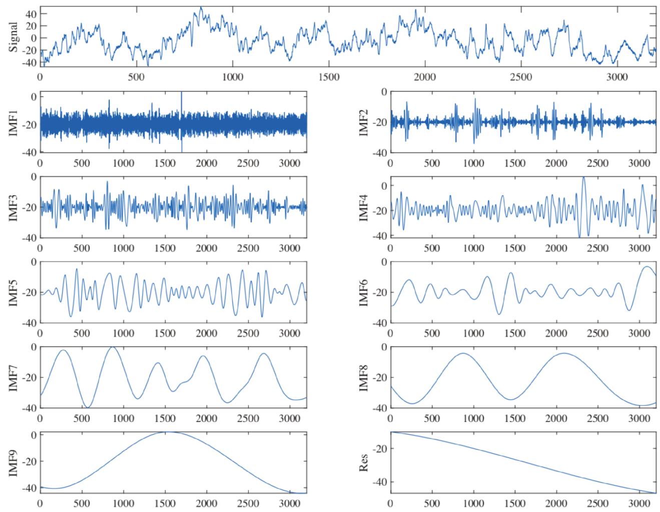

Fig. 2: Focal Non-Specific Seizure Signal with its IMF and Residue

The definition of these seizures can be seen in Table I. All the data in TUSZ were recorded using standard 10-20 channel configuration and saved in EDF file format. iz

B. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD), developed by Huang [25], decompose a non-linear or a non-stationary signal obtaining a number of its decomposition level, called intrinsic mode function (IMFs) which oscillatory in nature [25], [38]. Generally, EMD process from signal $x(t)$ is described by Eq.(1).

$$x(t) = \sum_{n} IMF_n + residue \tag{1}$$

The detailed procedure for calculating the IMF is described as follow:

1) Calculate the local max $M_i, i = 1, 2, ...$and min $m_k, k = 1, 2, ...$ of signal $x(t)$. Interpolate them $M(n) = f_M(M_i, n)$, and $m(n) = f_m(m_k, n)$ to obtain the envelopes by using cubic spline.
2) Find the local mean using $mn(t) = \frac{M(n)+m(n)}{2}$,
3) Find the detail using $d(t) = x(t) - mn(t)$

4) If the detail is not IMF, then the first two processes are repeated with $mn(t)$ as the new input.
5) If the detail is suitable with the IMF's criteria, then $d(t)$ is choosen as IMF, $cr_i(t) = d(t)$. The IMF removed from the original signal $r(t) = x(t) - cr_i(t)$, i refers to the ith IMF.
6) repeat the process from step 1, with $r(t)$ as the new signal while $cr_i(t)$ as the IMF.

We randomly selected 100 samples for each type of seizures and normal EEG data to get 500 data in total. We processed 19 channels of the EEG signal as shown in Fig. 1. After that, each channel were decomposed using EMD to obtained intrinsic mode functions (IMFs). The sample decomposed signal and its residue are shown in Fig. 2. This example is taken from a FNSZ data. From the picture, we can see that the oscillations are slowing down as we increase the number of decomposition.

Three IMFs are used by Shahbakhti et al. in [39] and [27] to remove the blink from EEG signal. Yadav et al. used 8 IMFs to discriminate apnea and normal sleep [29]. Other research by Shaikh et al. used 5 IMFs to detect seizure using Bonn University dataset [32], while Tripathi et al. [40], and Martis et al. [41] used 8 IMFs in the same dataset. We used IMF1-IMF5 because starting from IMF5, the signal oscillations were slowing down. Higher signal oscillations shows that ther is more significant information about the signal in EMD components [42].

C. Feature Extraction

Features of the EEG signal extracted using the first four statistical moments (mean, variance, skewness, kurtosis), standard deviation, and interquartile range (IQR). These features extract the information from all 5 IMFs. For each signal, we have six features and 5 IMFs, so the complete features per epoch 30 features. This processes done for all 19 channels of the EEG signals.

1) Mean
Mean is the average of the signal, it is calculated to obtain the central value of a signal. Eq. (2) show how to calculate the mean of signal S_x with signal length n.

$$\mu = \frac{1}{n}\sum_{x=1}^{n} S_x \tag{2}$$

2) Variance
Variance of a signal S_x with length n, can be calculated using Eq.(3).

$$var = \frac{1}{n}\sum_{x=1}^{n} |S_x - \mu|^2 \tag{3}$$

3) Skewness
Skewness is an asymmetry measurement of a signal around the mean. Skewness has two types, negative and possitive skewness. The negative value shows that the data are spread out in the left of the mean, while it is vise versa for the positive value. Skewness is defined in Eq.(4). Where $E(n)$ is the expected value of the quantity n while the σ is the standard deviation of S_t.

$$skew = \frac{E(S_x - \mu)^3}{\sigma^3} \tag{4}$$

4) Kurtosis
Kurtosis value represents the sharpness of normal curve. There are three types of kurtosis, which are leptokurtic, platykurtic and mesokurtic. Leptokurtic is the center of data distribution which has the kurtosis value bigger than 3. Platykurtic is when the peak of the data distribution is flatter. The kurtosis value is less than 3. The Mesokurtic is when the kurtosis value is equal with 3. Kurtosis is defined with Eq.(5).

$$kurt = \frac{E(S_x - \mu)^4}{\sigma^4} \tag{5}$$

5) Standard deviation
Standard Deviation is the variance square root. For a random signal S_x the standard deviation is defined with Eq.(6).

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{x=1}^{n} A_x} \tag{6}$$

6) IQR
Statistical dispersion between the 75% and 25% is called the interquartile range. The IQR is variability measurement by splitting a group of data into quartiles. Quartiles are obtained by calculating the median of the data.

D. Support Vector Machine

Support Vector Machine (SVM) has been widely used for classification method for pattern recognition, seizure detection, seizure prediction, and many other applications [43]. Cortes and Vapnik developed SVM in 1995 [44]. Generalization capability by only using a few parameters became the main key of this method [45]. The SVM generalization can optimize and make the data more dependence. The algorithm focused on maximizing the minimum hyperplane. Hyperplane represents a straight imaginary line that divides data into different classes. Optimum hyperplane can be obtained from maximizing the margin between two classes. The margin reflects the distance between the hyperplane and the closest data pattern in a class. SVM algorithm focused on detection to the shortest distance between the data's decision function. The closest position between each data pattern called the support vector. To solve the non-linear problem, we used a kernel trick method that used a non-linear field to separate the data classes that cannot be split using a straight line hyperplane [44], [46].

There are three SVM kernels used in this research, linear, quadratic and cubic. The linear kernel grouped a set of data by using a hyperplane. A good hyperplane or logic separator is the one that can equally localize two classes. The hyperplane is described by Eq. 7. Optimization of the hyperplane can be adjusted using Eq. 8, where T is the trade-off parameter between the separated classes and the error of the training set. ε showed the set of the slack variable. For the non-linear surface of data, the kernel trick approach is called as nonlinear SVM classifier. Two types of the nonlinear kernel are radial basis function and polynomial function. Representation of polynomial function is quadratic and cubic kernel [44], [47].

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

$$\frac{1}{2} \|\vec{w}\|^2 + T \sum_{i=1}^{k} \varepsilon_i \tag{8}$$

Since SVM is one of the supervised learning methods, we used N-fold cross-validation in order to split the train and testing data. Here we use 5-fold cross-validation. The dataset was first split into five datasets then, the four datasets used as training data while one dataset used as testing data. This process repeated until all the split datasets have been used as testing data. The SVM performance measured by calculating sensitivity, specificity, and accuracy.

III. Result and Discussion

The EEG signals reference used in this research is the left ear reference (LE) referring to Lopez et al. [48] which mentioned that the system developed using the LE trained data better than the one using Averaged Reference (AR). Each seizure signals were extracted and labeled based on the information from the dataset. We attained the seizure signals from four seizure types, each consist of 100 seizure signals. The data then added with 100 normal EEG signal. We have five classes of data used as the dataset.

The next process was decomposed the EEG signals using EMD to get the IMFs. We need to determine the optimum amount of IMFs to be extracted using the six extraction processes. As we know, the occurring seizure period was different for each sample because of the different condition from the patients. The time differences affect the number of IMFs produced by the EMD process. In this research, we obtained different IMFs for each class sample starting from 8-15 IMFs.

Shahbakhti et al. in [39] and [27] choose the IMFs level by evaluating the entropy of the IMFs. Higher level IMF decreased the entropy value, and when the entropy value rises, then it decided to take the last entropy as the end of the decomposition level. We adopt the entropy measurement technique by calculating the minimum increase of the entropy value from all IMF level. The minimum increasing value of the entropy found in the fifth level of IMF as shown in Fig. 3.

TABLE II: Classification Result using N Level of IMFs

SVM kernel	1 IMF	2 IMF	3 IMF	4 IMF	5 IMF
Linear	75,00%	88,60%	92,40%	92,20%	92,80%
Quadratic	72,40%	90,00%	93,20%	93,80%	**95,00%**
Cubic	55,60%	89,20%	94,20%	93,20%	94,80%

Based on this finding, the decomposed signals used to calculate the features are IMF1-IMF5. The next process is obtaining the signal features by calculating the kurtosis, mean, variance, skewness, standard deviation, and interquartile range of IMF1-IMF5 and fed them to the classifier. We combine those feature to find the best accuracy result, such as shown in Fig.4.

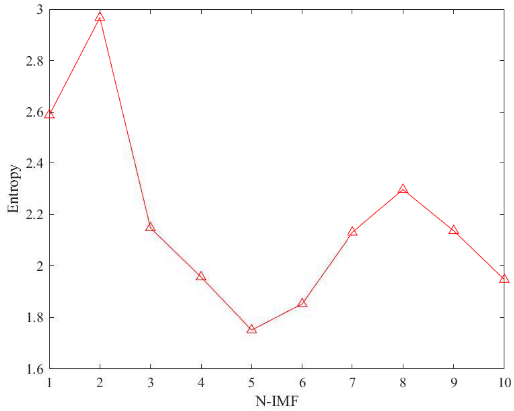

Fig. 3: The increasing of entropy indicates the last level of decomposition used

TABLE III: Classifier performance using Quadratic SVM

Pred / True	CP SZ	FN SZ	GN SZ	TC SZ	NO RM	Sens (%)	Spec (%)
CPSZ	91	6	3	0	0	**91**	**98,75**
FNSZ	0	97	3	0	0	**97**	**97,5**
GNSZ	5	3	90	1	1	**90**	**98,25**
TCSZ	0	0	0	99	1	**99**	**99,75**
NORM	0	1	1	0	98	**98**	**99,5**
Total Accuracy						**95%**	

We use the combination of a single IMF, two IMFs up to five IMFs as the feature input of the SVM. It is shown that more extracted IMFs may increase accuracy. The best accuracy achieved by extracting five IMFs, and using quadratic SVM kernel was 95%. Table II showed the performance of SVM classifier, while Table III showed the specific performance of quadratic SVM for detecting four types of seizure and normal EEG signals.

Research for detecting seizure by Wijayanto et al. [20] was conducted using multilevel wavelet packet entropy (MWPE) as the feature extraction. The method was based on wavelet packet entropy that calculated for all decomposition level of the signal. We used the feature extraction technique in TUSZ dataset and compared with our method. The MWPE used to extract five decomposition level of EEG signal and used them for classifier input. The performance of our method outperformed the MWPE which can be seen in Table IV.

TABLE IV: Comparison with other method

SVM kernel	MWPE [20]	This Research
Linear	78,60%	92,80%
Quadratic	81,40%	95,00%
Cubic	83,80%	94,80%

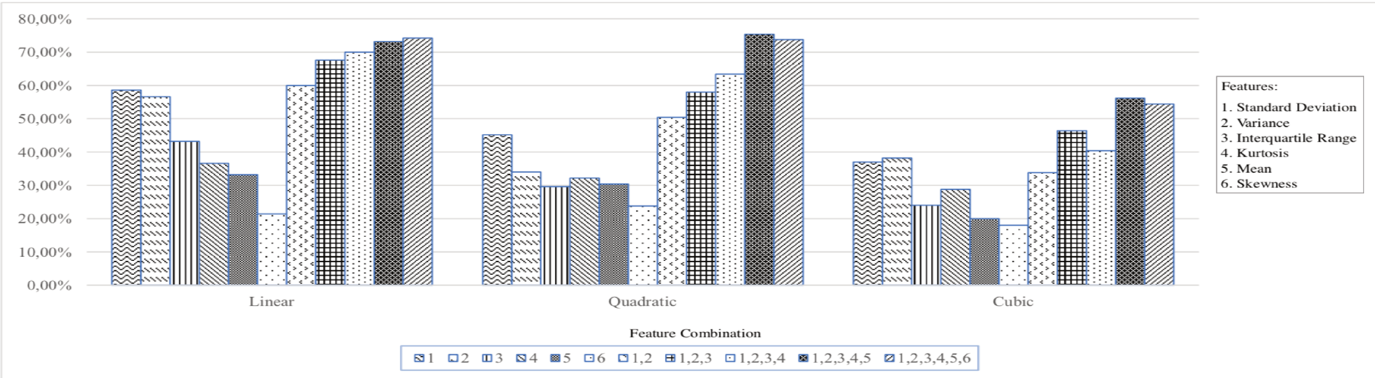

Fig. 4: Feature Combination Test

IV. Conclusion

In this paper, we are exploring the use of EMD and SVM algorithm to classify four seizure type and normal EEG signals. EMD can be used to decompose EEG signal to detect seizure types effectively. By using six statistical calculation we extracted the signal feature from five level of IMFs. The best accuracy is 95% which obtained by using five IMFs. For next improvement, all of the data in TUH EEG Corpus need to be used, by using the statistical methods such as box plot to cover the imbalance number of data each class.

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