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A Survey on Different Methods for Epilepsy Detection

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ABSTRACT: Epilepsy is a chronic neurological disorder of the brain that affects around 50 million people worldwide. The early detection of epileptic seizures using electroencephalogram (EEG) signals is a useful tool for several applications in epilepsy diagnosis. Many techniques have been developed for unscrambling the underlying features of seizures present in EEGs. This paper reviews different methods for epilepsy detection.

KEYWORDS: Epilepsy, EEG, Seizures.

I. INTRODUCTION

Epilepsy is a chronic neurological disorder of the brain that affects around 50 million people worldwide. It is characterized by sudden recurrent and transient disturbances of perception or behavior resulting from excessive synchronization of cortical neuronal networks; it is a neurological condition in which an individual experiences chronic abnormal bursts of electrical discharges in the brain. The hallmark of epilepsy is recurrent seizures termed "epileptic seizures". Epileptic seizures are divided by their clinical manifestation into partial or focal, generalized, unilateral and unclassified seizures. Focal epileptic seizures involve only part of cerebral hemisphere and produce symptoms in corresponding parts of the body or in some related mental functions. Generalized epileptic seizures involve the entire brain and produce bilateral motor symptoms usually with loss of consciousness. Both types of epileptic seizures can occur at all ages. Generalized epileptic seizures can be subdivided into absence (petit mal) and tonic-clonic (grand mal) seizures [1]. In epilepsy the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior, or sometimes convulsions, muscle spasms and loss of consciousness[2]. There are many possible causes of epilepsy. Anything that disturbs the normal pattern of neuron activity ranging from illness to brain damage to abnormal brain development can lead to seizures. Epileptic seizures are manifestations of epilepsy [3]. In the last couple of years, the EEG analysis was mostly focused on epilepsy seizure detection diagnosis. A seizure detection system can be divided into three stages: data acquisition and preprocessing, processing and feature extraction, and classification.

II. RELATED WORK

In biomedical signal processing, it is crucial to determine the noise and artifacts present in the raw signals so that their influence in the feature extraction stage can be minimized. Intracranial EEG (iEEG) signals were band-pass-filtered between 0.5 and 100 Hz to only allow the frequencies of interest and a notch filter was used to remove 50-Hz power line noise. Saturation and movement artifacts were identified. Segments for which the derivative of the iEEG signal was zero were marked as having saturation artifacts. Movement artifacts were discarded using a threshold; iEEG segments containing a signal with amplitude of larger than 1.5mV were considered as having movement artifacts [4]. A wavelet filter that requires the frequency content to be limited to the 0-60 Hz band is used, so the EEG is band-limited to the desired band by convolving with a low-pass finite impulse response (FIR) filter[5].

Independent component analysis (ICA) is specifically used for artifact cancellation. ICA identifies sources, in this case artifacts present in the EEG signal, based on blind source separation (BSS) and separates them from the EEG based on their statistical independence [6]. The pre-processing block also normalizes the signal to make the data comparable with those recorded by another acquisition system or from a different patient. An example of this is putting all the data in given amplitude range, allowing the signals to be compared directly [7].

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In time-domain techniques to detect EEG seizures, there is a need to analyze discrete time sequences of EEG epochs. This analysis can be accomplished through histograms of the epochs. Runarsson and Sigurdsson presented a simple time-domain seizure detection method that is based on tracing consecutive peaks and minima in the signal segment at hand and estimating the histograms for two variables: the amplitude difference and time separation between peak values as well as minima. The features used for classification of an epoch as a seizure or Non seizure are the estimated values of the histogram bins. The authors used a support vector machine (SVM) Classifier for this task and achieved an average sensitivity of about 90% on self-recorded data [8]. Another approach to deal with the EEG seizure detection method in time domain is to compute the signal energy during seizure and non-seizure periods. A better treatment to the energy estimation approach is to estimate the energies of the signal sub-bands not the signal as a whole in order to build a more discriminative feature Vector. They used a bank of seven band-pass filters covering the frequency range from 2 to 26 Hz on eight channels of the processed EEG signals. Eight highly dynamic analog channels, classification processor, and a 64-KB SRAM have been integrated in the SoC. A long-term seizure monitoring and storage device was built. The authors used an SVM as a classifier with a gain and bandwidth (GBW) controller to perform real-time gain and bandwidth adaptation to analog front end (AFE) in order to keep a high accuracy. This classifier is well suited for the hardware implementation. The SoC was tested on CHB-MIT scalp EEG database and it was verified in the presence of a rapid eye blink giving an accuracy of 84.4% with 2.03 μ J/classification energy [9]. One more approach to deal with time-domain seizure detection is to exploit some discriminating statistics between Seizure and non-seizure epochs. Dalton et al. developed a body sensor network (BSN) that can monitor and detect epileptic seizures based on statistics extracted from time-domain signals. These statistics include the mean, variance, zero-crossing rate, entropy, and autocorrelation with template signals. For autocorrelation estimation, they adopted a dynamic time warping (DTW) approach for best alignment between the signal segments to be tested and the template signal. The authors presented a network to be embedded in wearable kinematic sensors and an N810 Internet tablet. Data were recorded from the subjects using kinematic sensors such as triaccelerometer, gyroscope, and magnetic sensor for physical activity monitoring. This algorithm was, then, commercially distributed and a BSN was developed on a Mercury platform. The sensitivity of the proposed algorithm for a dataset of 21 seizures was found to be 91% with a specificity of 84% and battery lifetime of 10.5 h [10].

The Fourier transform methods of automatic EEG processing are based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands. Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric methods for power spectrum estimation such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution. Since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals [11]. The use of autoregressive (AR) model is examined by Abdulhamit Subasi et al. by using utmost likelihood estimation (MLE) also interpretation together with the performance of this method to dig out classifiable features from human EEG by means of Artificial Neural Networks (ANNs). It is noticed that; ANN classification of EEG signals with AR produced noteworthy results. Their approach is on the basis of the earlier where the EEG spectrum enclosed a few characteristic waveforms which fall primarily within four frequency bands-delta (< 4 Hz), theta (4–8 Hz), alpha (8–14 Hz), and beta (14–30 Hz). For the automatic classification of seizures a method is offered as well as attained a classification rate of 92.3% by means of a neural network with a single hidden unit as a classifier. The classification percentages of AR with MLE on test data are over 92%. As a result of employing FFT as preprocessing in the neural net an average of 91% classification is attained [12].

A wavelet-chaos-neural network methodology for classification of electroencephalograms (EEGs) into healthy, ictal, and interictal EEGs has been offered by Samanwoy Ghosh-Dastidar et al. In order to decompose the EEG into delta, theta, alpha, beta, and gamma sub-bands the wavelet analysis is utilized. Three parameters are used for EEG representation: standard deviation (quantifying the signal variance), correlation dimension, and largest Lyapunov exponent (quantifying the non-linear chaotic dynamics of the signal). The classification accuracies of the following techniques are compared: 1) unsupervised - means clustering; 2) linear and quadratic discriminant analysis; 3) radial basis function neural network; 4) Levenberg–Marquardt back propagation neural network (LMBPNN). The research was carried out in two phases with the intention of minimizing the computing time and output analysis, band-specific analysis and mixed-band analysis. In the second phase, over 500 different combinations of mixed-band feature spaces

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com-prising of promising parameters from phase one of the research were examined. It is decided that all the three key components the wavelet-chaos-neural network methodology are significant for enhancing the EEG classification accuracy. Judicious combinations of parameters and classifiers are required to perfectly discriminate between the three types of EEGs. The outcome of the methodology clearly let know that a specific mixed-band feature space comprising of nine parameters and LMBPNN result in the highest classification accuracy, a high value of 96.7% [13]. The efficiency of utilizing an ANN is assessed by Steven Walczak and William J. Nowack in order to determine epileptic seizure occurrences for patients with lateralized bursts of theta (LBT) EEGs. By means of the examination of records of 1,500 successive adult seizure patients training and test cases are obtained. Owing to the development of the ANN categorization models the small resulting pool of 92 patients with LBT EEGs requisite the usage of a jackknife procedure. Evaluations of the ANNs are for accuracy, specificity, and sensitivity on categorization of each patient into the correct two-group categorisation: epileptic seizure or non-epileptic seizure. By means of eight variables the original ANN model generated a categorization accuracy of 62%. Consequently, a modified factor analysis, an ANN model using just four of the original variables attained a categorization accuracy of 68% [14].

Gabor and Seyal introduce a neural network algorithm that relies primarily on the spike field distribution. MLP networks with the number of input and hidden nodes equal to the number of channels in the record and a single output node are used. Five bipolar 8 channel records from the EMU with durations ranging from 7.1 to 23.3 min are used for training and testing. Two networks are trained on only the slopes of the spike's half-waves, and there is no notion of background context. The first uses the slope of the half-wave before the spike's apex for all 8 channels as inputs, and the second uses the slope after the apex. The output of the algorithm is a weighted combination of the two network outputs with a value near 1.0 indicating a spike has been found. The duration (not specified) of the spike half waves is fixed so that no waveform decomposition is required. The algorithm slides along the data one sample at a time and identifies a spike when the output is greater than a threshold (e.g. 0.9). The method requires a distinct network for each patient and spike foci, so 7 networks were trained because two of the patients had independent foci. The training required 4–6 example spikes and the non spikes were generated by statistical variation resulting in 4 times more non-spikes. Although this method does not seem to be well suited for general detection, it might be a promising method for finding similar events [15].

Hojjat Adeli et al. have offered a wavelet chaos methodology for analysis of EEGs and delta, theta, alpha, beta, and gamma sub-bands of EEGs. In the form of the correlation dimensions (CD, representing system complexity) and the largest Lyapunov exponent (LLE, representing system chaoticity) the nonlinear dynamics of the original EEGs are quantified. The new wavelet-based methodology isolated the changes in CD and LLE in specific sub-bands of the EEG. The methodology was applied to three diverse groups of EEG signals: healthy subjects, epileptic subjects during a seizure-free interval (interictal EEG), and epileptic subjects during a seizure (iEEG). The effectiveness of CD and LLE in distinguishing between the three groups is examined based on statistical importance of the variations. It has been noted that in the values of the parameters acquired from the original EEG there may not be noteworthy differences, differences may be recognized when the parameters were employed in conjunction with particular EEG sub-bands and concluded that for the higher frequency beta and gamma sub-bands, the CD distinguished between the three groups, in disagreement to that the lower frequency alpha sub-band, the LLE distinguished between the three groups [16].

M.Akin, M.A.Arserim, M.K.Kiyimik, I.Turkoglu have tried to find a new solution for diagnosing the epilepsy. For this aim, the Wavelet Transform of the EEG signals have taken, and the δ , θ , α , and β sub frequencies are extracted. Depending on these sub frequencies an artificial neural network has been developed and trained. The accuracy of the neural network outputs is too high (97% for epileptic case, 98% for healthy case, and 93% for pathologic case that have been tested). This means that this neural network identifies the health conditions of the patients approximately as 90 of 100. From this point we can say that an application of this theoretical study will be helpful for the neurologists when they diagnose the epilepsy [17]. Ganesan.M, Sumesh.E.P, Vidhyalavanya.R proposed a technique for the automatic detection of the spikes in long term 18 channel human electroencephalograms (EEG) with less number of data set. The scheme for detecting epileptic and non epileptic spikes in EEG is based on a multi resolution, multi-level analysis and Artificial Neural Network (ANN) approach. The signal on each EEG channel is decomposed into six sub

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bands using a non-decimated WT. Each sub band is analyzed by using a nonlinear energy operator, in order to detect spikes. A parameter extraction stage extracts the parameters of the detected spikes that can be given as the input to ANN classifier. The system is evaluated on testing data from 81 patients, totaling more than 800 hours of recordings. 90.0% of the epileptic events were correctly detected and the detection rate of non epileptic events was 98.0% [18].

III. CONCLUSION

Progress in epilepsy detection research follows two main lines. One is the development of methods that allow non-invasive and precise detection for diagnostic applications. The principal difficulty to overcome is the presence of artifacts that overlap the signal of interest. The other one is in the neuro stimulation and drug delivery field, where the recording and therapy are necessarily invasive, but the aim is to achieve onset detection and seizure quantification with maximum exactitude. Another important issue in the epileptic seizure detection field is the need for a standardization of methods. First, the unification of metrics used to evaluate detector performance is needed in order to make homogenous comparisons. Second, some guidelines are required for the EEG record type (scalp or intracranial) and as well as the duration of these records (it is not the same testing the detector in a record of a few seconds that in a one of an hour long) used the implementation and testing the algorithms. In general terms, a good epilepsy detector should show at least 80% sensitivity and specificity.

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