Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

The Use of Time-Frequency Distributions for Epileptic Seizure Detection in EEG Recordings

Alexandros T. Tzallas, *Student Member*, *IEEE*, Markos G. Tsipouras, *Student Member*, *IEEE*, and Dimitrios I. Fotiadis, *Senior Member, IEEE*

***Abstract*—Epileptic seizures are manifestations of epilepsy, which is a serious brain dynamic disorder. The analysis of the electroencephalographic (EEG) recordings provides valuable insight and improved understanding of the mechanisms causing epileptic disorders. An epileptic seizure is usually identified by polyspike activity; rhythmic waves for a wide variety of frequencies and amplitudes as well as spike-and-wave complexes. The detection of all these waveforms in the EEG is a crucial component in the diagnosis of epilepsy. Time-frequency analysis is particularly effective for representing various aspects of nonstationary signals such as trends, discontinuities, and repeated patterns where other signal processing approaches fail or are not as effective. In this paper a novel method of analysis of EEG signals using time-frequency analysis, and classification using artificial neural network, is introduced. EEG segments are analyzed using a time-frequency distribution and then, several features are extracted for each segment representing the energy distribution over the time-frequency plane. The features are used for the training of a neural network. Short-time Fourier transform and several time-frequency distributions are compared. The proposed approach is tested using a publicly available database and satisfactory results are obtained (89-100% accuracy).**

I. Introduction

EPILEPSY is a disorder of the normal brain function, characterized by an excessive and uncontrolled activity of either a part or the whole central nervous system. The hallmark of epilepsy is recurrent seizures. The epileptic seizures are due to sudden development of synchronous neuronal firing in the cerebral cortex and are recorded using the electroencephalogram (EEG) by electrodes on or inside the brain [1]. This anomalous synchrony may occur in the brain locally (partial seizures) which is seen only in a few channels of the EEG recording, or involving the whole brain (generalized seizures) which is seen in every channel of the EEG recording. Given that recordings during an epileptic seizure (ictal) were rarely obtained, EEG analysis of epileptic patients usually relied on inter-ictal findings. In those inter-ictal EEGs, epileptic seizures are usually activated with photostimulation, hyperventilation and other methods [2]. However, provoked epileptic seizures do not necessarily have the same behavior as the spontaneous ones.

The introduction of long-term video-EEG monitoring has been an important milestone providing not only the possibility to analyze ictal events, but also contributing with valuable information in those candidates evaluated for epilepsy surgery. Moreover, the development of ambulatory EEG in the 1980s allowed the characterization of seizures and seizure-like events in the home setting [3]. This has the advantage that patients are monitored in their normal environment without the reduction in seizure frequency usually occurring during inpatient sessions. Since long-term and ambulatory EEG recordings are extended over several days, while the epileptic seizure may be characterized by occasional waveforms, data reduction is an important consideration for the expert. An expert detects epileptiform activity by visual inspection of the EEG, which requires considerable skills and is a time-consuming procedure for recordings that are days long. In addition, the subjective nature of the examination affects the outcome. Hence, automation of this process could save time, making the decision more objective and uniform.

Generally, good automated seizure detection schemes facilitate diagnosis of epilepsy and enhance the management of long-term EEG recordings. However, the nonstationary and multicomponent nature of EEGs tends to increase the complexity of the automated seizure detection problem. Dealing with this type of problem, time-frequency based methods were shown to outperform conventional methods of frequency analysis since combine both time and frequency information in a single representation.

In this paper, we explore the ability of the time-frequency (*t-f*) analysis to classify EEG segments which contain epileptic seizures. A novel three-stage method is employed, including (i) *t-f* analysis of the EEG signal and computation of the power spectrum density (PSD), (ii) feature extraction from the PSD and (iii) classification of the EEG recording, using artificial neural networks (ANNs). We have tested our method, using several different methods for *t-f* analysis, like short-time Fourier transform (STFT) and *t-f* distributions (TFDs). To our knowledge there is no study in the literature related to *t-f* analysis and feature extraction, reflecting the energy distribution over the *t-f* plane, for epileptic seizure detection. The proposed method has been evaluated using a benchmark database and the results are presented.

Manuscript received June 16, 2007.

A.T. Tzallas is with the Department of Medical Physics, Medical School, University of Ioannina, GR 45110, Ioannina, Greece (e-mail: me00716@cc.uoi.gr).

M.G. Tsipouras is with the Unit of Medical Technology and Intelligent Information Systems, Department of Computer Science, University of Ioannina, GR 45110, Ioannina, Greece (e-mail: markos@cs.uoi.gr).

D.I. Fotiadis is with the Unit of Medical Technology and Intelligent Information Systems, Department of Computer Science, University of Ioannina, GR 45110, Ioannina, Greece (corresponding author; tel: +30 26510 98803, fax: +30 26510 97092, e-mail: fotiadis@cs.uoi.gr).

II. RELATED WORK

Automated epileptic seizure analysis refers collectively to methods for: (i) epileptic seizure detection, (ii) epileptic seizure prediction, and (iii) automatic focus channel identification. These analyses are primarily performed on the EEG [1-3]. In this study, we focus only on the detection of epileptic seizures.

Over the past three decades a lot of work has been done with the use of conventional temporal and frequency analysis measures in the detection of epileptic seizures in EEG recordings and comparatively good results have been obtained [4-11]. Many researchers focus their studies on the quantitative characterization of the underlying nonlinear systems (chaos) based on some evidence of a deterministic value of the EEG dynamics [12,13]. The complexity measures of the underlying EEG dynamics, such as correlation dimension [14], Lyapunov exponents [11,15] and kolmogorov entropy [16], have been derived and investigated. These measures can then be combined for the classification of EEG signals using nearest neighbour classifiers [17], decision trees [6], ANNs [4,15], support vector machines [11] or neuro-fuzzy inference systems [9,10] in order to identify the occurrence of seizures.

III. MATERIALS AND METHODS

A. Dataset

We used the dataset described in reference [18]. The complete dataset consists of five sets (denoted as Z, O, N, F and S) each containing 100 single-channel EEG segments each having 23.6 sec duration. Sets Z and O have been taken from surface EEG recordings of five healthy volunteers with eyes open and closed, respectively. Signals in two sets have been measured in seizure-free intervals from five patients in the epileptogenic zone (F) and from the hippocampal formation of the opposite hemisphere of the brain (N). Set S contains seizure activity, selected from all recording sites exhibiting ictal activity. Sets Z and O have been recorded extracranially, whereas sets N, F and S have been recorded intracranially.

In our analysis we use the above described dataset to create three different classification problems and then we tested our method with each one of them. In the first problem, two classes are examined, normal and seizure. The normal class includes only the Z type EEG segments while the seizure class includes the S type. The second problem includes three classes, normal, seizure-free and seizure. The normal class includes the Z type EEG segments; the seizure-free class the F type EEG segments and the seizure class S type. In the third problem, all five classes are used, including all EEG segments from the initial dataset. According to the previous description, the datasets consist of 200, 300 and 500 EEG segments, for the three problems, respectively. The different problems, related to the classes which are included in the classification were constructed since the medical interest is different for each of them, i.e. it is very important to evaluate the proposed method on the seizure-normal classes classification. Furthermore, these three problems are the most widely used in the literature and therefore we have selected them for the evaluation to be able to compare our approach with other approaches proposed in the literature.

B. Time-Frequency Analysis

STFT and various TFDs are used for the *t-f* analysis of the datasets [19-20]. The TFDs used in our study belong to the Cohen's class of distributions:

$$\rho(t,f) = \iiint e^{i2\pi\upsilon(u-t)} g(\upsilon,\tau) x^*\left(u-\frac{1}{2}\tau\right) x\left(u+\frac{1}{2}\tau\right) e^{-i2\pi f\tau} d\upsilon du d\tau, \quad (1)$$

where t is the time, f is the frequency, $x(t)$ is the signal, $x^*(t)$ is its complex conjugate and $g(\upsilon,\tau)$ is an arbitrary function called kernel, which is different for each TFD. Some of the TFDs employ a frequency and/or a time smoothing window. All time and/or frequency smoothing windows were set as Hamming 64-point length windows. Using *t-f* analysis, the PSD of the signal was calculated, which represents the distribution of the energy of the signal over the *t-f* plane.

C. Feature extraction

The PSD, calculated in the previous stage, is used to extract several features. A grid is used, based on a partition in the time and in the frequency axis. In the time domain three equal sized windows were selected while, in the frequency domain the employed partition divided the frequency domain in five subbands; Fig. I presents a sample PSD with the grid used for feature extraction.

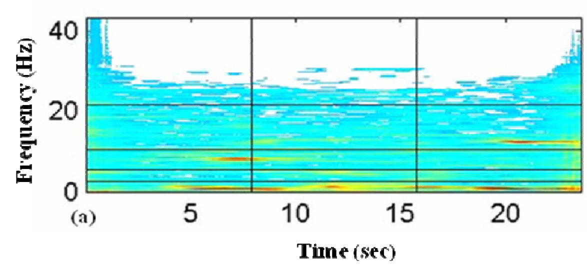

FIGURE I
PSD, TIME WINDOWS AND FREQUENCY SUBBANDS USED FOR FEATURE EXTRACTION

The frequency subbands, which were defined based on medical knowledge on EEG, are 0-2.5Hz, 2.5-5.5Hz, 5.5-10.5Hz, 10.5–21.5Hz and 21.5-43.5Hz.; specific features are expected to be found in certain frequency bands for the EEG segments included in the dataset. Each feature, $f(i,j)$, is calculated as:

$$f(i,j) = \int_{t_i}\int_{\omega_j} PSD_x(t,\omega)\, d\omega dt, \quad (2)$$

where PSD_x is the PSD of the signal x calculated using one of the above methods, t_i is the i^{th} time window and ω_j is the j^{th} frequency band. Each feature represents the fractional energy of the signal in a specific frequency band and time window; thus, the feature set depicts the distribution of the signal's energy over the *t-f* plane. It is expected that the feature set carries sufficient information related to the non-stationary properties of the signal. The total energy of the signal is used as an additional feature. Therefore, each feature set is a 16 size vector $(3*5+1)$. Principal component analysis (PCA) was employed to reduce the dimension of the feature set.

D. Classification

The calculated features are fed into a feed-forward ANN. The architecture of the ANN is the same for all problems: N inputs (N is the size of the feature vector), one hidden layer with $5*N$ neurons and K outputs (K is the number of the classes), each of them being a real number in the interval [0,1]. The units in the hidden layer are sigmoid units with hyperbolic tangent as activation function, while the outputs are linear. Each network is trained using a standard backpropagation algorithm [21]. The architecture of the ANNs was defined heuristically.

IV. Results

The three classification problems, described above, are used to evaluate the proposed method. STFT and all twelve TFDs were tested for each classification problem. These result to a total of 39 different test cases ($13*3$). For each test case, 10 ANNs were trained and tested, using half of the data for training (randomly selected) and the remaining for testing. Thus, 10 confusion matrices were obtained and classification accuracy is calculated for each of them. The final result (classification accuracy) is calculated as the average of them. The size of the confusion matrix depends on the classification problem: 2x2 for the first classification problem, 3x3 for the second and 5x5 for the third. The computed average classification accuracies and standard deviations, for the three classification problems and all employed *t-f* analysis methods are presented in Table I. Also, for each classification problem, overall results have been derived, i.e. for STFT and all TFDs, the minimum and maximum accuracy is calculated as well as the average accuracy and the standard deviation.

TABLE I
OBTAINED ACCURACY (%) FOR ALL CLASSIFICATION PROBLEMS

	Classification problems		
Distribution	**1**	**2**	**3**
Short time Fourier transform	99.8	91.8	65.3
Margenau-Hill	69.6	74.8	54.6
Wigner-Ville	96.3	94.3	82.6
Rihaczek	73.7	79.5	58.0
Pseudo Margenau-Hill	95.1	97.7	84.2
Pseudo Wigner-Ville	99	99.3	86.4
Born-Jordan	98.1	99	88.4
Butterworth	99	99.3	87.2
Choi-Williams	98.2	98.2	84.8
Generalized rectangular	98.1	98.8	88.8
Reduced interference	**100**	**100**	**89**
Smoothed pseudo Wigner-Ville	100	98.3	88
Zhao-Atlas-Marks	98.6	99.9	87.1
minimum accuracy	69.6	74.8	54.6
maximum accuracy	100	100	89
average accuracy	94.3	95.1	80.6
Standard deviation	10.2	8.3	12.5

V. Discussion

We have proposed an automated method for epileptic seizure detection in EEG recordings. The method is based on *t-f* analysis of the EEG segments and extraction of several features from the PSD of the signal. These features are fed into an ANN, which provides the final classification of the EEG segments. The method is evaluated using three different classification problems, originated from the type of medical diagnosis which can be obtained. The effect of employing different methods for *t-f* analysis (STFT and several TFDs) is examined for each classification problem.

The obtained results indicate high classification ability in epileptic seizure detection. For the first and second classification problems, almost all TFDs present excellent results (95%-100%), except MH and R distributions; both of them do not employ smoothing windows and thus the cross terms introduced reduce the quality of the obtained features and, subsequently, the classification results. Regarding the third classification problem, the results vary from 54.6% to 89%, again with the TFDs that employ smoothing windows presenting the best results (84.8%-89%). STFT presented excellent results for the first classification problem (99.8%) and very good results for the second (91.8%), but it had a significant reduction in the third (65.3%), while WV distribution, presents satisfactory results for all three classification problems. TFDs employing both time and frequency smoothing windows indicate the highest performance; 98.8%, 99% and 87.6% average accuracy for the three classification problems, respectively.

To our knowledge, *t-f* analysis and feature extraction, which reflect the energy distribution over the *t-f* plane, have not been applied in the analysis of EEG signals. Moreover the quality of the proposed method can be proven from the obtained results. The accuracy achieved by our method for the epileptic seizure detection is more than satisfactory and also its automated nature makes it suitable to be used in real clinical conditions. Besides the feasibility of a real-time implementation of the proposed method, diagnosis can be made more accurate by increasing the number of parameters. A system that may be developed as a result of this study may provide feedback to the experts for the classification of the EEG signals quickly and accurately.

TABLE II

COMPARISON WITH METHODS PROPOSED IN THE LITERATURE FOR EPILEPTIC SEIZURE DETECTION

Authors	Method	Dataset	Accuracy
Nigam et al. [5]	Nonlinear pre-processing filter-Diagnostic neural network	Z, S	97.2
Srinivasan et al. [4]	Time & frequency domain features-Recurrent neural network	Z, S	99.6
Kannathal et al. [16]	Entropy measures-Adaptive neuro-fuzzy inference system	Z, S	92.22
Kannathal et al. [13]	Chaotic measures-Surrogate data analysis	Z, S	~90
Polat et al. [6]	Fast fourier transform-Decision tree	Z, S	98.72
Subasi [8]	Discrete wavelet transform-Mixture of expert model	Z, S	95
This work	**Time frequency analysis-Artificial neural network**	**Z, S**	**100**
Guler et al. [15]	Lyapunov exponents-Recurrent neural network	Z, F, S	96,79
Sadati et al. [9]	Discrete wavelet transform–Adaptive neural fuzzy network	Z, F, S	85,9
This work	**Time frequency analysis-Artificial neural network**	**Z, F, S**	**100**
Guler et al. [10]	Wavelet transform-Adaptive neuro-fuzzy inference system	Z, O, N, F, S	98.68
Guler et al. [11]	Wavelet transform, Lyapunov exponents-Support vector machine	Z, O, N, F, S	99.28
Übeyli et al. [7]	Eigenvector methods–Modified of Mixture of expert model	Z, O, N, F, S	98.60
This work	**Time frequency analysis-Artificial neural network**	**Z, O, N, F, S**	**89**

Table II presents a comparison between our method and other methods proposed in the literature. Only methods evaluated in the same dataset are included. For the first and the second classification problems, the results obtained from our method are the best reported. However, in the third classification problem, our results are not satisfactory; being almost 89%, while the best reported results for this dataset is 99.28% [11].

VI. CONCLUSIONS

A novel method for EEG epileptic seizure detection is presented. The method is based on *t-f* analysis and features reflecting the distribution of the signal's energy. Both of these features have not been employed for epileptic seizure detection, while the obtained results, obtained using a benchmark database, demonstrate the scientific added value of the proposed method. However, there is an important aspect which must be addressed; currently the method is used to characterize predetermined (with respect to their length) EEG segments. The modification of the proposed method in order to be able to automatically detect highly suspicious segments (regardless of their length) into long time EEG recordings and classify them regarding epileptic seizure, is an aspect that will be addressed in a future communication.

REFERENCES

[1] F. Mormann, R.G. Andrzejak, C.E. Elger, and K. Lenhnertz, "Seizure Prediction: the long and the winding road," *Brain*, vol. 130, no. 2, pp. 314-33, 2007.

[2] J. Gotman, "Automatic detection of seizures and spikes," *J. Clin. Neurophysiol,* vol. 16, no. 2, pp. 130-40, 1999.

[3] E. Waterhouse, "New horizons in ambulatory electroencephalography," *IEEE Eng. Med. Biol. Mag.*, vol.22, no. 3, pp. 74-80, 2003.

[4] V. Srinivasan, C. Eswaran, and N. Sriraam, "Artificial Neural Network Based Epileptic Detection Using Time-Domain and Frequency Domain Features", *J. Med. Syst.*, vol.29, no.6, pp. 647-60, 2005.

[5] V.P. Nigam, and D. Graupe, "A neural-network-based detection of epilepsy", *Neurol. Res.*, vol. 26, no. 6, pp. 55-60, 2004.

[6] K. Polat, and S. Güneş, "Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform", *Appl. Math. Comput.*, vol. 32, no. 2, pp 625-31, 2007.

[7] E.D. Übeyli, and İ. Güler, "Features extracted by eigenvector methods for detecting variability of EEG signals", *P. Recogn. Lett.*, vol. 28, no. 5, pp 592-603, 2007.

[8] A. Subasi, "Signal classification using wavelet feature extraction and a mixture of expert model", *Exp. Syst. Appl.*, vol. 32, no. 4, pp. 1084-93, 2007.

[9] N. Sadati, H.R. Mohseni, and A. Magshoudi, "Epileptic Seizure Detection Using Neural Fuzzy Networks", in *Proc. of the IEEE Intern. Conf. on Fuzzy Syst.*, 16-21 Jul. 2006, Canada, pp. 596-600.

[10] İ. Güler and E.D. Übeyli, "Adaptive neuro-fuzzy inference system for classification of EEG signals using wavelet coefficients", *J. Neurosc. Meth.*, vol. 148, no. 2, pp. 113-21, 2005.

[11] I. Güler, and E.D. Übeyli, "Multiclass Support Vector Machines for EEG Signals Classification", *IEEE Trans. Inform. Techn Biomed.,* to be published.

[12] L.D. Iasemidis, and J.C. Sackellares, "Chaos theory and epilepsy", *The Neurosc.*, vol. 2, pp. 118-26, 1996.

[13] N. Kannathal, U.R. Acharya, C.M. Lim, and P.K. Sadasivan, "Characterization of EEG-A comparative study", *Comp. Meth. Prog. Biomed.*, vol. 80, no. 1, pp. 17-23, 2005.

[14] D.E. Lerner, "Monitoring changing dynamics with correlation integrals: case study of an epileptic seizure", *Physica D*, vol. 97, no. 4, pp. 563-76, 1996.

[15] N.F. Güler, E.D. Übeyli, and İ. Güler, "Recurrent neural networks employing Lyapunov exponents for EEG signals classification", *Exp. Syst. Appl.*, vol. 29, no. 3, pp. 506-14, 2005.

[16] N. Kannathal, M.L. Choo, U.R. Acharya, and P.K. Sadasivan, "Entropies for detection of epilepsy in EEG", *Comput. Methods Programs Biomed.*, vol. 80, no. 3, pp. 187-94, 2005.

[17] H. Qu, and J. Gotman, "A patient-specific algorithm for the detection of seizure onset in long-term EEG monitoring: possible use as a warning device", *IEEE Trans. Biomed. Eng.*, vol. 44, no. 2, pp. 115-22, 1997.

[18] 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*, vol. 64, no. 6, pp. 061907(1-8), 2001.

[19] L. Cohen, "Time-frequency distributions-a review, *Proc. IEEE*, vol.77, no.7, pp. 941-81, 1989.

[20] F. Auger, P. Flandrin, P. Goncalves, and O. Lemoine, "Time-Frequency Toolbox Tutorial", CNRS, RICE University, France, USA, 1995-1996.

[21] C.M. Bishop, "Neural Networks for Pattern Recognition", Oxford University Press, New York, 1995.