Advancements in Computer Aided Methods for EEG-based Epileptic Detection

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Abstract: During the diagnosis of epilepsy, computer aided methods can significantly supplement a neurologist by automatically identifying the epileptic patterns in an EEG. In the last decade immense amount of work has been done in the field of EEG based computer aided diagnosis of epilepsy. Even after so much work these tools are not getting used up to their full potential. In this paper we have very briefly discussed some of the previously used signal processing and machine learning techniques which are proposed for epileptic pattern detection. We have concluded this paper by suggesting some additions in the previous method which can make these systems more helpful, detailed and precise for the neurologist.

1 INTRODUCTION

Epilepsy is a recurring neurological disorder, which is characterized by excessive neural activity yield in the brain. Almost 1% of the human population suffers from epilepsy (WHO | Epilepsy 2012) (Adelia, Zhoub & Dadmehrc 2003). Detection and localization of abnormal, epilepsy-related brain activity is very important for diagnosing and curing of an epileptic disorder. Electroencephalogram (EEG) is a method for recording of electrical activity along the scalp. EEG signal represents fluctuations in the voltage caused by the flow of ionic current in the neurons. Epileptic seizures are accompanied by unique patterns in EEG, and therefore EEG is widely used to detect and locate the epileptic seizure and zone.

Duration of a typical diagnostic EEG recording varies from 40 minutes to a few hours. However, prolonged EEG is opted if a seizure is not detected in shorter recordings. A prolonged EEG can last as long as 72 hours. Diagnostic procedures like this generate a huge amount of data to be manually inspected by the neurologist. Manual inspection of all of the data for multiple patients could prove to be a daunting task for a neurologist.

Computer assisted analysis of an EEG supplements a neurologist in efficiently analysing the EEG data. It highlights the epileptic patterns in the EEG up to a significant level, thus reducing the data to be analysed and lessening up the fatigue. These analysis software tools apply different signal processing and machine learning techniques on the EEG data to detect the epochs with epileptic patterns. Currently available commercial computer assisted diagnosis tools for epilepsy are not a lot user-friendly and lack adaptability/intelligence (NeuroExplorer Home n.d.) (Neuralynx ~ Spike Sort 3D Software n.d.). These software tools require the clinician to have an understanding of signal processing algorithms to exploit the full potential of the software (Tucker-Davis Technologies n.d.) (Brain Products GmbH / Products & Applications / Analyzer 2 n.d.). For this they hire technicians and rely on them which make this analysing procedure prone to misinterpretation and over-interpretation as the manual marking get dependent on the expertise of the technicians (Benbadis and Tatum 2003) rather than the clinician himself.

In the next section we will briefly describe about the existing work in the field of computer assisted analysis of EEG for Epilepsy. Then in Section 3 we will discuss the key factors involved in a computer assisted analysis of EEG. After wards in Section 4 we will discuss the future research direction which according to our analysis can be followed to improve the existing work.

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2 EXISTING WORK

EEG signals are non-stationary. Methods for analysing non-stationary signals, such as Discrete Wavelet Transform (DWT), Empirical Mode Decomposition (EMD) and time-frequency analysis, have been frequently used for automated seizure detection using EEG signals. Epileptic seizures give rise to changes in certain frequency bands which are δ (0.4 – 4 Hz), θ (4 – 8 Hz), α (8 - 12 Hz) and β (12 – 30 Hz) (Adelia, Zhoub and Dadmehrc 2003). That's why usually the spectral content of the EEG is used for diagnosis.

Usually the approach toward the detection of epileptic patterns start with dividing the EEG data in multiple small epochs, then multiple signal processing steps are applied on these epochs to extract out the features which are then used to classify that epoch as epileptic or non-epileptic.

Majority of the work done in the line of epileptic pattern detection usually do not involve fusion of information obtained from multiple channels. Instead, all the channels are processed in series/sequentially, as if the EEG signal source is one long signal instead of multiple parallel signals. However Chang *et al.* (Chang et al., 2010) appreciated the effects of multiple channels' being processed in parallel. They grouped 0.3 sec epochs of multiple channels simultaneously in five different clusters to avoid noise. Then they used FastICA to discriminate between features, noise and background of the signal. They then applied DWT with Daubechies-4 (db4) as mother wavelet on the two most independent parts of the signal. Then they applied customized threshold to classify them as epileptic or not. In this work Chang *et al*. showed that consideration of multiple channels in group improve the accuracy of your system.

Xanthopoulos *et al.* (Xanthopoulos et al., 2010) used sliding variance on Continuous Wavelet Transformed (CWT) epochs to detect the clinically important epileptic patterns up to 98.625% accuracy.

Luo *et al.*'s (Luo and Luo 2010) work advocates the importance of feature reduction techniques like Principal Component Analysis (PCA). He evaluated the effectiveness of six features. The PCA showed that almost three of the six features has contribution ratio of 79 %. So discarding of other three features could improve the processing time without a significant damage to the classification accuracy. His stance was verified by the Artificial Neural Network (ANN) classifier whose accuracy only dropped by 2.5% with the exclusion of three features. The six features were Hurst Index, Standard Deviation and Periodicity, Shannon Entropy, Approximate Entropy and periodicity of smoothed EEG signal, where the first three are the most contributing features.

Petersen *et al.*'s (Petersen et al., 2011) work shows that to detect the generalised seizure using only one channel, usage of the energy of the detail coefficients of the wavelet transformed one second epoch of a F7-FP1 in an SVM classifier can result with as good as 99.1% sensitivity.

In Abdullah *et al.*'s (Abdullah, Abdullah and Abdullah 2012) work Hidden Markov Model (HMM) was applied on vector quantized Stationary Wavelet Transform coefficients of intracranial EEG signal. Their work resulted with 96.38% and 96.82% average sensitivity and specificity respectively.

Sousa et al. (Sousa, Mendes and Ribeiro, 2012) studied how rhythms analysis identifies the various events recorded in the EEG. Their work resulted with 95.5% accuracy.

Abdullah *et al.* (Abdullah, Saufiah and Ibrahim 2012) simultaneously used features extracted from DWT and Fourier transform in an ANN classifier. Their work resulted with 98.889% accuracy.

Khan *et al*. (Khan, Rafiuddin and Farooq 2012) used energy and normalized coefficients of variance of multi-level DWT coefficients. These features were used by a Linear Discriminant Analysis (LDA) to classify the EEG epochs with an accuracy of 91.8%.

Due to the heavy computational burden of marching pursuit (MP) algorithm (Guo et al., 2012) proposed a reduce complexity of sparse representation to adopt harmony search method in searching the best atoms. Their efforts resulted with huge amount of improvement in the latency. Wang *et al.* (Wang et al., 2012) used these features with Adaptive Neuro-Fuzzy Inference System (ANFIS) as a classifier. Here they integrated the artificial neural networks and fuzzy logic together. Their effort resulted in 97.4% accuracy.

Choi *et al.* (Choi, Zeng and Qin, 2012) selected the optimal frequency band features by using the Sequential Floating Forward Selection (SFFS) algorithm. These features were fed to three types of classifier. These classifiers were linear, quadratic and cubic discriminant function. They found QDF with best accuracy which was 97.2%.Sezer *et al.* (Sezer, Işik and Saracoğlu, 2012) tested multiple types of ANN and found Elman method to be most accurate along with DWT as feature extraction method.

Alam *et al.* (Alam and Bhuiyan, 2013) used the higher order statistical parameters like variance, skewness and kurtosis of empirical mode decomposed EEG signal with ANN.

Seng et al.'s (Seng et al., 2013) used simple features like mean, variance, dominant frequency, mean of power spectrum and the signal data itself of the EEG epochs in linear SVM. They tried multiple epoch sizes which were 23.6 sec, 11.5 sec, 5.8 sec, and 1 sec. The result showed that smaller epoch size results in better accuracy whereas bigger epoch size results in better latency.

Ocbagabir et al. (Ocbagabir, Aboalayon and Faezipour 2013) used Butterworth band pass filter to decompose the EEG signal into 5 sub-bands and then used Energy, Entropy, and Standard Deviation as features for a SVM classifier. This classification approach resulted in 95% accuracy.

Kaleem et al. (Kaleem, Guergachi and Krishnan 2013) applied a novel variation of the EMD called Empirical Mode Decomposition-Modified Peak Selection (EMD-MPS). They used Energy, sum of the amplitude spectrum, sparsity of the amplitude spectrum and the sum of derivative of the amplitude spectrum as the input features to a simple 1-NN classifier which resulted with 98.2% accuracy.

Murugavel *et al.* (Muthanantha Murugavel et al., 2013) used a novel feature named as Combined Seizure Index as a feature which they extracted from wavelet packet coefficients. These features in a multi scale SVM resulted with 97.3% accuracy.

3 DISCUSSION

After providing a short literature survey we proceed to discuss the state-of-the art research from different important perspectives.

3.1 EEG Databases

There are two major databases for scalp EEG which are used for validating the performance of the automatic epileptic pattern detection algorithms.

First of the two data sets are from Klinik fur Epileptologie at the Universitat Bonn, German (Klinik fur Epileptologie, Universitat Bonn n.d.). This dataset has two sets of 100-channel EEG data consisting of normal and epileptic subjects with segment duration of 23.6sec, 4096 sampling point and 173.61 Hz sampling frequency. The first EEG data set is a scalp EEG of 5 normal subjects. The other EEG data set is a intracranial EEG of 5 epileptic patients, recorded during the occurrence of the epileptic seizures.

The second most used EEG database is the CHBMIT scalp EEG database (Goldberger et al. 2000). It been provided by Children Hospital Boston and is available at physionet website (Shoeb, 2000). This database consists of 916 hours of continuous scalp EEG recordings collected from 24 subjects suffering from intractable seizures. Out of 664 EEG recordings files, 129 files consisted of one or more seizures. The 23 channel EEG signal has a sampling frequency of 256 Hz with 16 bit resolution.

In the following lines we will discuss some of our observations on these databases.

3.1.1 Size of Database & over-fitting

The first database is less versatile in comparison to the second one and it also has lesser number of examples. This makes the classifiers trained on the first dataset more prone to over-fitting. Probably this is the reason behind algorithms not performing with the cited accuracy on the real life data.

3.1.2 Labelling

Another issue with both of these databases is that the labelling does not specify the epileptic pattern type. Apparently they are labelled for generalized 3Hz spike & wave which is a symptom for absence seizure which is one of many types of epilepsy.

3.2 Epileptic Patterns

EEG recorded from epileptic patient exhibits distinctive signal patterns. Patterns like Spikes, Sharp wave, Benign epileptiform discharges of childhood, Spike-wave complexes, Slow spike-wave complexes, 3-Hz spike-wave complexes, Polyspikes, Hypsarrhythmia, Seizure pattern, Status pattern are considered as epileptiform (Lüders and Noachar, 2000; Noachtar et al., 1999).

Mostly 3Hz spike & wave detection has remained the focus of the past work. Whereas other epileptic patterns detection are usually ignored. Sousa *et al.* (Sousa, Mendes and Ribeiro, 2012) are among those few people who have addressed the detection of multi-type epileptic patterns.

3.3 Feature Extraction & Reduction

3.3.1 Epoch Size

The choice of epoch size depends a lot on the sampling frequency and feature extraction techniques. Epoch size as low as 0.3 sec (Chang et al., 2010) and as high as 23.6 sec (Ocbagabir, Aboalayon and Faezipour, 2013) has been cited, but the most commonly used epoch size is of 1 sec. A comparison among 23.6 sec, 11.5 sec, 5.8 sec, and 1 sec in Seng *et al.*'s work resulted with 1 sec epoch size to be working best in terms of accuracy.

3.3.2 Feature Types

The most commonly used feature extraction method is WT with db4 or Morelet as a mother wavelet. This also seems to be a promising method yielding the best performance figures. Majority of the algorithms use detailed coefficients' energy, variance, standard deviation, entropy, mean, maxima and minima or any combination or slight modification of these as features whereas few algorithms use the detailed coefficients without any modification.

Other than Wavelets, Fourier transform, EMD, MP, SFFS or their modified versions has also been cited as the feature extraction techniques.

3.3.3 Feature Reduction

There are few examples where some authors like Luo *et al.* (Luo and Luo, 2010) have used feature reduction techniques like PCA before classifying. The motivation behind applying reduction is to avoid noise and redundancy.

3.4 Classifiers

SVM, Linear/ Quadratic/ Cubic Discriminant Analysis, ANN, Genetic Algorithms (GA), HMM, Fuzzy Based classifier and the adaptive thresholding techniques have been cited to be used as a classification method.

Support Vector Machine (SVM) is the most widely used classifier. Multiple comparative studies like (Yuan, 2010), (Mohamed Bedeeuzzaman, Farooq and Khan, 2010), and (Harikumar, Vijaykumar and Palanisamy, 2011) shows that SVM yielded one of the best with least amount of latency alongside different and versatile feature extraction method. Yuan showed that it works 0.44% more accurate than Neural Networks.

In some particular conditions number of these classifier has been cited to perform with 100% accuracy. This accuracy is probably a result of over-fitting as same techniques when applied on real life data do not result with such high accuracy. So there should be method which should keep these algorithms improving their detection with increment in the available examples. There should be a method introduced where a neurologist can suggest corrections as per his desire while observing wrong marking by the computer aided system and the system should learn from that correction.

3.5 Latency

To make these computer aided system useable in real life condition, latency is important. There are multiple reasons behind an increment of latency. It is the training process which usually takes a lot of time. Other then the computation involved during an algorithm, latency also largely depends up on the processing power, speed and size of the memory devices in a machine which is running the algorithm.

Selection of appropriate Epoch size is not only important for batter accuracy but it also affects the latency. According to Seng *et al.* (Seng et al., 2013) shortening the epoch size improves the accuracy on the cost of latency.

Different algorithms result in different ways when training examples are increased. Nasehi *et al.* (Nasehi and Pourghassem 2011) reported that their algorithms' latency and detection delay got decreased with the increment in training examples with seizures. Geetha *et al.* (Geetha and Geethalakshmi, 2011) and Abdullah *et al.* (Abdullah, Saufiah and Ibrahim, 2012) describe that after a certain amount of training examples, increment in the training examples worsen the accuracy and latency.

4 FUTURE RESEARCH DIRECTIONS

In this section we will highlight the shortcomings of the existing approaches and suggest some possible future research directions.

Firstly, most of the existing work is about detecting the generalized 3Hz spike & wave pattern which is a symptom for absence seizure. To detect localized epileptic activities, each channel should be classified separately. This addition in the current method will help in diagnosing focal epilepsy.

Secondly, many types of epilepsy are diagnosed by EEG. These epilepsies are identified by unique patterns or combination of few epileptic patterns. 3Hz spike & wave is just one of the many. Noachtar *et* al. described ten types of epileptic patterns. To counter this issue there should be exclusive and independent trainers for each channel and each channel should have exclusive and independent trainer for each epileptic patterns. In this way we could detect, classify and label all types of epileptic patterns.

Commercially available EEG analyzing software tools are too user dependent. They need the user to have a prior knowledge of signal processing to fully exploit the full potential of this software. In this case neurologist seeks the help of neurotechnicians, which in case of inexperience or naive neurotechnicians may lead to misinterpretation or over-interpretation.

Seizure detection methods should be able to improve their detection capability after initial training. Addition of some post development training mechanism can help the system improve its performance over time. One way to handle this issue is that after initial training and classification of the EEG, a user interface showing the labelled epileptic wave should allow the neurologist to mark an epileptic chunk a.k.a *"an epoch"* as wrongly classified. These markings will be saved in the background as training example and they will be later used to retrain the classifier alongside previous examples. This addition will make the classifier improve its detection with passage of time.

There are few papers that have cited that increasing training data above a certain point can drop down the accuracy, for this we suggest that before classifier's training feature reduction techniques like PCA should be applied so that we can remove the noise and redundancy without compromising the important data.

In long term, this may make the system adapt itself according to a neurologist's corrective marking, thus the system may start mimicking neurologist detection by time regardless of any merit. This is in accordance to our motivation i.e. facilitating the neurologist. Another issue is that of personalizing this software tool according to a neurologist's liking. Neurologists some time have a disagreement with each other's diagnostic markings. So instead of forcing those to follow our brand of detected patterns our suggested solution will resolve both issues at a time. It will adapt its classification ability as per every neurologist own desire. (Noachtar & Rémi 2009)

5 CONCLUSIONS

Epilepsy is an important neurological disorder. Computer assisted analysis of EEG for diagnosing Epilepsy significantly helps a neurologist. To avoid misinterpretation and over-interpretation a computer assisted system should be user friendly, accurate, robust and above informative. Lots of work has been done in this regard. With the addition of our suggested steps in the existing work robustness and the classification accuracy can be improved. Other than the approach we will like to suggest that there should be a post development training system attached to our-all detection algorithm so that it may improve itself from the correction marked by the neurologist. Though with the passage of time, training system will try to adapt itself according to the neurologist choice and its classification will get biased as per his choice, but the whole point of this effort was to supplement the neurologist.

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