Automated Epileptic Seizure Detection in Intracranial EEGs Using Wavelet Transform and SVM Classifier

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***Abstract*—Epilepsy is a common neurological disorder with more than 20% of epilepsy patients suffering from medically refractory epilepsy. The intent of this research is to develop an algorithm to detect seizures as they happen so that an alarm could be triggered to inform everyone that the patient needs assistance.**

To address this problem, this study proposes a seizure detection algorithm to automate the identification of seizure events in EEG recordings. Seizure detection is usually subdivided into two problems: feature extraction and classification. Described in the literature is an algorithm that makes use of patient-specific statistical and wavelet features to characterize seizure waves. The study focuses on the comparison on the use of Dual Tree Complex Wavelet Transform and Daubechies Wavelet at level 4. SVM classifier is used to distinguish seizure and non-seizure segments of an EEG recording. Results show that Daubechies wavelet produce an overall better detection rate than DTCWT. The detector achieved a 97.234% highest patient-specific accuracy and a 83.2891% overall accuracy for a set of 24 patients using Daubechies wavelet. Accuracy results gives good average estimate for seizure detection. Results can significantly be improved upon further research.

I. Introduction

Epilepsy is a neurological disorder characterized by recurrent, unprovoked bouts of seizures. Patients take antiepileptic drugs (AEDs) daily to treat epilepsy, while surgery can be applied if the epileptogenic focus is accurately identified [2]. But more than 20% of epilepsy patients suffer from medically refractory epilepsy, where medications are inadequate as methods for treating or eliminating seizures [1] [2] [5]. Most seizures terminate within the first five minutes, but persistent seizure activity is associated with a significant risk of mortality for the patient [1].

Neurologists visually analyze EEG signals to determine seizure onsets and origins so that the proper medication may be applied. The seizure event itself is called the ictal period. Monitoring and determining seizure events is a tedious and time-consuming task since EEG recordings create lengthy data [5] [12] [18]. In addition, EEG analysis is prone to discrepancies and disagreements among experts in the field due to its subjective nature [11] [17] and due to the variety of inter-ictal spike morphology [6]. Moreover, EEG patterns of epileptic seizures are similar to waves that are part of the background noise or artefacts, such as eye movement, muscle activity, electrical interference, electromyogram (EMG), electrocardiogram (ECG), etc [6] [10]. For these reasons, automating seizure detection accurately and efficiently will greatly help in the research and treatment of epilepsy, as well as provide better treatment for epilepsy patients. Detecting seizures as early as possible will help speed up the process of diagnosing patients, and it would aid clinicians in providing immediate medical treatment. For patients with medically refractory epilepsy, early detection of seizure onset would be helpful in getting an accurate localization of epileptogenic focus for resective surgery. Furthermore, accurate seizure detection will also aid in furthering epilepsy research. and solving other epilepsy-related problems.

II. Seizure Detection

Seizure detection can be treated as a classification problem between normal and ictal EEG signals. Automated detection of seizures can be performed in two stages: feature extraction and classification. Normally, an EEG recording may be corrupted with the presence of artefacts and noise. These are filtered from the data in the pre-processing stage such as downsampling and denoising. Features that describe or represent the characteristics of ictal activity are then extracted from the filtered signal. These features are used to train a classifying model, and becomes the basis of classifying data and distinguishing from ictal and non-ictal segments. The accuracy of the study depends on the classifier and the right combination of features extracted, while its optimization depends on the machine learning algorithms employed.

Over the years, many researchers have used several machine learning techniques to develop algorithms to analyze EEG data. Some researchers consider that seizure morphology differs from person to person [9] [12] and opt to use personalized, patient-specific seizure detection techniques in their studies. Fourier transform is commonly used in the early days of processing EEG signals [2] [11]. However, Fourier transform does not provide accurate results because of the nonstationary nature of EEG recordings [2] [3]. Feature extraction using Fourier transform can perfectly isolate the frequency content of the signal, but it cannot localize when these components happened in relation to time [7]. Hence, it is more suitable to use time-frequency domain transforms, such as wavelet decomposition [2] [7]. Wavelet decomposition represents a signals properties in different scales, showing both time and frequency content in relatively good resolution [11].

It is designed to address the non-stationary nature of the EEG signal. The main advantage of the wavelet transform is that it has a varying window size, leading to a better time-frequency resolution across all frequency ranges [18], as opposed to the Fourier transform which provides the frequency components of the signal, but with a lack of time resolution. Hence, this study makes use of wavelet-based features in the design of the seizure detection algorithm.

Artificial Neural Networks have also been used in the development of seizure detection algorithms [3] [4] [15]. However, ANNs require various training sets to reduce the influence of artefacts. The training of such networks are troublesome and unrealistic in real-life systems [10]. Other machine learning techniques employed by other researchers include: linear classifiers [2] [5] [18], Support Vector Machines [1] [13] [14], random forest [9], and Independent Component Analysis [16].

III. METHODOLOGY

A. EEG Datasets

The study involves seizure detection testing on the intracranial EEG data of epilepsy patients. The dataset is obtained from the CHB-MIT scalp EEG database [21]. It is publicly available online via Physionet at physionet.org. The dataset consists of EEG signals recorded from 22 pediatric patients with intractable seizures. All signals were sampled at 256 Hz with 16-bit resolution having varying numbers of electrodes and recorded using the International 10-20 system of EEG electrode positions and nomenclature.

For each patient, 80% of the files with seizures is used for training and 20% is used for testing. In each seizure file, the seizure event is divided into 1-second segments, extracted along with an equal duration of the non-seizure event recorded in the same file.

B. Wavelet Transform

The wavelet transform is designed to address the non stationary nature of the EEG signal. The main advantage of the wavelet transform is that it has a varying window size, leading to a better time-frequency resolution across all frequency ranges [18], as opposed to the Fourier transform which provides the frequency components of the signal, but with a lack of time resolution. One would need to restore the transformed signal to the original in order to analyze its time components. With wavelet decomposition, one can conveniently analyze the signal in the time-frequency domain. Figure 1 shows a 1-second seizure signal and its wavelet form.

Wavelet decomposition makes use of square-integrable, localized basis functions [11]. The basis is formed by translations and dilations of one basis-generating function called the mother wavelet. In this study, the features are extracted using the Daubechies family of wavelets, named after the Belgian mathematician and physicist Ingrid Daubechies.

The wavelet transform can be classified into two: continuous wavelet transform and discrete wavelet transform. Continuous wavelet transform is a correlation of the original signal and the wavelet-transformed signal at different scales. In the discrete wavelet transform, the signal is analyzed at

Fig. 1. An 1-second ictal signal representing a single channel

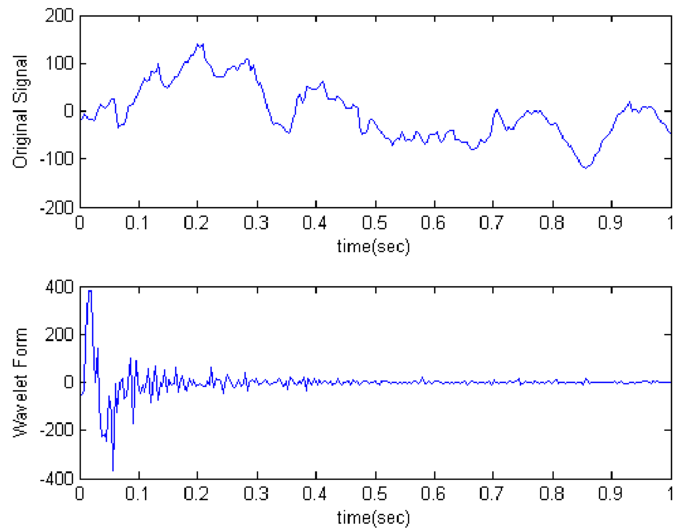
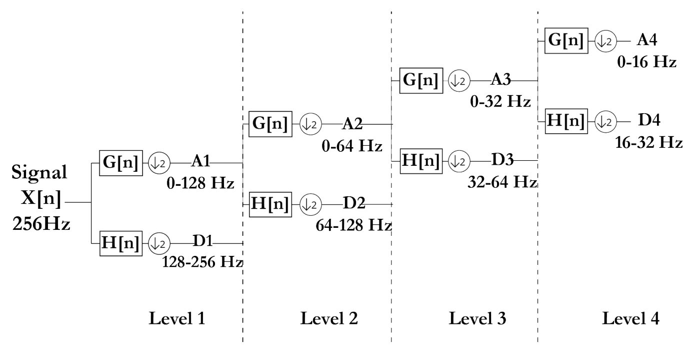


Fig. 2. Discrete wavelet Decomposition Tree up to 4th level (on a signal sampled at 256 Hz)



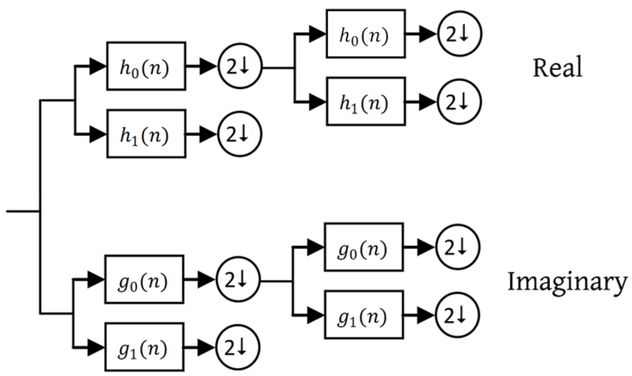
different scales using a set of filters or mother wavelet. To analyze the high frequencies, the signal is passed through a series of high pass filters $H[n]$ or the scaling function, schematically shown in Figure 2. Similarly, to analyze the low frequencies, the signal is passed through the low filters $G[n]$ or the wavelet function. The first decomposition will down-sample signal $X[n]$, where subsampling is denoted by $\downarrow 2$, into the detail D1 and the approximation of the original signal $A1$, both having frequency band equal to half of the input. The output of this sub-sampling is given in equations (1) and (2)

$$A_{j+1}[p] = \sum_{n=-\infty}^{\infty} G[n-2p]A_j[n] \quad (1)$$

$$D_{j+1}[p] = \sum_{n=-\infty}^{\infty} H[n-2p]D_j[n] \quad (2)$$

Discrete wavelet transform can be further performed on the approximation A_j if the length of A_j is an integer power of two, where j is the level of decomposition. Seizure detection

Fig. 3. Dual Tree Wavelet Decomposition



often relies on abnormal amounts of energy (seen as spikes) recorded in EEG. Hence in this study, discrete wavelet transform is used to extract some of the features that characterize a seizure event.

C. Dual-Tree Wavelets

For some applications of the discrete wavelet transform, more information may be produced by using an expansive wavelet transform instead of a critically sampled wavelet transform. An example of an expansive wavelet transform is the Dual-Tree Complex Wavelet Transform. It is a relatively recent enhancement on DWT that has a shift invariant property and achieves a lower redundancy rating.

The DTCWT of a signal x uses two critically-sampled DWTs in parallel on the same data, making the transform twice as expansive. If the filters for the upper and lower DWTs are designed in different ways, then we can treat the subband signals for the upper DWT as the real part of the complex transform, and the subbands of the lower DWT as the imaginary part. In this way, the transform provides more information than critically-sampled DWT, with the added property of it being shift-invariant.

Previous research in the field has shown 100% accuracy for seizure detection in single-channel EEG recordings using DTCWT features [22]. In this study, experiments will run on multi-channel EEG recordings using DTCWT features, and again using normal statistical features from Daubechies wavelet.

D. Feature Extraction

Neurologists visually detect seizure events by identifying spikes and making use of contextual information (both spatial and temporal) [6]. A good combination of features would ideally lead to a better understanding of the distinctive attributes of spikes (which have an imprecise definition even amongst expert neurologists) and the general spike morphology of an EEG signal.

TThe data in EEG signals can be compressed into features that can be used to distinguish between ictal and non-ictal segments. Variance-based features, wavelet features, and statistical features are commonly used in seizure detection algorithms. In this study, each signal file is divided into one-second segments. Each EEG signal is obtained from different electrodes identified into channels. For each channel of a segment, wavelet decomposition is done by performing Dual-Tree Complex Wavelet Transform, and again with Daubechies wavelets of order 4 chosen as the mother wavelet. Since signals from the data set used are sampled at 256Hz, the number of decomposition levels is set to 4 since most of the energy of an EEG signal is located in low frequencies typically ranging from 0-30 Hz. [20]. The study focuses on the comparison of both wavelet transform as methods of extracting features of multi-channel EEG recordings for seizure detection, especially how DTCWT (which has a 100% accuracy in single-channel EEG recordings [22]) fares against the usual Daubechies wavelet commonly found in most research.

The decomposition process will yield into wavelet subbands consisting final approximation of the signal A4(0-16Hz) and sets of detail coefficients D4(16-32 Hz), D3(32-64 Hz), D2(64-128 Hz) and D1(128-256 Hz). In this study only A4 and D4 are the subbands used since these are the subbands that satisfy the frequency range of interest for EEG signals [20]. Given x is a subband of length N, the statistical features calculated on each of the subbands A4 and D4 consist the following:

1. The 90th percentile of the absolute values of the wavelet coefficients

2. The 10th percentile of the absolute values of the wavelet coefficients

3. The mean of the absolute values of the wavelet coefficients, given by equation (3)

$$\upsilon_{abs} = \frac{1}{N}\sum_{i=1}^{N}|x_i| \tag{3}$$

4. The standard deviation of the wavelet coefficients, given by equation (4)

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N}|x-\upsilon|}{N-1}} \tag{4}$$

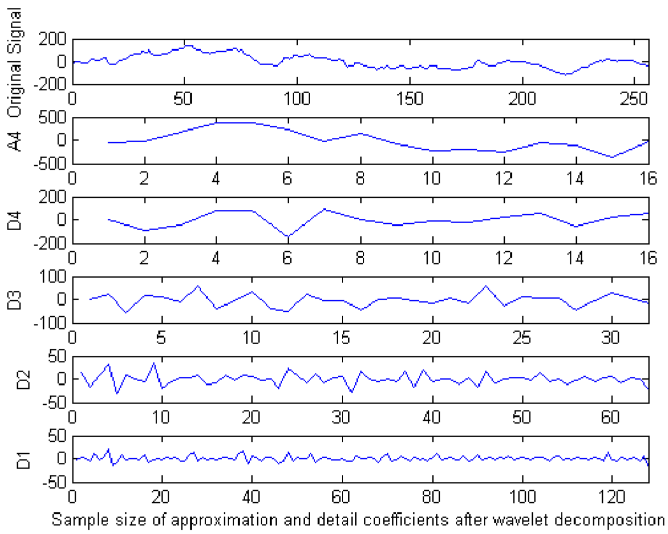
where υ is given by equation (5)

$$\upsilon = \frac{1}{N}\sum_{i=1}^{N}x_i \tag{5}$$

The 90th and 10th percentiles are calculated instead of the usual extrema (maximum and minimum). This eliminates possible outliers which may significantly increase the variance within a class.[18]

In this study, each segment is obtained from signals using 23 channels. The extracted features from all the channels are placed horizontally in a vector. The resulting feature vector for each segment is a row vector containing of (4 statisical features * 2 subbands * 23 channels). Therefore each segment of a signal is represented by a feature vector of length 184. The same feature extraction method is applied to ictal and non-ictal segments. Each feature vector is placed as a row into a training data matrix with final dimension of 184 rows * N columns where N is the number of training segments.

Fig. 4. Approximation and detailed coefficients obtained from an ictal segment using Daubechies order 2 with 4 levels of decomposition



E. Classifier Module (SVM)

In machine learning, support vector machine (SVM) is a supervised learning technique which is suitable for binary classification tasks. SVMs are binary classifiers that categorize data between two classes. An SVM classifies data by finding a linear or N-dimensional hyperplane that separates all data points of one class from those of the other class with the largest gap possible. SVM is also a kernel-based technique. There are cases that separating data by using a non-linear region is more efficient than using a straight line or set of hyperplanes. To handle this, SVMs use kernel functions which are non-linear functions which first map the points from the data set into a higher-dimensional feature space to have a more desirable linear separation between two classes.

Referring to 5, implementing an SVM becomes a matter of selecting the variables s and b so that our training data can be described by equations 6 and 7.

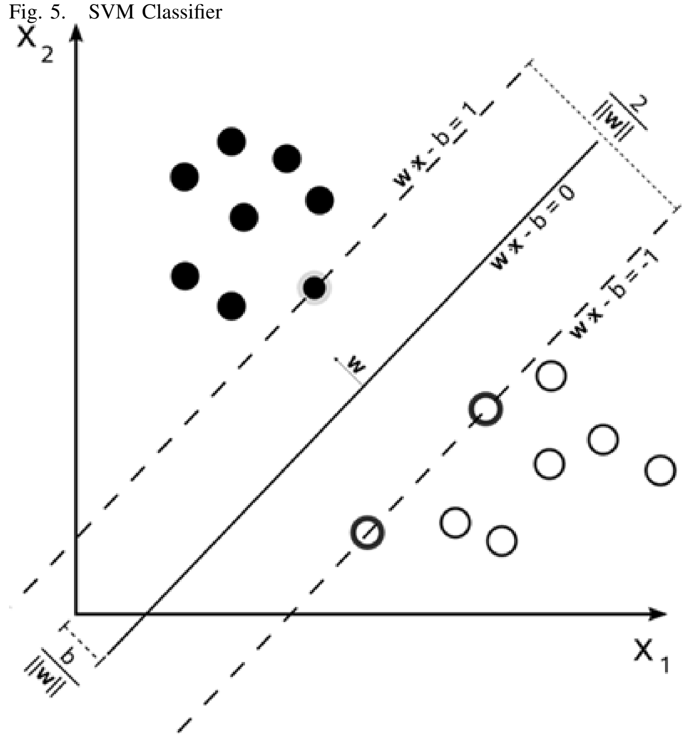
$$x_i \cdot w + b \geq +1 \qquad for \;\; y_i = +1 \tag{6}$$

$$x_i \cdot w + b \leq -1 \qquad for \;\; y_i = -1 \tag{7}$$

To select the most appropriate kernel function, experiments are conducted on using different kernel functions namely linear, polynomial and radial basis function (RBF). SVM with linear kernel function shows reliability in its results and comes the second most accurate. It performs better with more training data. Previous experiment on the dataset show that RBF with a scaling factor of 8 gives the best overall results. Therefore, RBF is set as the kernel function. MATLAB provides a machine learning toolbox which includes a function to train an SVM classifier. It provides an option to set the kernel scale parameter to 'auto' where MATLAB uses a heuristic procedure to select the scaling factor value.

The training data matrix obtained from the training set is used to build an SVM model which gives a binary output (1 and 0 for the ictal and inter-ictal classes respectively) which is used to classify items in the testing set. Training is carried out with performing a 10-fold cross validation.

Fig. 5. SVM Classifier



F. Performance Metrics

In the present study, the performance of classification test is based on the following criteria:

1. Sensitivity - This indicates the number of seizure events successfully classified (8). This is also known as true positive rate.

$$sensitivity = \frac{\text{number of correctly detected seizure events}}{\text{actual number of seizure events}} \tag{8}$$

2. Specificity - This indicates the number of non-seizure events successfully classified (9). This is also known as true negative rate.

$$specificity = \frac{\text{number of correctly detected non-seizure events}}{\text{actual number of non-seizure events}} \tag{9}$$

3. Accuracy - This indicates the quantity of correctly detected seizure and non-seizure events. (10).

$$accuracy = \frac{\text{number of correct detections}}{\text{actual number of events}} \tag{10}$$

4. Latency - This refers to the delay between the actual seizure onset and the detection of seizure onset

IV. Results and Discussion

The source code runs in the Matlab environment, and requires functions from the Digital Signal Processing toolbox, the Wavelet toolbox and the Machine Learning toolbox. The experiment was conducted using Ubuntu 14.10 with Intel(R) Core(TM) i5-4210U CPU at 1.70GHz.

The individual results of the experiments for each patient are summarized in Table I and Table II). The results show a comparison of the Dual-Tree wavelet and Daubechies wavelet; the better results are shown in bold. The training for the Dual-Tree wavelet experiment and the Daubechies wavelet experiment lasts 1966 seconds and 1607 seconds respectively.

TABLE I. Experiment results on accuracy and latency

	Accuracy		Latency	
Patient	Dual Tree	Daubechies	Dual Tree	Daubechies
1	83.821	**96.179**	**1**	2.4
2	69.474	**83.684**	**0**	0.1
3	80.127	**86.017**	1	1
4	**52.017**	50.773	**4.3**	9.4
5	83.745	**97.234**	0	0
6	82.8	**85.4**	2.1	**2**
7	71.672	**82.997**	**0**	2.1
8	78.62	**83.157**	**1**	8
9	85.6	**94.4**	**0**	1
10	81.042	**95.938**	**0**	0.05
11	87.5556	87.5556	0	0
12	83.2303	**84.073**	2.15	**1.7125**
13	**68.0556**	64.4444	1.5	1.5
14	61.212	**87.576**	**1.5**	2
15	**80.792**	80.616	0.25	**0**
16	74.118	**76.176**	**0.5**	1
17	92.3204	**92.4862**	2	2
18	75.161	**76.452**	**1**	2
19	**92.025**	88.405	1	1
20	72.4	**78.667**	**0.5**	1.15
21	53.6	**56.4**	**0**	1
22	**96.1538**	95.1282	1	1
23	88.166	**88.639**	**0**	1
24	**87.4766**	86.5421	**2.9333**	3

TABLE II. Experiment results on specificity and sensitivity

	Specificity		Sensitivity	
Patient	Dual Tree	Daubechies	Dual Tree	Daubechies
1	69.021	**96.701**	**98.469**	95.663
2	35.556	**77.778**	**100**	89
3	68.718	**78.547**	91.345	**93.361**
4	**89.224**	83.621	15.128	**18.205**
5	67.35	**97.009**	**100**	97.458
6	**94.5833**	92.0833	71.9231	**79.308**
7	56.224	**86.993**	**87.014**	79.028
8	62.273	**86.629**	**94.906**	79.698
9	75.806	**96.774**	**95.238**	92.063
10	66.783	**97.413**	**95.103**	94.483
11	**92.7273**	92.2727	82.6087	**83.0435**
12	79.9425	**80**	86.3736	**87.967**
13	**43.7143**	39.7143	**91.0811**	87.8378
14	48.75	**93.75**	72.941	**81.765**
15	**85.355**	84.007	76.294	**77.273**
16	56.25	**77.5**	**90**	75
17	**98.8889**	**98.4444**	85.8242	**86.5934**
18	52.174	**65.652**	**97.66**	87.021
19	94.444	**100**	**89.634**	76.951
20	47.162	**68.514**	**96.974**	88.553
21	3.3333	**25.833**	**100**	84.615
22	**98.4483**	97.069	**93.8983**	93.2203
23	82.976	**98.69**	**93.294**	78.706
24	49.643	**99.0385**	**76.1818**	74.7273

Patient 5 (using normal statistical features from Daubechies wavelet) shows the best results, achieving 97.234% accuracy as well as relatively high specificity and sensitivity. The detector shows relatively low accuracy for some patients, and this may be attributed to the lack of training data. Not all patients contain the same amount of data that can be used for training and testing, with some patients experiencing more seizures than others.

An average of 82.5642% of ictal segments and 83.9181% of non-ictal segments are correctly identified using Daubechies wavelet. On average, there is a 1.85 second delay in detecting seizure events in patients, and 83.2891% of the time the detector will be able to correctly detect seizure events. This shows a very balanced result that can be improved upon further research.

Meanwhile, DTCWT achieves an average of 78.3827% accuracy rating, markedly lower than its Daubechies counterpart. Only 86.7455% of ictal segments are 67.4728% of non-ictal segments are correctly identified, achieving an unbalanced result that makes it less reliable for seizure detection.

However, DTCWT has a lower latency value for most patients (an average of 0.99 seconds). The latency in most patients are small, usually within 0 an 1 seconds barring a few exceptions. Considering that neurologists visually analyze EEG signals to detect the end points of a seizure events, and are therefore subject to human error, DTCWT shows a very promising latency result, allowing for faster recognition of seizure events than Daubechies wavelet. But this comes with a trade-off of a much lower accuracy rating. Although DTCWT has high sensitivity, its very low specificity rate makes it a less viable option for detecting seizures.

V. Conclusion

This study addresses the problem of medically refractory epilepsy by presenting the use of SVM classifier on EEG data as a seizure detection algorithm. The technique makes use of patient-specific wavelet and statistical features, which are obtained from Daubechies wavelet decomposition at level 4 and Dual-Tree wavelet.

Using the methodology presented in the literature, the highest accuracy achieved was 97.234% for Patient 5 using Daubechies wavelet, but most of the patients receive a relatively high accuracy result. Accuracy rating for Daubechies wavelet is 83.2891% on average and 78.3827% for Dual-Tree wavelet. Dual-Tree wavelet shows a much more promising latency result than Daubechies wavelet. However, because of its very low specificity and accuracy, it fares poorly in detecting seizure events overall compared to Daubechies wavelet.

The algorithm presented in the study provides better results with more data, and low accuracy results from some patients are due to the fact that some patients provide relatively little data compared to the others. It provides a good average estimate for seizure detection, but results can significantly be improved upon further research. It is recommended that future research will make comparative studies on the performance of other seizure detection algorithms to further improve the performance. Experimenting on the correlation of channels to extract the features that best represents a seizure or a non-seizure data should also be considered in future research.

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