30. Classification Between Interictal and Ictal States of Epileptical Patients using Alpha Subband

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ABSTRACT

In this study, alpha subband (8-12 Hz) is used for distinguishing between interictal and ictal states using Haralick features. Most of the previous methods is based on the whole frequency spectrum. This work use only alpha subband of electroencephalogram (EEG) for classification using image descriptors. To convert one dimensional EEG data into image Short Time Fourier Transform (STFT) has been used. Alpha subband is cut from the time frequency (t-f) plane and Haralick features is used as image descriptors to fed in the k-NN classifier. The results have been evaluated using accuracy metric and receiver operating characteristic (ROC) analysis. Maximum classification accuracy of 79% and maximum area under curve (AUC) of 0.84 is obtained to classify between interictal and ictal. Advantage of this work is rather using whole frequency band it utilizes only a particular band which reduces computational load.

Index Terms— *EEG, alpha subband, epilepsy, Haralick features, k-NN.*

INTRODUCTION

Epileptical seizures is one of the most severe neurological disease in the world. Electroencephalogram (EEG) which measures the electrical activity of the brain is generally used for the detection of seizures due to its low cost and high temporal resolution. It is recorded by placing electrodes on the scalp using international 10-20 system.

Seizures should be delimited in time, but the borders of ictal (during a seizure), interictal (between seizures) and postictal (after a seizure) in EEG often are indistinct [1]. Classification between different states i.e. interictal, ictal, pre-ictal [2] of epileptic patients is a complex task from EEG signal acquired from patients. In [3], authors reported nonlinear dynamic modelling approach of global principal dynamic modes for classification between interictal and ictal states of epilepsy.

To analyse the EEG pattern faithfully, it requires an expert neurologist still there is a high probability of misinterpretation. So there is a need to have an automated system which can assist the doctor. To make an automated system there are following steps: (1) preprocessing of EEG data i.e. removal of line noise and artifacts, (2) analyse the preprocessed data either in time, frequency, time-frequency (t-f), time-scale or any another domain, (3) extraction of appropriate features which characterise the data, (4) classification of data using machine learning techniques. This paper has used STFT, and extracted alpha subband (8-12 Hz) from the time-frequency plane. Haralick features are used to characterise the data and fed to the decision tree to distinguish between interictal and ictal classes.

DATASET USED

The publicly available University of Bonn, Germany EEG dataset has been used in this study [4]. It was collected with the use of 128 channels and includes five different classes of data, named as Z, N, O, F and S. Each class of the dataset consist 100 segments acquired from individual channel of duration 23.6 seconds and have the sampling frequency of 173.61 Hz, which is collected using 12 bit of resolution.

Table 30-1 represents the description of dataset. The classes N and F consists data of epileptic patients but during seizure free periods. These data have been taken from intracranial EEG signal, data of class N collected from hippocampal formation and F is acquired from the epileptogenic zone. Data of class S is recorded from epileptic patients during seizures. Fig 30-1. shows EEG segment of (a) N and (b) F class (c) S class.

Table 30-1 REPRESENTATION OF DIFFERENT CLASSES OF DATASET

SUBJECTS TO COLLECT EEG DATA	CLASS	NUMBERS OF SIGNAL	WAY OF DATA ACQUIRED
Epileptic Patients	N-(Seizure free)	100	EEG signal from the hippocampal formation
	F- (Seizure free)	100	EEG signal from epileptogenic Zone
	S-(Seizure)	100	EEG signal acquired during seizure period

METHODOLOGY

To detect epileptical seizures, this work has followed different steps presented in Fig.30-2. The available data is already pre-processed, hence without using any noise removal technique it has been used. Further, STFT has been applied on data.

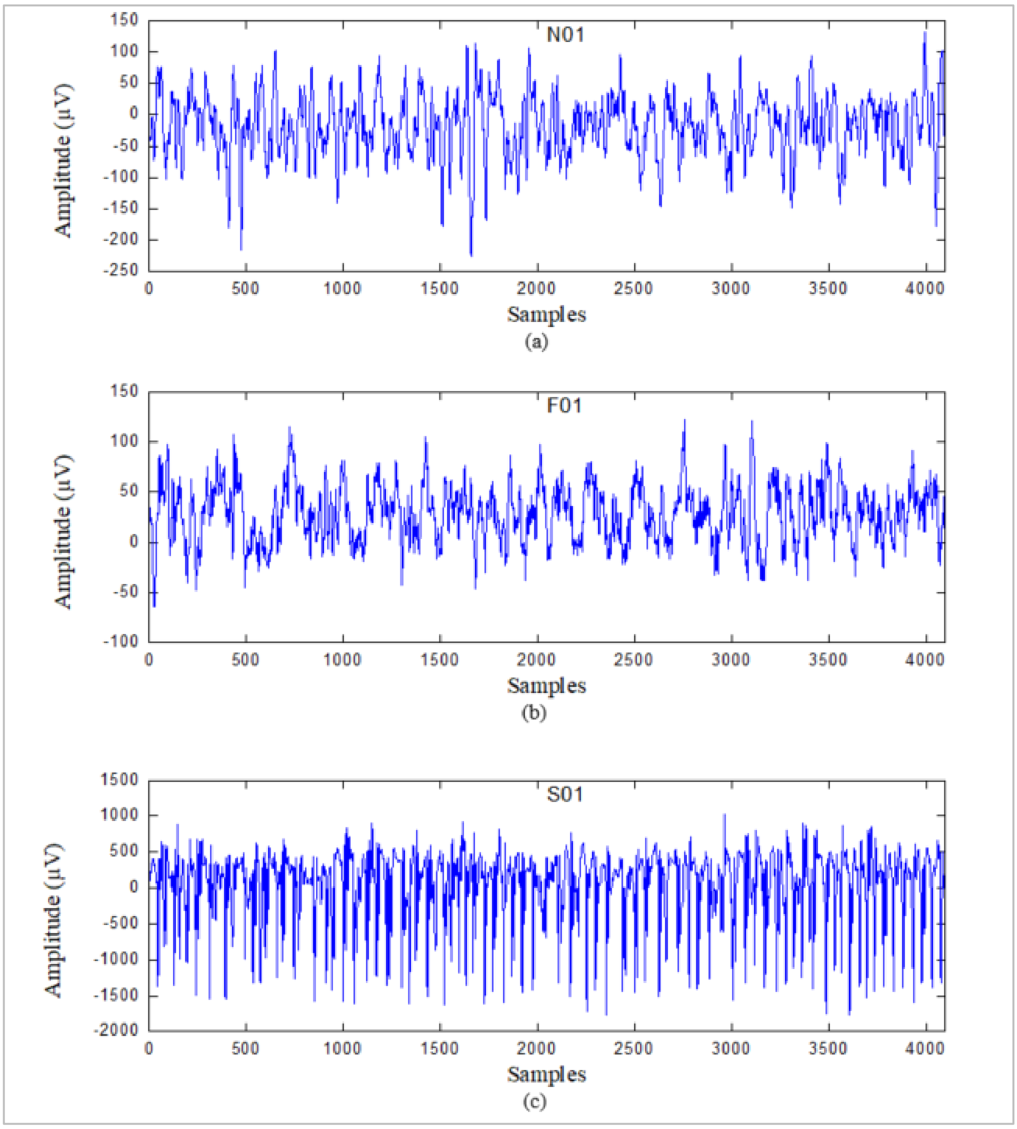

Figure 30-1 EEG segment of (a) N class (b) F class (c) S class

A. SHORT-TIME FOURIER TRANSFORM

There are various time-frequency methods available to perform analysis. For real time processing STFT is more preferable to wavelet transform methods [5] . In this paper, STFT has been used to perform time-frequency analysis of EEG data [6]. This method is useful for localization of frequency in time and vice versa. It transforms one dimensional (time domain) EEG data to two dimension (time-frequency). In this work hamming window of size odd (N/4), where, N is the number of data points, has been used. STFT of message (EEG) signal x (t) using short duration hamming window h (t) is given by the expression (1):

$$STFT(t,f) = \int_{-\infty}^{\infty} x(\tau)\, h(\tau - t) e^{-if\tau}\, d\tau \quad (1)$$

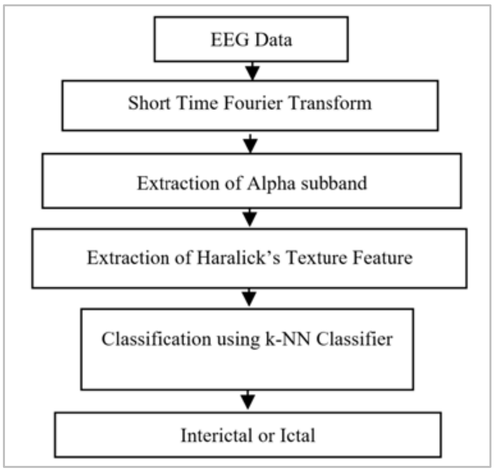

Figure 30-2 Steps performed in the work

B. FEATURE EXTRACTION

In this paper, Haralick's texture features [7] have been extracted, which is obtained from two dimensional time-frequency representation of EEG signals to detect any kind of seizure activity in it. Here, to extract Haralick's features, STFT has been performed over EEG data firstly to get an image data. Processing it as texture image helps to collect visually any information related to soaring amplitude, seizure activity or normal pattern on it. To evaluate all these selected features, gray-level co-occurrence matrix has been obtained from two dimensional EEG data, represented by P (having size S×S, where S is the number of gray levels in image data). This matrix can be generated by evaluating how often pairs of pixel corresponding to particular values occurs in an image. It can be formed by pixel pairs located at particular value of distance δ and angle θ. In this paper, angle θ has been selected as 0o, 45o, 90o and 135o.

C. K-NN CLASSIFIER

This classifier is comparatively simple, nonlinear, non-parametric and a form of instance based learning methodology can be applied for classification purpose even though dataset distribution in unknown. This method response quickly for limited set of data, whereas huge data size algorithm can be slow. That is all because of every calculations are postponed till completion of classification. This algorithm follows brute force approach, in which each data points are need to compared with target. The k-NN (nearest neighbor) classifier works on the principle of measurement of similarity. This classifier first helps to find the k samples, which are nearer to the unknown sample data. With the help of k nearest sample classifier will be able to find its average, to get similarity. Similarity can be measures in form of distance also termed as Euclidian distance (ED).

RESULTS AND DISCUSSION

In this research work, a total of 260 features of alpha subband has been extracted. Three experiments have been performed using three groups of EEG data (N, F and S). K-fold cross validation technique has been used for training and testing the data. Feature vector set has been partitioned into K parts of same size. One subset is used as testing set and left over sets are used as training set. This process is repeated K times. The average accuracy of all trials is taken into consideration. The results have been shown in Table II. Maximum AUC achieved between interictal and ictal classes is 0.84. For all three experiments the success rate is above 80%. In [8] maximum accuracy achieved is 79%. Fig. 30-3 shows the ROC curve for healthy and seizure patients [9].

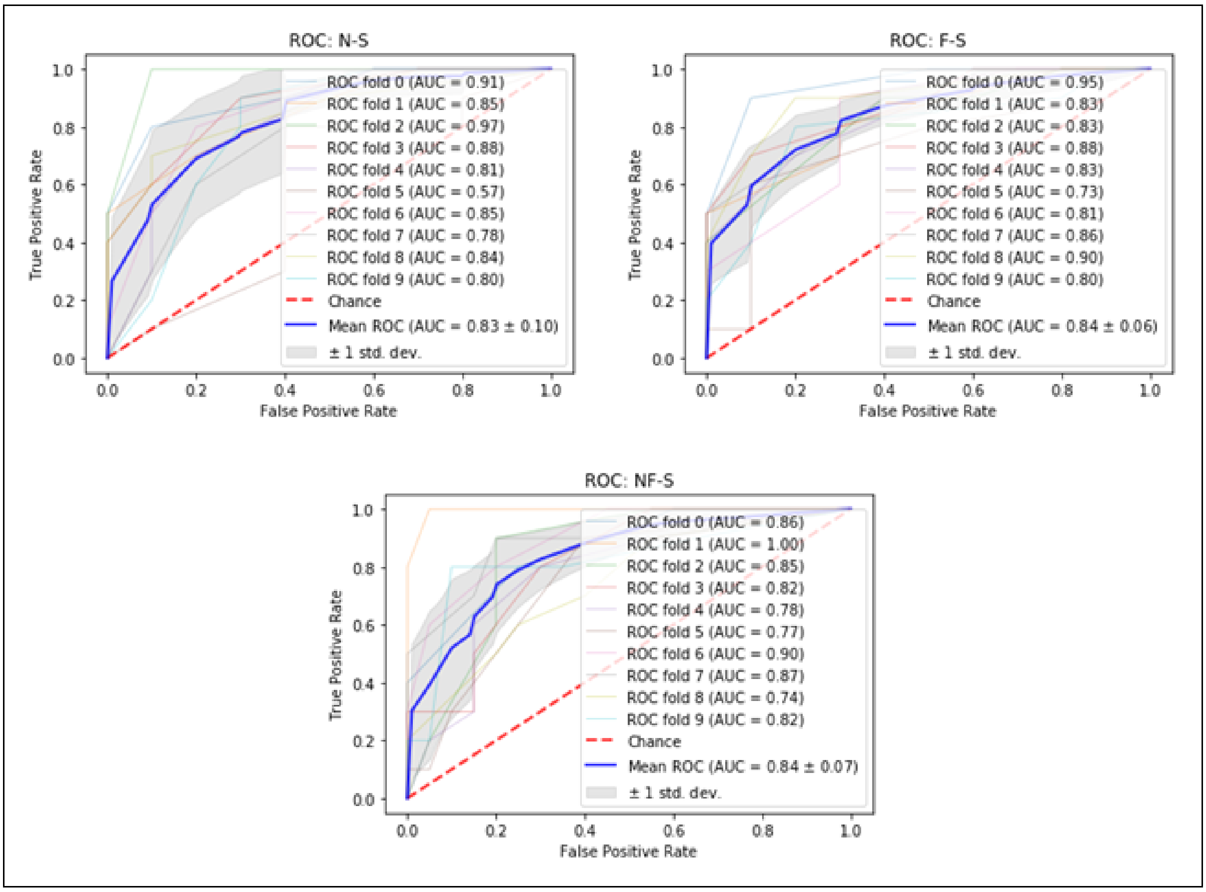

Figure 30-3 ROC to distinguish between interictal and ictal patients

CONCLUSION AND FUTURE WORK

In this paper, three experiments on epilepsy patient's data of Bonn dataset using k-NN classifier has been presented. STFT has been used for conversion of one dimensional data to two dimension. Textural features of alpha subband have been used as feature in this work. F-S and |NF-S data clusters achieved best AUC value of 0.84. This study depicts without using full spectrum only alpha subband is able to differentiate between ictal and interictal groups. As a future work different classifiers with optimized parameters would be used to increase the accuracy.

REFERENCES

[1] R. S. Fisher, H. E. Scharfman, and M. DeCurtis, "How can we identify ictal and interictal abnormal activity?," Adv. Exp. Med. Biol., 2014.

[2] B. K. Karumuri, I. Vlachos, R. Liu, J. A. Adkinson, and L. Iasemidis, "Classification of pre-ictal and interictal periods based on EEG frequency features in epilepsy," in Proceedings - 32nd Southern Biomedical Engineering Conference, SBEC 2016, 2016.

[3] Z. Hameed, S. Saleem, J. Mirza, M. S. Mustafa, and Qamar-ul-Islam, "Characterisation of ictal and interictal states of epilepsy: A system dynamic approach of principal dynamic modes analysis," PLoS One, 2018.

[4] R. G. Andrzejak, K. Lehnertz, F. Mormann, C. Rieke, P. David, and C. E. Elger, "Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state," Phys. Rev. E - Stat. Physics, Plasmas, Fluids, Relat. Interdiscip. Top., 2001.

[5] M. K. Kiymik, I. Güler, A. Dizibüyük, and M. Akin, "Comparison of STFT and wavelet transform methods in determining epileptic seizure activity in EEG signals for real-time application," Comput. Biol. Med., 2005.

[6] L. Cohen, "Time-frequency distributions-a review," Proc. IEEE, vol. 77, no. 7, pp. 941–981, Jul. 1989.

[7] R. M. Haralick, I. Dinstein, and K. Shanmugam, "Textural Features for Image Classification," IEEE Trans. Syst. Man Cybern., 1973.

[8] A. Gupta, P. Singh, and M. Karlekar, "A novel signal modeling approach for classification of seizure and seizure-free EEG signals," IEEE Trans. Neural Syst. Rehabil. Eng., 2018.

[9] ANACONDA, "vers. 2-2.4.0, Anaconda Software Distribution. Computer software," Anaconda Software Distribution. Computer software, 2016.