Analysis and classification of EEG signals using spectral analysis and recurrent neural networks

Mohammad Ali Naderi
Electrical Engineering Department, Islamic Azad Univ.
Najafabad Branch
Najafabad, Esfahan, Iran
naderikharaji@gmail.com

Homayoun Mahdavi-Nasab
Electrical Engineering Department, Islamic Azad Univ.
Najafabad Branch
Najafabad, Esfahan, Iran
mahdavinasab@iaun.ac.ir

Abstract: This study proposes a three stages technique for automatic detection of epileptic seizure in EEG signals. In practical application of pattern recognition, there are often diverse features extracted from raw data which needs to be recognized. Proposed method is based on time series signal, spectral analysis and recurrent neural networks (RNNs). Decision making was performed in three stages:(i)feature extraction using Welch method power spectrum density estimation (PSD) (ii)dimensionality reduction using statistics over extracted features and time series signal samples (iii)EEG classification using recurrent neural networks. This study shows that Welch method power spectrum density estimation is an appropriate feature which well represents EEG signals. We achieved higher classification accuracy (specificity, sensitivity, classification accuracy) in comparison with other researches to classify EEG signals exactly 100% in this study.

Keywords-EEG signals classification, Welch PSD, Recurrent neural networks, Sensitivity, Specificity.

I. INTRODUCTION

The whole process of methodologies used for automated diagnosis can be subdivided into a number of separated processing modules: pre-processing, feature extraction/selection and classification. The essential operation in the course of the pre-processing includes signal/image acquisition, artifact removing, averaging, thresholding, signal/image enhancement and edge detection. Since signal/image acquisition contributes significantly to the overall classification results, its accuracy is very important. The feature extraction module subsequently processes the markers. The module of feature selection is an optional stage, wherewith the feature vector is reduce in size including only, from the classification viewpoint, what may be considered as the most relevant features required for discrimination. The final stage in automated diagnosis is the classification module. The input feature vector is examined by classification module and based on its algorithmic nature, produces a suggestive hypothesis [1].

One of the most common sources of information used to study brain abnormalities is Electroencephalogram (EEG) which is a highly complex signal. EEG monitoring systems generate a lot of data for electroencephalographic changes, so their complete visual analysis is not routinely possible. Computers have long been proposed to solve this problem and thus, automated systems to recognize electroencephalographic changes have been under study for several years. The development of such automated devices, due to the increased use of prolonged and long-term video EEG recordings for proper evaluation and treatment of neurological diseases and prevention of the possibility of the analyst missing (or misreading) information is essential [1],[2].

Neural networks (NN) are structures built up of many nodes, each one simulating (in a very simplified way) the behaviour of biological neuron. Neuron behaviour is governed by very simple rules but they result in a classification tool. NN has an important role in a variety of applications like pattern recognition and classification tasks [3].

In this study we proposed a new method for EEG classification based on Welch method power spectral density estimation and recurrent neural networks. This method has three stages (i) feature extraction using FFT based Welch method spectral analysis (ii) dimensionality reduction using statistics over each EEG segment and features extracted in pervious stage (iii) classification task using recurrent neural networks. In this paper we worked on two classes (epileptic and normal) of EEG signals. First of all we divided each class dataset to 1600 segments using a rectangular window with 256 discrete data. Then we applied Welch (FFT) method on each EEG segment and we obtained 129 attributes. In the next stage we reduced the dimension of each feature vector using statistics over feature vectors and time series EEG segments. We achieved feature vectors with 8 attributes. Finally we applied recurrent and MLP neural networks as a classifier for classification of EEG signal to epileptic and healthy. These networks were implemented using MATLAB R2008a software package with neural networks toolbox and results were compared from the specificity, sensitivity and classification accuracy point of views. The flow chart of the proposed system was shown in Fig.1.

II. MATERIAL AND METHODS

In this study, EEG signals, publicly available data described in [4] was used. The data were processed using Welch method power spectral density estimation and statistical features. Then we used recurrent and MLP neural networks as classifier on these processed data for classification EEG signals to normal and epileptic.

A. Data description and selection

We used the data described in [4], which is publicly available. Regardless the different recording electrodes used for extracranial and intracranial EEG registration, all other recording parameters were fixed. Some of the morphological characteristics of the different EEG time series under examination, which are obvious to an expert's eye, will be sketched in the following.

EEG time series recorded extracranially during the relax state of healthy subjects with eyes closed show a predominant physiological rhythm, the so-called alpha rhythm in a frequency range of 8-13 Hz, an activity which is most pronounced at the back of the head. In contrast, broader frequency characteristics are obtained for open eyes. EEG time series are also recorded intracranially in humans, however only in the framework of a presurgical evaluation of focal epilepsies. In this context implantation of electrodes is carried out to exactly localize the seizure generating area which is termed the epileptogenic zone. During the seizure free interval the EEG recorded from within the epileptogenic zone is often characterized by intermittent occurrences of so-called interictal epileptiform activities. Investigation of these steep, sometimes rhythmic high amplitude patterns in EEG recordings contributes to localization of the epileptogenic zone. Finally, the EEG recorded during epileptic seizure, termed ictal activity, is almost periodic and of high amplitude, resulting from hypersynchronous activity of large assemblies of neurons.

The complete data set consists of five sets (denoted A-E) each containing 100 EEG signals of 23.6 s period. After visual inspection for artifacts, e.g., due to muscle activity or eye movements, we select the signals and cut out them from continuous multichannel EEG recordings. Sets A and B consisted of signals taken from surface EEG recordings that were carried out on five healthy volunteers using standardize electrode placement scheme.

Volunteers were relaxed in an awake state with eyes open (A) and eyes closed (B), respectively. Sets C, D, and E originated from the EEG archive of presurgical diagnosis. The EEGs from five patients were selected, all of them had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Signals in set D were recorded from within the epileptogenic zone, and those in set C from the hippocampal formation of the opposite hemisphere of the brain. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of data acquisition computer system at a sampling rate of 173.61 Hz. Band-pass filter setting were 0.53-40 Hz [1]-[3],[5]-[6].

In this paper we used two classes data sets, normal and epileptic (set A and E), for EEG signals classification.

B. Spectral analysis using Welch method

The Welch method is a power spectrum density estimator that applies the periodogram. It is based on Bartlett's idea of splitting of the data into segments and finding the average of their priodograms. Difference is that the segments are overlapped, where the overlaps are usually 50% or 75% large, and the data within the segment are windowed. L is the length of the segments, the i-th segment is denoted by $\{x_i[n]\}_0^{L-1}$, and the offset of the successive sequences by D samples. Then

$$N = L + D(k-1) \qquad (1)$$

where N is the total number of observed samples and K=N/L, and if there is 50% overlap, K=2N/L-1. The i-th sequence is

$$x_i[n] = x[n+(i-1)D], \qquad n \in \{0,1,\ldots,L-1\} \qquad (2)$$

where i=1,2,...,K, and its periodogram by

$$\hat{P}_M^{(i)}(f) = 1/L\left|\sum_{n=1}^{L-1} w[n]x_i[n]e^{j2pfn}\right|^2. \qquad (3)$$

Here $\hat{P}_M^{(i)}(f)$ is the modified periodogram of the data because the samples $x[n]$ are weighted by a nonrectangular window $w[n]$. The Welch spectrum estimate is then given by

$$\hat{P}_B(f) = 1/K(\sum_{i=1}^{K} \hat{P}_M^i(f)). \qquad (4)$$

By permitting overlap of sequences, we can form more segments than in the case of Bartlett's method. Also, if we keep the same number of segments, the overlap allows for longer segments. The increased number of the segments reduces the variance of the estimators, and the longer segments improve its resolution. Thus, with the Welch method we can trade reduction in variance for improvement in resolution in many more ways than with the Bartlett's method. It can be shown that if the overlap is 50%, the variance of the Welch estimator is approximately 9/16 of the variance of the Bartlett estimator [7].

C. Recurrent neural networks

Multilayered architecture is a special architecture of neural models. With respect to the direction of their connection, multilayered networks are divided to feed forward and feedback networks. Highly nonlinear dynamic mappings can be performed by RNNs and therefore have temporally extended application, whereas multilayer feed forward networks are confined to performing static mappings. RNNs have many applications such as associative memory, spatiotemporal pattern classification, control, optimization and generalization of pattern sequences.

Fully recurrent networks use unconstrained fully interconnected architectures and learning algorithm that can deal with time-varying input and /or output in nontrivial ways. Fully recurrent networks are still complicated when dealing with complex problems. Therefore, partially recurrent networks whose connections are mainly feed forward were used including a carefully chosen set of feedback connections. In this study Elman RNN were used as a classifier. An Elman RNN is a network which is set up as a regular feed forward network. Architecture of Elman recurrent neural network is shown in Fig.2. All neurons in one layer are connected with all neurons in the next layer. A copy of the output of the hidden neurons is held in neurons in context layer. The output of each hidden neuron is copied into a specific neuron in the context layer. Therefore the Elman network has an explicit memory of one time lag.

The weights from the hidden layer to the context layer are set to one and are fixed in an Elman network because the values of the context neurons have to be copied exactly. We can train the Elman network with gradient descent backpropagation algorithm. The backpropagation has some

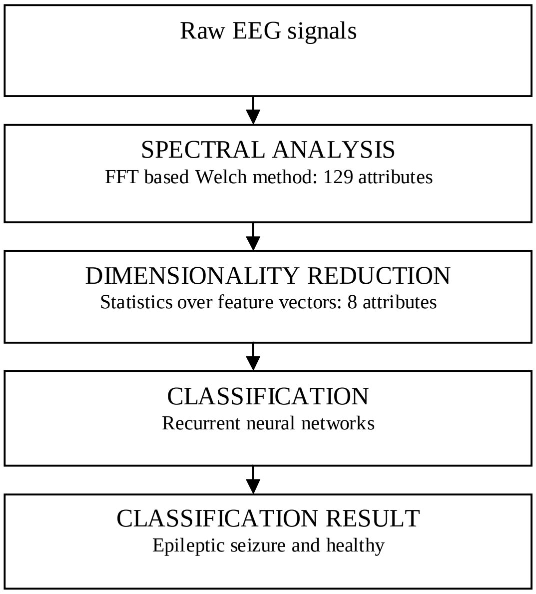

Fig.1: the flow chart of the proposed technique

problems like that gradient descent may get stuck in local minima. The Levenberg-Marquardt algorithm is least-squares estimation. This algorithm combines the best features of the Gauss-Newton technique and the steepest-descent algorithm but avoids many of their limitations [1].

III. PROPOSED SYSTEM

In this study, we proposed a new scheme for detection of epileptic seizure in EEG signals using power spectrum density (PSD) estimation and recurrent neural networks. This system is implemented using MATLAB R2008a software package (with neural networks and signal processing toolboxes). In this research we choose two types (epileptic seizure and normal) of EEG signals that are publicly available for use in [4].

Selection of the NN inputs is the most important component in designing the NN for pattern classification since even the best classifier will perform poorly if the inputs are not selected well. Transforming of NN input data into a more appropriate representation can facilitate the learning process. Using a smaller number of parameter, which are often called features, to represent the signal under study is particularly important for recognition and diagnostic purpose [2].

First of all, we divided each class of EEG signals to 1600 segments which was formed into 256 discrete data using a rectangular window. The length of each EEG segment was 256 samples. In Fig.3, EEG signals belonging to two classes were shown. Then FFT based Welch method was applied to each EEG segment to obtain power spectral density (PSD) of each segment. After applying Welch method PSD the number of samples in each segment was reduced from 256 samples to 129 samples. High dimension feature vectors increased computational complexity. To solve this problem, statistics over the time series EEG segments and power levels of PSD

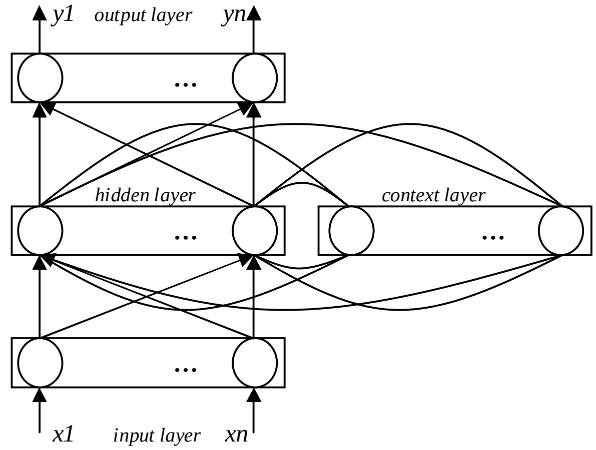

Fig.2: Architecture of Elman recurrent neural networks

were used to reduce the dimension of the feature vectors. To do this the following statistical features were used:

- Maximum of each EEG time series segment and maximum of power levels of the Welch method.
- Minimum of each EEG time series segment and minimum of power levels of the Welch method.
- Mean of each EEG time series segment and mean of power levels of the Welch method.
- Standard deviation of each EEG time series segment and standard deviation of power levels of the Welch method.

Using the above mentioned statistical features the dimension of each feature vector was reduced to 8 attributes. In this research we proposed recurrent neural networks (RNN) as a classifier for classification of two classes (epileptic seizure and healthy) of EEG signals. The RNN network was implemented with MATLAB software with neural networks toolbox.

100 time series of 4096 samples for each class of EEG signals (epileptic seizure and normal) were divided into 1600 segments of 256 samples for each class. The training and test data sets of neural networks were formed by 3200 vectors (1600 vectors with 8 attributes for each class).We assigned 1600 vectors (800 vectors from each class) for training set and 1600 vectors (800 vectors from each class) for test set. In order to examine the performance of the RNN, for the same classification problem, the multilayer perceptron neural network (MLPNN) with the Backpropagation learning algorithm was used.

IV. EXPERIMENTAL RESULTS

The performance of the classifier in this scheme was calculated by following measures.

- Specificity: number of correct classified healthy segments/ number of total healthy segments.
- Sensitivity: number of correct classified epileptic seizure segments/ number of total epileptic seizure segments.

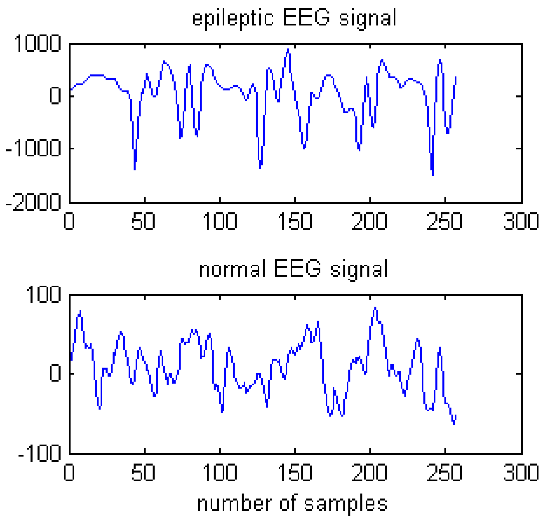

Fig.3: Examples of EEG signals of epileptic and normal subjects

- Classification accuracy: number of correct classified segments/ number of total segments.

The classification performances (specificity, sensitivity, total classification accuracy) on the test datasets were presented in TABLE 1.

In TABLE 2 the performance of the proposed method were compared with other algorithms. It shows obviously that the current work has higher accuracy than other methods.

As can be seen from results, we conclude that Welch method PSD presents very strong features which well represent EEG signals and by usage of these features a good distinction between classes can be obtained. Also statistical features were used in dimensionality reduction of the extracted feature vectors representing the EEG signals (these statistical features were used as inputs of the classifier). The classification results indicate that RNN has considerable success in classification of EEG signals.

V. CONCLUSION

The aim of this study was to find a new scheme for classification of EEG signals and detection of epileptic seizure with high accuracy using power levels of PSD and neural networks. This study demonstrates that Welch method power spectrum density estimation provides very strong features which well represent EEG signals. The high dimension of feature vectors increases computations. In order to solve this problem, statistical features were obtained from extracted feature vectors and time series EEG segment. The dimension of feature vectors was reduced to 8 attributes. Then for classification of these feature vectors, we used recurrent neural networks (RNN) as a classifier. For performance evaluation of proposed system, we computed sensitivity, specificity and classification accuracy (100%) using recurrent neural networks as a classifier.

TABLE 1: The classification performances

Classifiers	Specificity (%)	Sensitivity (%)	Classification accuracy (%)
RNN	100%	100%	100%
MLPNN	99.75%	98.12%	98.93%

TABLE 2: Comparison of different methods for EEG classification

method	Classification accuracy
A neural network based method[8]	97.2%
Wavelet coefficient and combined NN[2]	94.83%
Current work	100%

REFERENCES

[1] E.D. Ubbeyli, "Analysis of EEG signals by implementing eigenvector methods /recurrent neural networks" , Digital Signal Processing, Vol. 19, pp. 134-143, 2008

[2] E.D. Ubbeyli, "Combined neural network model employing wavelet coefficients for EEG signals classification", Digital Signal Processing, Vol.19, pp. 297-308, 2008

[3] G. Tezel, E.D. Ubbeyli, "A new approach for epileptic seizure detection using adaptive neural network", Expert Systems with Applications, Vol.36, pp.172-180, 2007

[4] http://www.meb.uni-bonn.de/epileptogie/science/physik/eegdata.html

[5] E.D. Ubbeyli, "Lyapunov exponent/probabilistic neural networks for analysis of EEG signal", Expert Systems with Applications, Vol.37, pp.985-992, 2009

[6] K. Polat, S. Gunes, "artificial immune recognition system with fuzzy resource allocation mechanism classifier, principal component analysis and FFT method based new hybrid automated identification system for classification of EEG signals", Expert Systems with Applications, Vol.34, pp.2039-2048, 2007

[7] Digital Signal Processing Handbook, Chapman & Hall/ CRC Press LLC, London, 1999, pp. 336-337

[8] V.P. Nigam, D. Graupe, "A neural-network-based detection of epilepsy", Neurol. Res., Vol.26, pp. 55-60, 2004