

Early Detection of Epilepsy using Automatic Speech Recognition

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Abstract

Objectives: Epilepsy is a neurological disorder that is characterized by occurrence of seizures. The Electroencephalogram (EEG) signals are used as the primary source of data for the study of epilepsy. This study uses Mel Frequency Cepstral Coefficients (MFCC) for early detection of epilepsy in adults. **Method:** Use of MFCC is a de-facto method of Automatic Speech Recognition (ASR). Extending the use of the same method for EEG signals yields reliable results as the properties of EEG signals resemble the properties of speech signals. The training and test samples were taken from EEG database of the University of Bonn. Using the database a support vector machine was trained and then was used for testing. **Findings:** The use of MFCC and along with Support Vector Machine (SVM) has an average accuracy of 98.5%. Therefore, an epileptic EEG signal can be detected with a high accuracy. The results reaffirmed the fact that there is a high correlation between the speech signals and EEG signals. The newer methods of ASR may be explored for finer results. There is a significant improvement in accuracy over other methods of epilepsy detection.

Keywords: Automatic speech recognition, Epilepsy detection, MFCC

1. Introduction

The International League Against Epilepsy (ILAE) defined epilepsy as enduring predisposition to generate epileptic seizures¹. An epileptic seizure is characterized by extreme neural discharges in the regions of origin. There are about 50 million people worldwide who have epilepsy². Out of these 50 million about an estimated 10 million people are in India. There are two main types of epileptic seizures, generalized seizures and partial seizures. These types are further divided into several sub categories. There are no conclusive prediction model to predict the time and duration of the seizures. EEG is the primary diagnostic tool used for the detection of epilepsy³. The seizures may or may not be convulsive. The seizures are classified into several categories. These categories encompass the severity, region of origin, time duration of the seizure.

Temko *et al* emphasised on the use of feature sets that are conventionally used in contemporary domains of signal processing such as speech processing. One of the most prominent features used are the cepstral coefficients. The

spectral coefficients are highly capable of identifying the feature information. The ASR uses logarithmically scaled versions of the frequencies to replicate the hearing senses in the humans. The limited use of these features for feature extraction in other signal types is due to the fact that they have been wrongly perceived to be based upon some speech model⁴. A. Singh *et al* exploited the quasi periodicity property of the speech signal and the electroencephalogram to extract the features of the signal. Since the properties of these signals match, the feature extraction method used in speech signals known as MFCC was applied on the brain waves. The authors⁵ proposed the use of MFCC for feature extraction along with the use of Hjorth parameters. Y.T Shen *et al* proposed a dual line method of seizure detection using a prolonged video of the seizure. A method was developed using the fusion of audio and video features using the Dempster-Shafer theory for seizure detection⁶.

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2. Research Methodology

The EEG signals are used as input to the process which calculates the MFCC. The obtained cepstral coefficients are used as the feature vectors. These vectors are studied and are classified into the groups using the SVM, epileptic and non-epileptic. This classification helps us in arriving at a conclusion about the nature of signals. Figure 1 gives an overview of the research methodology that is embraced.

3. MFCC

The MFCC method of ASR is one of the most efficient way to find the intrinsic features of a speech signal in form of Cepstral Coefficients. It involves the following steps:

1. Framing and windowing the input signal.
2. Calculating the power spectrum of each frame.
3. Apply the mel filterbank to the power spectra and sum the energy in each filter.

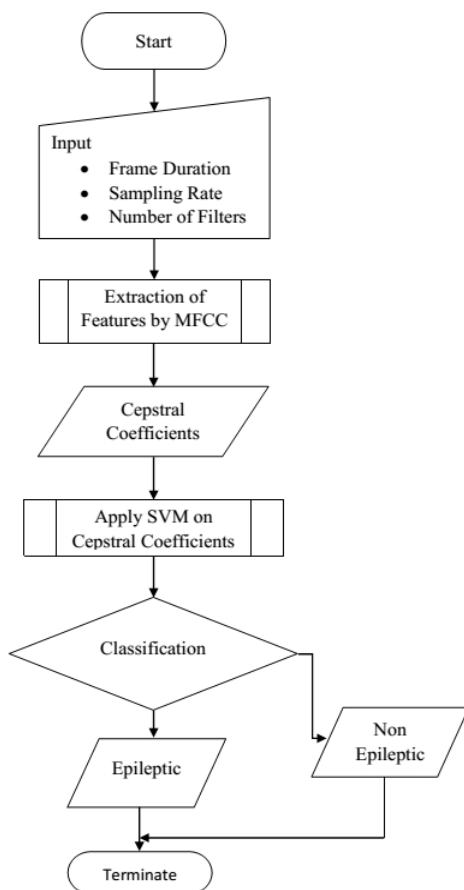


Figure 1. Research methodology embraced.

4. Take the logarithm of all filterbank energies.
5. Take the DCT of the log filterbank energies. Retain the DCT coefficients 2-15 and discard the rest⁷.

4. SVM

The support vector machine is a popular classification algorithm that has found its use in many fields. It is based on classifying the samples based upon the distance from the hyper plane formulated from the support vectors⁸. SVM have an ability to handle large datasets and generalize the data. They are widely used in 3D object recognition, speaker and facial recognition, and bio-informatics.

5. Results

The Bonn University datasets⁹ as described in¹⁰ were used to train the SVM and the samples from same dataset along with Physionet dataset¹¹ was put to test according to the proposed methodology. The simulations were done on Matlab 2015a, running on a core i3 machine using a 4 gigabyte RAM. In this study, the training data used was from set A, B, D and E. Ninety five segments from each set were used for the training. The rest five from each were used for testing. The set C was not used for the training. However five samples from set C were used for testing. Test samples from Physionet were also put to test. The results obtained during the test phase were confirmed using visual inspection in case of set C. The use of the proposed methodology yielded a decent result with an accuracy of 96% for the BonnUniversity database and 100% accuracy for Physionet database. The average 98%. The results have been compiled in the tabular form in the table 2

6. Analysis

The results obtained are analysed using the classification functions. These functions have been defined and have been used in statistics for the performance analysis of the binary classification problem such as this study. These terms have been defined in context of this study.

6.1 Specificity

Specificity defines the ability to positively detect the non-epileptic EEG samples. It identifies if the test subject is normal. Mathematically,

$$\text{Specificity} = \frac{TN}{TN + FP}$$

6.2 Sensitivity

Sensitivity illustrates the test's ability to positively detect patients who suffer from the condition. Considering the case of a medical test, it suggests the prevalence of a disease. Sensitivity determines if the test subject is epileptic. It is also termed as true positive rate. Mathematically,

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

6.3 Precision

The precision is mathematically defines as a ratio between the true positives and the sum of true positives and false positives. It is alternately known as positive predictive value. Mathematically,

$$\text{Precision} = \frac{TP}{TP + FP}$$

It is the proportion of the positives in the population under study.

6.4 Accuracy

The accuracy of the system takes into account all the statistical quantities and demonstrates the ability of a system to accurately come to a conclusion about the prevalence of a disorder. Mathematically,

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

These classification functions have been computed and tabulated to present a picture of the efficacy of the proposed methodology. Using the following specifications, the following results have been tabulated.

The Table 1 contains the specifications used in the feature extraction process using MFCC. The results do not significantly vary for an insignificant change in the specifications especially the number of filters. There is a

Table 1. Specifications for feature extraction

Sampling Rate(Hz)	176.31
Frame Duration (s)	0.8
Type of Window	Hamming at 50% Overlapping
Number of Filters	40

Table 2. Performance parameters

Parameter Evaluated	Performance Bonn University Database	Performance Physionet Database
Sensitivity	0.93	1.00
Specificity	1.00	1.00
Accuracy	0.97	1.00
Precision	1.00	1.00

Table 3. Performance comparison

Parameter	Sharanreddy et al ¹²	P.S. Kumar et al ¹³	Author Findings
Accuracy	89%	98%	98.5%

significant effect on the accuracy for changes in the frame duration. The accuracy increases for a frame duration greater than 60ms. However, for frame sizes greater than 1 second, the speed of calculation is greatly reduced.

Table 2 clearly indicates that the performance parameters are at the most optimum value achievable. The overall accuracy of 98.5% at the specifications stated in table 1 was achieved by virtue of the proposed methodology. The comparison with the other methods was done. The performance comparison clearly displayed that there was a substantial improvement over the previous methods. The results support the claim that the automatic speech processing algorithms can very well be used on other signal types. A comparison has been made with the previous methods as well.

The comparison in the Table 3 is made between the average accuracy of the other methods and the proposed method. The proposed methodology displayed a high accuracy with respect to the dataset used therefore, self-attesting its validity and rationale.

7. Conclusion

The approach using the automatic speech recognition was not explored and is still open for exploration. The use of automatic speech recognition algorithms identify the EEG class based upon the intrinsic nature of the EEG signals. Since the properties of the EEG and speech signals have a high resemblance, the method is interchangeable with methods for ASR.

The ASR method used is known as MFCC which calculated the cepstral coefficients. Using these cepstral coefficients, the classifier was able to group the signals as epileptic or non-epileptic. The proposed method seems

promising as the results obtained proved that the method of MFCC worked flawless for the available dataset. The overall accuracy obtained was 98.5% for the available datasets.

8. References

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