Seizure detection using empirical mode decomposition and time-frequency energy concentration

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***Abstract*— The aim of this study is to evaluate a new method for seizure detection using the tripolar Laplacian electroencephalography signal (tEEG) recorded using a tripolar concentric ring electrode (TCRE) on the scalp surface of rats based on empirical mode decomposition (EMD) and time-frequency energy concentration. Data from 10 rats were examined with the proposed algorithm. After EMD decomposition, three oscillation components named intrinsic mode functions (IMFs) were selected. An energy estimate of the TFR for the selected IMFs was calculated and used as a feature for automatic seizure detection of the tEEG signals. After classification the obtained results using the proposed method produced an accuracy of 98.61%. This study developed the proposed algorithm to work with TCREs, and shows it to be effective to detect seizures from rat's tEEG signals.**

Keywords - seizure detection; tripolar Laplacian EEG (tEEG); tripolar concentric ring electrode (TCRE); empirical mode decomposition (EMD); time-frequency representation (TFR); energy estimate.

I. Introduction

Epilepsy is a disorder characterized by an unexpected and repeated malfunction of the brain called "seizure", which reflects the clinical signs of an excessive and hyper synchronous activity of neurons in the brain [1]. The electroencephalogram (EEG) measures the electrical activity of the brain using electrodes that are placed on the scalp. The EEG is an important resource in determining the presence or absence of neurological disorders like epileptic seizures. Seizures are manifested in the EEG as paroxysmal events characterized by stereotyped repetitive waveforms that evolve in amplitude and frequency before eventually decaying [6]. Therefore, it is possible to detect seizure occurrences from significant parameters and dynamical changes in the EEG of patients with epilepsy, such as transient signals called spikes, sharp waves, and spike-and-wave activity.

Time-frequency representations (TFRs) of signals are techniques that map a one-dimensional signal of time into a two-dimensional function of time and frequency [8]. TFRs have been developed for a wide range of problems with signals that contain highly localized events such as bursts, spikes, and discontinuities, which typically occur in EEG signals during seizures. Different algorithms, some using TFRs, were applied for spike detection during epilepsy [14]. There are various forms of TFRs: the Wavelet transform, short time Fourier transform, Wigner distribution (WD), pseudo Wigner-Ville distribution (PWV), smoothed pseudo Wigner-Ville distribution (SPWV) etc., and each has advantages and limitations [7].

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One method used to separate an oscillation from the original signal is the empirical mode decomposition (EMD). EMD is a signal processing technique introduced by Huang et al. [4] for multi-component nonlinear and non-stationary signals. The EMD decomposes the signal and extracts its local oscillations, referred to as intrinsic mode functions (IMFs) [6]. These IMFs can be considered as new non-stationary bands extracted from the original signal. The spectral content of the IMF extracted at a given iteration is lower than that of the IMF extracted from the previous iteration, which permits analyzing the signal at different frequencies. The EMD technique has been used in the field of biomedical signal processing, especially for seizure detection in EEG signals [9, 10].

Analysis of scalp EEG is used for seizure detection. Recently, improvements have been applied to EEG recording techniques, making it more accurate by increasing the spatial resolution. One such improvement is the application of the surface Laplacian to the EEG [5, 6]. Previously, we have shown that EEG signals recorded using the tripolar concentric ring electrode (TCRE, Fig. 1) configuration (referred to as tEEG signals) has significantly better spatial selectivity, signal-to-noise ratio, and mutual information than conventional EEG from disc electrodes [5, 6]. The TCREs also exhibit strong attenuation of common mode artifacts [6]. These findings suggest that new tEEG may be useful for seizure detection or other neurological disorders analysis [9].

In this paper, an alternative approach for tEEG seizure detection is proposed. The analysis method consists of three steps. In the first step, the tEEG Baseline and Seizure segments are adaptively decomposed into IMFs using the EMD algorithm [4]. In this paper, three IMFs were selected using an algorithm proposed by Flandrin et al [16] and used for further analysis. In the second step, the SPWV TFR [8] is computed for the three selected IMFs for each segment. Thirdly, the localized energy estimate from the TFR was computed. This energy varies for each segment of the three selected IMFs components for the tEEG signal and will be used as a feature for automatic seizure detection.

In Section 2 of this paper, we describe in detail the proposed method, the dataset and the techniques used. Then, in Section 3 we summarize the results obtained with an extended discussion. Finally, some conclusions are given.

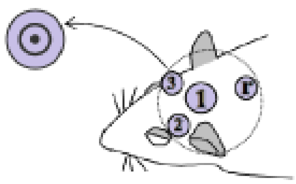

Figure 1. The location of the tripolar concentric ring electrodes on the rat scalp used to record the data. Electrode (1) is 1 cm dia. and used for stimulation and recording. Electrodes (2) and (3) are both 0.6 cm dia. and used only for recording. Electrode (r) is the reference. An example of a tripolar concentric ring electrode is shown to the left of the rat head.

II. MATERIALS AND METHODS

A. Experimental setup

The animal protocol used for recording the tEEG signal was approved by the University of Rhode Island IACUC. Approximately twenty-four hours before the induction of seizures caused by pentylenetetrazole (PTZ), an adult male Sprague-Dawley rat 220~320 g was given a combination of 80 mg/kg of ketamine and 12 mg/kg xylazine (i.p) for anesthesia. The scalp was shaved and prepared with NuPrep abrasive gel (D. O. Weaver & Co., Aurora, CO, and USA). Three TCRE [11] were applied to the scalp (see Figure 1) using conductive paste 0.5 mm Ten20, Grass Technologies, RI, USA, and adhered with Teet's dental acrylic (Pearson Lab Supply, Sylmar, CA, USA). The electrodes were made of gold-plated copper. After a 5 minute recording of baseline EEG, the PTZ was given (55 mg/kg, i.p.). The EEG signals were preamplified (gain 100 and 0.3 Hz high-pass filter) with a custom built preamplifier and then amplified using a Grass NRS2 Neurological Research System with Model 15A54 AC amplifiers (Grass Technologies, West Warwick, RI, USA) with a gain of 1,000 and band pass of 1.0-100 Hz with the 60 Hz notch filter active, and digitized (16 bits, 256 Samples/second). The two differential signals from the electrode elements (outer ring, inner ring, and center disc) were combined using an algorithm giving a Laplacian derivation of the signal as described by Besio [11].

B. Data description

In order to evaluate the performance of the proposed method for seizure detection, the recorded tEEG data from ten rats have been used. Two sets of tEEG data corresponding to the Baseline data and Seizure data were used as the investigational data set for seizure detection. The data set from the ten rats contained 65 single-channel tEEG Baseline segments and 70 single-channel tEEG Seizure segments. All selected tEEG segments had 30s duration, with sampling rate of 256 Hz. The selection of the Seizure periods was performed by an experienced behaviorist through visual inspection of the video recordings. Because of a large amount of artifacts and noise caused by grooming, chewing, and roaming of the rats during the recording, Baseline periods were selected after visual inspection where the tEEG data appeared to be relatively calm and noise free. Also, the numbers of baseline and seizure segments are not necessarily the same for each rat and there were more than one seizure segment selected for all the rats.

C. Related work

Different methods for automatic seizure detection have been proposed [2, 3, 5, 9, and 10]. In this paper, the detection is based on the decomposition of tEEG segments into several oscillating components via the EMD algorithm followed by TFR analysis. A localized energy estimate is extracted and considered as a feature for discrimination between Seizure and Baseline data. The different steps of the detection process are summarized as follow: (1) Downsample the tEEG signal to reduce the sampling rate from 256 Hz to 128 Hz to reduce the amount of data which will reduce the number of computations without losing the necessary data for analysis. The signal was filtered first using an anti-aliasing low-pass filter with a cutoff frequency 64 Hz to meet the Nyquist criteria and avoid aliasing. The MATLAB function *downsample* was used for the down-sampling procedure. (2) Decompose each tEEG signal into IMFs using the EMD algorithm [4]. The algorithm proposed by Flandrin et al [16] was used to select three IMFs for seizure detection. (3) The three selected IMFs from each signal were partitioned into one-second epochs using a non-overlapping, sliding Hamming window to avoid redundancy caused by an overlap. In this study, several different epoch sizes from 1s to 5s were tested; one-second EEG epochs with a non-overlapping window provided the best detection accuracy. (4) The analytic signal for each epoch is used [19] to eliminate the negative frequencies for better cross term reduction in TFRs. For a given signal x(t), the corresponding analytic signal is define as: $y(t) = x(t) + jHT(x(t))$; where HT() is the Hilbert transform. (5) The SPWV is computed for each analytic epoch [8, 21]. (6) An estimate of the localized TF energy is extracted for each epoch, used as a feature, and classified to determine whether a given epoch contains a seizure or not.

III. FEATURES EXTRACTION PROCEDURE

In this study, feature extraction methods consisted of three steps. First, the data segments were adaptively decomposed into oscillating components, the IMFs. The SPWV distribution was carried out for each epoch for selected IMFs (to be described later) and the estimate of the localized TF energy was calculated and used as a feature to discriminate between Seizure and Baseline. The method is briefly described in the following sections.

A. Empirical Mode Decomposition (EMD)

The principle of the EMD technique is to decompose a signal automatically into a set of band limited functions, called Intrinsic Mode Function (IMFs) [4]. An IMF is defined as a function that satisfies the following two conditions [4]: (1) The number of extrema and the number of zero crossings must be equal or differ by at most one. (2) The mean value of the envelope defined by the local maxima and by the local minima must be zero or close to zero at all points. The EMD has several advantages: (1) it is a decomposition method developed for non-linear and non-stationary signals which can provide a better numerical description of temporal patterns than traditional methods such as wavelet and Fourier methods [4]. (2) EMD can break down complex signals into a finite set of band limited signals or intrinsic mode functions (IMFs) without a need for basis functions in contrast to the traditional methods like wavelet decomposition where the basis functions are fixed. (3) Also, the EMD algorithm is considered as a type of filter bank decomposition method used to isolate different constituents from multi-component signals like the EEG [12]. Moreover, the EMD procedure allows for TF interpretation of transient signals, which is not the case for stationary, one-dimensional Fourier transform based methods [13]. These properties make the EMD decomposition suitable in biomedical engineering applications like the case of detection of seizures from EEG signals. The EMD MATLAB code used in this paper is available at [22].

B. Selection of iMFs

To identify which IMFs to use in the proposed analysis, we need to know whether a specific IMF contains useful information or primarily noise. A statistical model based on energy distribution of the noise between IMFs has been developed by Flandrin et al [16]. The method suggests decomposing of the noisy signal into IMFs, and then comparing the IMF energies with the theoretical estimated noise-only IMF energies. The model is based on studying the energy in the modes of fractional Gaussian noise (fGn) after EMD decomposition. fGn is a generalization of white noise; it exhibits a flat spectrum and its statistical properties are determined solely by a scalar parameter *H* known as Hurst exponents. In this paper, we take $H = 0.5$, so the process is reduced to uncorrelated white noise. We consider that the EMD of a discrete-time signal x[n] for $n = 1,\dots, M$ results in a set of *K* IMFs $f_k[n]$ for $k = 1,\dots,N$. The signal $x[n]$ is considered to be corrupted with white noise (fGn with $H = 0.5$). The energy of the first IMF is:

$$W_H[1] = \sum_{n=1}^{M} f_1^2[n] \quad (1)$$

The energy of the noise in the other IMFs for a given Hurst exponent $H = 0.5$ is:

$$W_H[k] = \frac{W_H[1]}{0.719} 2.01^{-k},\ k = 2,3,\dots,N \quad (2)$$

Moreover, there is a linear relationship between the logarithm of the confidence interval $T_H[k]$ and the number of the IMF k given by:

$$\log_2(\log_2(T_H[k]/W_H[k])) = a_H k + b_H \quad (3)$$

For a confidence interval of 99%: $a_H = 0.45$ and $b_H = -1.95$. The algorithm proposed by Flandrin et al. [16] is the following: (1) Assuming that the first IMF captures most of the noise, estimate the noise level in the noisy signal by computing $W_H[1]$ from equation 1. (2) Estimate the "noise only" model by using equation 2. (3) Estimate the corresponding model for a chosen confidence interval from equation 3. (4) Compute the EMD of the noisy signal, and compare the IMF energies by using the confidence interval as a threshold. (5) Compute a partial reconstruction by keeping only the residual and those IMFs whose energy exceeds the threshold (confidence interval).

This technique works very well when the noise is in a different frequency band from the signal, so the noise is captured in specific IMFs. Its performance degrades when signal and noise share the same bandwidth. The Flandrin algorithm for IMF selection was run on each 30-second segment of the signal to identify which three IMFs should be selected for the next algorithmic step of TFR energy feature classification. In this study, the algorithm determined that IMF3 was the first IMF to cross the threshold for the vast majority of the data set used. Figure 2 shows an example using a 30-second Seizure segment; the figure shows that the IMF energy increases significantly at IMF3. Consequently, IMF numbers 3, 4, and 5 were used in subsequent analysis to best represent the dataset used in this study and to reduce algorithm computational complexity.

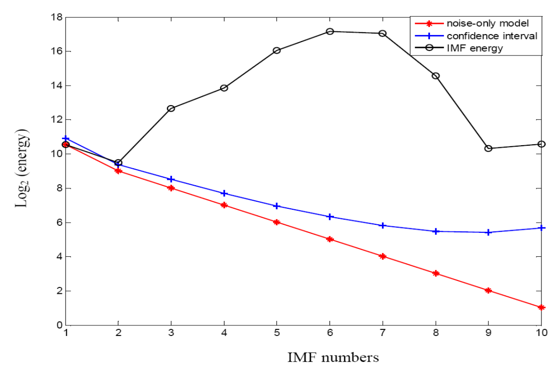

Figure 2. An example of IMF selection criteria using equation 3. The noise-only model in red and the confidence interval in blue are presented. The IMFs numbers 3 to 10 have energies which exceed the confidence interval (or threshold).

C. Time-frequency energy

TFRs are the transformations of time-varying signals that illustrate how the spectral content of a signal is changing with time [7]. The EEG signal is considered a non-linear and non-stationary signal, so it is helpful to select an appropriate TFR with good TF resolution and reduced interference terms. In this paper, we focus only on the SPWV distribution, since it offers good TF resolution and good interference reduction [8]. The SPWV distribution permits two independent smoothing windows, one in time and the other in the frequency domain to improve the readability of the Wigner-Ville distribution. The SPWV distribution is defined as follows:

$$SPWV_X(t,f) = \int h(\tau)\left(\int g(s-t)x\left(s+\frac{\tau}{2}\right)x^*\left(s-\frac{\tau}{2}\right)ds\right)e^{-j2\pi f\tau}d\tau \quad (4)$$

where *x* is the signal, *t* is the time variable, *f* is the frequency variable: *g()* and *h()* are the smoothing (or cross-terms reduction) time and frequency windows, respectively.

TF energy distributions are very important in analysis and processing of non-stationary signals like the EEG. An energy TFR $T_x(t, f)$ combines the concepts of instantaneous power

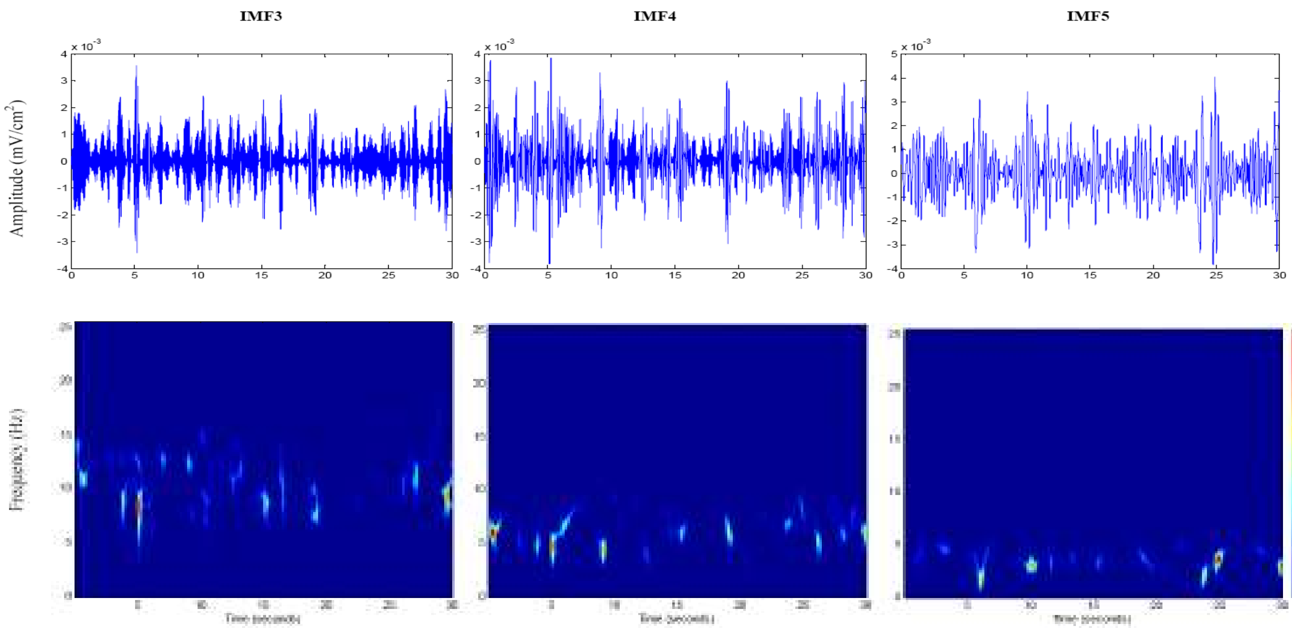

Figure 3. Top plots represent the third, fourth, and fifth IMF decompositions (IMF3, IMF4, and IMF5) of Baseline tEEG signal. Shown at the bottom are the corresponding SPWV TF distributions (two Hamming windows with 0.5s and 1s duration are used respectively, for the time and frequency domain smoothing) of IMF3, IMF4 and IMF5 decomposed from baseline data. They show that the frequency content of IMF3 is higher than the frequency of IMF4 which has higher frequency content than that of IMF5.

$p_X(t) = |x(t)|^2$ and spectral energy density $P_X(f) = |X(f)|^2$, where X(f) is the Fourier transform of X(t). An energy TFR satisfies the following marginal properties [8]:

$$\int T_x(t, f)df = p_x(t) = |x(t)|^2 \quad (5)$$

$$\int T_x(t, f)dt = P_x(f) = |X(f)|^2 \quad (6)$$

$$E_x = \iint T_x(t, f)dtdf = \int |x(t)|^2 dt = \int |X(f)|^2 df \quad (7)$$

Equations (5) and (6) indicate that if the TF energy density is integrated along one variable, the energy density corresponding to the other variable can be obtained. The total signal energy is derived by integrating the TFR $T_x(t, f)$ over the entire TF plane (the total energy condition E_x in equation (7)). Many TFRs, including SPWV distribution, do not strictly obey the marginal properties in (5-7); that is, the frequency and time integrals of the distribution do not exactly equal the instantaneous signal power and the spectral energy density, respectively [8]. However, some can still be used to generate estimates of localized signal energy [8]. The total energy can be a good feature to detect signal events in the SPWV representation because the energy in EEG seizure is usually larger than the one during normal activity [3]. The approximate localized energy extracted from TFRs was calculated for each epoch of the three selected IMFs components, IMF3, IMF4, and IMF5, to construct the feature vector used for automatic seizure detection.

D. Classification and performance calculation

In this study, three IMFs for each 30 second segment (for both Seizure and Baseline) were selected after EMD decomposition. Each thirty second IMF is partitioned into epoch of one second length and the time-frequency energy concentration is calculated for each epoch. This results in a feature vector set consisting of 90 samples (3 IMFs x 30 x 1 second) for each segment. A ten-fold cross-validation technique was applied during the training periods to estimate how well the classification method will classify the new data which were not seen during the testing validation period. In ten-fold cross validation, the data set is split into 10 equal sub-set partitions. Each time, one of the 10 subsets is used for testing whereas the other 9 subsets are used for training the dataset. The total data were randomly split into ten subsets. The whole procedure is repeated ten times. The final result is the average of all 10 repetitions. After selecting the training and testing features, they were then applied to a discriminant analysis classifier [17]. Discriminant analysis is a technique used to discriminate a single classification variable using various features. Discriminant analysis also assigns observations to one of the pre-defined groups based on the knowledge of the multi-features [20]. The usefulness of a discriminant model is based on its ability to predict the relationships between known groups in the categories of the dependent variable. In this paper, the MATLAB command “classify” was used and “diagQuadratic” was selected as a discriminant function type [17]. In order to evaluate the performance of the proposed method for seizure detection, the following statistical parameters were calculated [15]:

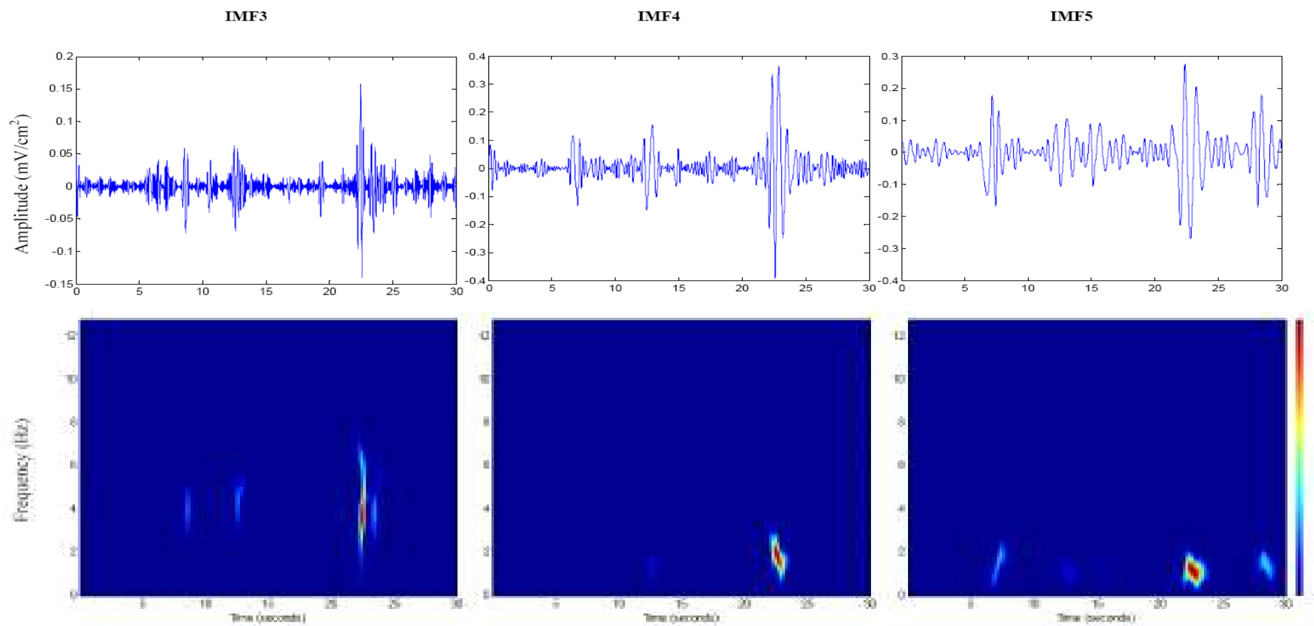

Figure 4. Top plots shows IMF3, IMF4, and IMF5 and their SPWV distributions in the bottom (two Hamming windows with 0.5s and 1s duration are used respectively, for the time and frequency domain smoothing), of the tEEG signal with seizure. It is very clear from these SPWVs, that the frequency of IMF3 is higher than the frequency of IMF4 which has higher frequency content than that of IMF5.

(1) Sensitivity: Is the percentage of epileptic seizure segments correctly classified by the algorithm. (2) Specificity: Is the proportion of segments without seizures correctly classified by the algorithm. (3) Accuracy: Is the percentage ratio of correctly classified segments to the total number of segments considered for classification.

IV. RESULTS AND DISCUSSION

In this study, a new method for automatic seizure detection is proposed. The method is based on TF analysis of several oscillating components broken down from the original signal via the EMD algorithm. Localized energy estimates were extracted and considered as features fed into a classifier for discrimination between Seizure and Baseline data. The SPWV distribution was used to calculate the localized energy distribution of the signal.

After the EMD decomposition, the Baseline and Seizure segments may have different number of IMFs because the number of IMFs depends on the frequency content of each signal [4]. The method proposed by Flandrin et al. [16] was used to automate selection of the IMFs used to reduce impact of noise. Figure 2 show that IMFs 3 to 10 have energies which exceed the confidence interval (or threshold, blue). So, in this paper, the IMF3, IMF4, and IMF5 were selected for further analysis. The three selected IMFs from each signal were partitioned into one-second epochs using a non-overlapping, sliding Hamming window.

TFR analysis of each epoch was applied using SPWV. The main reason we used TFR was to have more energy concentration. The idea is to analyze behaviors of the energy distribution, i.e., the concentration of energy at certain time instants or certain frequency bands or more generally, in some particular time and frequency region. The total energy can be a good feature to detect signal events in the SPWV representation because the energy in the EEG during seizures is usually larger than during normal activity. Figures 3 and 4 show examples of SPWV distribution on 30-second duration Baseline and Seizure segments after the IMFs were selected (IMF3, IMF4 and IMF5) using two Hamming windows with 0.5s and 1s duration respectively, for the time and frequency domain smoothing. From Figures 3 and 4 it can be seen that there is a higher concentration of energy in Seizure segments compared to Baseline and depends on the frequency content of each IMF. The best obtained accuracy is 98.61%, with sensitivity of 98.68% and specificity of 98.54%, achieved using two Hamming windows with 0.5s and 2s duration are used respectively, for the time and frequency domain smoothing.

These results are very promising, and show that the proposed method has the ability to recognize and classify Seizure from Baseline tEEG segments. The same dataset used in this study has already been used and tested in our previous work [18] using different features; the obtained accuracy varied between 84.81 and 96.51%. Comparing the results from [18] with the results obtained in this current study achieving 98.61% accuracy shows that the estimated time-frequency localized energy is a better feature to detect the presence of a seizure in a tEEG signal. Furthermore, the classifiers (SVM and AdaBoost) used in our previous work [18] using the same dataset were tested in this study with the new selected features. The obtained results with the classifier used in this paper gave better performance than SVM and AdaBoost.

Furthermore, there are other studies based on EMD decomposition for seizure detection such as Tafreshi et al. [9] where they could distinguish non-Seizure from Seizure data with success rates up to 95.42%. Pachori & Bajaj [10] used the area measured from the trace of the analytic IMFs as features to analyze normal and epileptic human seizure EEG signals and they showed that those calculated areas gave good discrimination performance. Comparing our results to those in the literature which used EMD and TF for seizure detection, the high accuracy obtained from our method, with 98.61% accuracy, using data from freely moving rats' shows that our proposed method for seizure detection is competitive with other methods disclosed.

V. CONCLUSION

Automatic detection of seizures is an important step in the diagnosis of epilepsy. In this paper, the proposed method for classification of Seizure and Baseline tEEG segments is based on the EMD method. The localized energy extracted from TFR was applied on some signal components. The EMD is applied to decompose the signal adaptively into oscillating components or IMFs. TFR is carried out on each epoch of a few IMFs selected, using Flandrin's method, and the localized energy is calculated and used as a feature to discriminate between Baseline and Seizure data. The results showed that the proposed method has the ability to accurately recognize and classify tEEG segments taken from freely moving rats with an overall accuracy reached 98.61% in a ten-fold cross validation study. We believe these results are significant as the EEG data earn from freely moving rats, hence contained large amounts of noise and artifacts. These high accuracy results on highly contaminated rat data encourage us to further test the proposed method on a large population human datasets. Many of the other results using TFR methods published in the literature were applied to relatively noise free human data.

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