Comparative study of classifiers for patient specific seizure detection

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Abstract: **Automatic seizure detection methods basically decrease the workload of EEG monitoring units. In this study, there is considerable interest in improved offline patient specific approaches because they perform better (High sensitivity & lower false detection rate) than patient-independent ones. In this paper, we present a comparative analysis of different patient specific methods w.r.t different classification models. We consider five patient specific methods, two methods with Gaussian mixture model (GMM), next two methods with Support vector machine (SVM) and one with neural network (NN). We noted that NN based method in compare to the GMM and SVM based method had the best result applied on the same database.**

Keywords: **Electroencephalogram (EEG), Patient specific epileptic seizure detection, Gaussian mixture model (GMM), Support vector machine (SVM), Neural network (NN).**

I. INTRODUCTION

The abnormalities of transient in the brain's activity are represented by alteration in EEG and these sudden changes are recognized as seizures which usually occur without notification. EEG is the microvolt size electrical signal which is collected from different electrodes placed on scalp. These automatic seizure detection techniques perform analysis of EEG signals of brain in order to recognize a seizure with the shortest possible delay. So the proper analysis of microvolt size brain signals have key role to improve the quality of automatic seizure detection technique [1].

Epileptic seizures are identified by an involuntary alteration in behaviour, movement, sensation, or consciousness. These sudden changes due to seizures are observed by EEG alterations that include discharges of single-frequency waveforms, multiple frequency components, spiky and sharp waveforms, and varying slope of waveform [2, 3]. Vairavan Srinivasan et al., discussed two different types of neural networks, namely, Elman network (EN) and probabilistic neural networks (PNN) for the automated detection of epileptic seizures. It uses a single feature called approximate entropy (ApEn) for detection of seizures. N. Kannathala,b et al. make use of entropy measures to distinguish normal and epileptic EEG and it also provides comparison of the different entropy estimator. Y.U. Khan et al. present a scheme based on discrete wavelet transform (DWT) and classification using two classifier FEBANN (Feed forward error back propagation ANN) and DWN (Dynamic wavelet neural network). Hasan Ocak et al. deals with a method based on discrete wavelet transform (DWT) and approximate entropy (ApEn) analysis for detection of seizures from EEG signals. V. Srinivasan et al. discussed an automatic seizure detection method using an Elman network (EN). Alexandros T. Tzallas et al. present the *t-f* analysis for determination of epileptic seizures from EEG segment. Number of patient-specific method to exploit the consistency of seizure and nonseizure EEGs within patients are discussed in this paper.

II. PATIENT SPECIFIC SEIZURE DETECTION

Several methods have been proposed for detection of seizure, in this section some of these methods will be introduced and the results will be presented in the next section.

1) GMM based method using zero crossing intervals (GMM1) - In this method seizure detection is based on the analysis of positive zero-crossing intervals in scalp electroencephalogram (EEG). The time intervals between successive positive zero-crossing is used for analysis of dynamics of EEG. Zero-crossing intervals are a type of threshold-crossing interspike intervals and these intervals can be interpreted as return times to a Poincar´e secant in phase space. Zero-crossing method provides robustness against undesired artifacts and amplitude noise. In this method, EEG epochs are represented by set of zero-crossing intervals and then EEG dynamics are identified by histogram of set of zero-crossing intervals in each epoch. The varying-bin-width method is used for construction of histogram [1] and on the basis of selection of values of specific bins, different set of observation are formed. Variational Bayesian Gaussian mixture model is used to compare the set of current observations with preictal and interictal reference sets of data points through novel measures of similarity and dissimilarity. GMM is used to measure the distance of the current EEG dynamics to the reference preictal and interictal states, respectively. A combined index is then computed and compared with a patient-specific threshold to form an alarm sequence for each channel. Finally, information from individual channels is combined to trigger a seizure prediction alarm (warning) for upcoming seizures. This method provides high sensitivity of 88.34% with a false prediction rate of 0.155 h−1 and an average prediction time of 22.5 min for the test dataset.

2) GMM based method using linear discriminant analysis (LDA) transform and principal component analysis (PCA) (GMM2) - This patient specific seizure detection method is based on a Gaussian mixture model classifier. Due to heightened periodicity of EEG during seizures, frequency domain features, time domain features and information theory based features can be extracted from the EEG. In this method, total of 55 features are extracted per channel from each EEG epoch. Preprocessing of feature vectors is performed by comparison of linear discriminant analysis (LDA) and principal component analysis (PCA). The preprocessing of feature vectors is used to reduce the dimensionality and to enhance the discriminative information of the feature space [9]. The feature vectors are transformed using either the linear discriminant analysis (LDA) transform or principal component analysis (PCA) transform.

In the training stage, a GMM is trained for seizure class and non-seizure class. The likelihood estimates are obtained for the seizure class and for the non-seizure class in the testing stage. Bayesian formula is used to yield the posterior probability of seizure using combined likelihood estimates. The GMM classifier is the combination of GMM (Gaussian mixture model) and the Bayesian formula.

The probability of seizure estimate is used to obtain postprocessing scheme in order to reduce false detection rate and to increase sensitivity. The post processing scheme consists of a moving average filter and a collar operation. The GMM classifier output is filtered using a central moving average filter. The filtered probability of seizure is compared to a threshold to yield a binary decision. The single channel binary decisions are then combined into a multichannel binary decision. The collar operation is consist in expanding all positive decision events forward and backward in time and is used to increase the sensitivity. The system achieves Sensitivity of 75% and Specificity of 90% at a cost of 0.5 FD/h and Sensitivity of 85.5% and Specificity of 84.1% at a cost of 1 FD/h.

3) SVM based method using wavelet transform (SVM1) - This patient-specific approach uses wavelet decomposition for feature extraction and support vector machine for classification. The multi resolution wavelet decomposition captures the morphology and spatial distribution of an EEG epoch. To obtain the spatial correlations between channels, features extracted from 21 channels are grouped into one large feature vector [13]. Support vector machine (SVM) is used to assigned feature vector to either the seizure or nonseizure class on the basis of previously acquired feature vectors representing patient-specific examples of seizure and non-seizure EEGs. When three consecutive EEG epochs are classified as members of the seizure class, then only seizure onset is declared.

If SVM determine the class membership of feature vector using separating hyperplane, then it uses linear kernel. If the classes cannot be well separated by a hyperplane, then SVM uses more complex kernels to determine nonlinear decision boundaries. The separating hyperplane is defined to be maximally distant from the boundary cases of each class. These boundary cases are also known as support vectors, and it carries the information relevant to solving the classification problem. It detected 131 of 139 seizure events and declared 15 false detections in 60 hours of clinical EEG with true detection of 91%.

4) SVM based method using spectral and special features (SVM2) - In this study, a patient specific seizure detection technique using SVM (support vector machine) is discussed. In this method spectral and spatial features are extracted from EEG for detection of seizures. EEG passes through a filter bank composed of eight filters, and then for extraction of spectral features, spectrum energy of sub-bands is determined [4]. For a particular channel, the energy measured by a particular filter. To determine the spectral and spatial information of each EEG epoch, concatenation of M = 8 spectral energies extracted from each of N = 18 EEG channels is performed. Support-vector machine (SVM) is used for classification of feature vectors. SVM are often not provides well separation of seizure and non-seizure classes by use of linear kernel, so it uses RBF kernel for determination of non-linear decision boundaries. This algorithm detected 96% of 173 test seizures with a median detection delay of 3 seconds and a median false detection rate of 2 false detections per 24 hour period.

5) NN based method using DFT and DWT- In this paper a patient-specific epileptic seizure onset detection algorithm is discussed. This method uses Discrete Wavelet Transform (DWT) and Discrete Fourier Transform (DFT) for extraction of spectral features. A neural network (NN) classifier based on improved particle swarm optimization (IPSO) is used to obtained optimal nonlinear decision boundary. IPSONN classifier provides better classification than BP (Back Propagation) because it allows adjusting the parameter of the NN classifier in more efficiently manner. EEG of each channel is divided to number of frames, and then DWT is applied on each frame. For extraction of spatial and spectral features, spectrum energy of sub-bands is determined by DFT. The training of extracted features is performed by using a three-layer MLP neural network with IPSO learning algorithm to create optimal nonlinear decision boundary. This algorithm uses traditional particle swarm optimization (PSO) [16] algorithm and the modified evolutionary direction operator (MEDO). The PSO algorithm provides the global solution. The MEDO provides optimal solution and it also increases the capability of the PSO. This detector achieves to average efficiency 98% as sensitivity. The false detection rate (specificity) was 3 false per 24 hours for this detector.

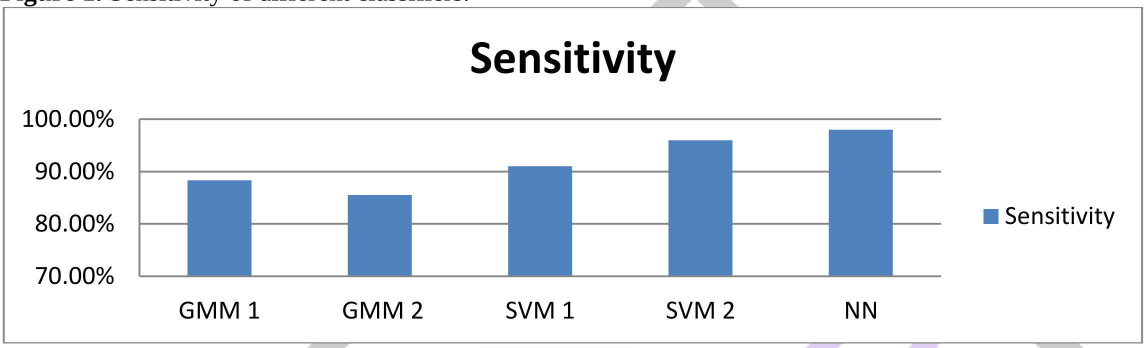
III. RESULTS AND DISSCUSSION

For comparison of the results of various algorithms, we used sensitivity and false detection rate as performance parameters. Table 1 show the best result of using GMM (Gaussian mixture model) and SVM (Support vector machine) for detection of seizure which, are elicited from [1], [4], [9], [13]. From Fig. 1, we can see that NN based classification provides best results in terms of highest sensitivity and fig. 2 shows that SVM provides lowest false detection rate (FDP).

Table 1. Results of classification which are extracted from various papers on same database.

Classification model	Sensitivity	False Prediction Rate
Gaussian mixture model(GMM 1)	88.34%	0.155 FD/h
Gaussian mixture model(GMM 2)	85.5%	1 FD/h
Support vector machine(SVM 1)	91%	0.13 FD/h
Support vector machine(SVM 2)	96%	0.083 FD/h
Neural network (NN)	98%	0.12 FD/h

Figure 1. Sensitivity of different classifiers.



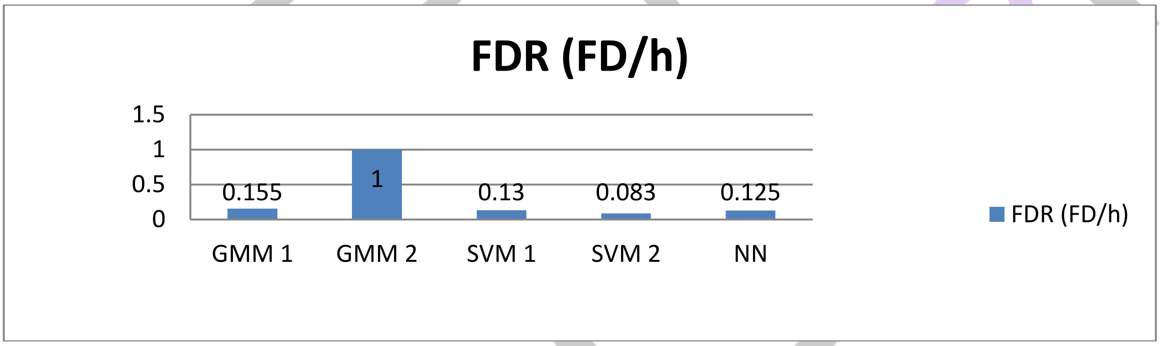


Figure 2. False detection rate of different classifiers.

IV. CONCLUSION

The analysis of the scalp EEG is performed to infer the onset of epileptic seizure. The characteristics of EEG vary significantly across patients. The characteristics of EEG appears with seizure onset in one patient may closely resemble a benign pattern within the characteristics of EEG of another patient [4]. Because of this cross-patient variability in seizure and non-seizure EEG waveform, patient independent detectors provides poor accuracy and larger delays for declaration of seizure onset. Patient specific method provides higher accuracy with lower false detection rate. From the table we can observe that support vector machine (SVM) based patient specific method provides lowest false detection rate and NN provides highest accuracy.

References:

1 Saadat Nasehi and Hossein Pourghassem, (2013) "Patient-Specific Epileptic Seizure Onset Detection Algorithm Based on Spectral Features and IPSONN Classifier" International Conference on Communication Systems and Network Technologies.

2 Y. Park, L. Luo, K. K. Parhi, and T. Netoff, (2011) "Seizure prediction with spectral power of EEG using cost-sensitive support vector machines," *Epilepsia*, vol. 52, no. 10, pp. 1761–1770.

3 W. A. Chaovalitwongse, R. S. Pottenger, S. Wang, (2011) "Pattern- and Network-Based Classification Techniques for Multichannel Medical Data Signals to Improve Brain Diagnosis," IEEE Trans. on Systems, Man and Cybernetics, Part A: Systems and Humans, Issue 99, pp. 1.

4 Ali Shoeb and John Guttag (2010) “Application of Machine Learning To Epileptic Seizure Detection” 27 th International Conference on Machine Learning, Haifa, Israel.
5 L. Chisci, A. Mavino, G. Perferi, M. Sciandrone, C. Anile, G. Colicchio, and F. Fuggetta, (2010) “Real time epileptic seizure prediction using AR models and support vector machines,” *IEEE Trans. Biomed. Eng.*, vol. 57, no. 5, pp. 1124–1132.
6 W. A. Shouyi Wang, S. Wong, (2010) "A novel reinforcement learning framework for online adaptive seizure prediction," IEEE Inter. Conf. on Bioinformatics and Biomedicine (BIBM), pp. 499.
7 A. Mirzaei, A. Ayatollahi, P. Gifani, L. Salehi, (2010) "EEG analysis based on wavelet-spectral entropy for epileptic seizures detection," 3rd Int. Conference on Biomedical Eng. and Informatics, Yantai, China, vol. 2, pp. 878- 882.
8 W. A. Shouyi Wang, S. Wong, (2010) "A novel reinforcement learning framework for online adaptive seizure prediction," IEEE Inter. Conf. on Bioinformatics and Biomedicine (BIBM), pp. 499.
9 Eoin M. Thomas and Shoeb et al. (2009) “A Gaussian mixture model based statistical classification system for neonatal seizure detection” IEEE *Trans. Biomed. Eng*, vol. 978, no. 1, pp. 4244-4948.
10 A. Yazdani, T. Ebrahimi, U. Hoffmann, (2009) "Classification of EEG signals using Dempster Shafer theory and a k-nearest neighbor classifier," 4th Int. IEEE/EMBS Conference Neural Eng., Antalya, pp. 327-330.
11 A. Klein, T. Sauer, A. Jedynak, W. Skrandies, (2006) "Conventional and wavelet coherence applied to sensory-evoked electrical brain activity," IEEE Trans. on Biomedical Eng., vol. 53, no. 2, pp. 266- 272.
12 F. Mormann, T. Kreuz, C. Rieke, R. G. Andrzejak, A. Kraskov, P. David, C. E. Elger, and K. Lehnertz, (2005) “On the predictability of epileptic seizures,” *Clin. Neurophysiol.*, vol. 116, pp. 569–587.
13 Ali Shoeb et al. (2004) “Patient-specific seizure onset detection” Epilepsy & Behavior, vol. 5, pp. 483–498.
14 J. M. Rennie, G. Chorley, G. B. Boylan, R. Pressler, Y. Nguyen, and R. Hooper, (2004) "Non-expert use of the cerebral function monitor for neonatal seizure detection," *Arch. Dis. Child Fetal Neonatal Ed*, vol. 89, pp. 3740.
15 L. D. Iasemidis, D.-S. Shiau, W. Chaovalitwongse, Sackellares, P. M. Pardalos, J. C. Principe, P. R. Carney, A. Prasad, B.Veeramani, and K. Tsakalis, (2003) “Adaptive epileptic seizure prediction system,” *IEEE Trans. Biomed. Eng.*, vol. 50, no. 5, pp. 616–627.
16 F. Mormann, R. G. Andrzejak, T. Kreuz, C. Rieke, P. David, C. E. Elger, and K. Lehnertz, (2003) “Automated detection of a preseizure state based on a decrease in synchronization in intracranial electroencephalogram recordings from epilepsy patients,” *Phys. Rev. E*, vol. 67, pp. 021912 1–10.
17 L. Hively and V. Protopopescu, (2003) “Channel-consistent forewarning of epileptic events from scalp EEG,” *IEEE Trans. Biomed. Eng.*, vol. 50, no. 5, pp. 584–593.
18 M. LeVan Quyen, J. Martinerie,V. Navaro, P. Boon, M. D’Hav´e, C. Adam, B. Renault, F. Varela, and M. Baulac, (2001) “Anticipation of epileptic seizures from standard EEG recordings,” *Lancet*, vol. 357, pp. 183–188.
19 B. Litt, R. Esteller, J. Echauz, M. Dalessandro, R. Shor, T. Henry, P. Pennell, C. Epstein, R. Bakay, M. Dichter, and G. Vachtsevanos, (2001) “Epileptic seizures may begin hours in advance of clinical onset: A report of five patients,” *Neuron*, vol. 30, pp. 51–64.
20 D. Evans and M. Levene, (1998) "Neonatal seizures," *Arch. Dis. Child. Fetal Neonatal Ed.*, vol. 78, pp. 70-75.
21 A. Legido, R. R. Clancy, and P. H. Berman, (1991) "Neurologic outcome after electroencephalographically proven neonatal seizures," *Pediatrics*, vol. 88, no 3, pp. 583-596.
22 A. Liu, J. Hahn, G. Heldt, and R. Coen, (1992) "Detection of neonatal seizures through computerized EEG analysis," *Electroenceph. clin. Neurophysiol.*, vol. 82, pp. 30-37.
23 N. Kannathala,b, Min Lim Choob, U. Rajendra Acharyab, P.K. Sadasivana, (2005) “Entropies for detection of epilepsy in EEG” in Computer Methods and Programs in Biomedicine, 80, 187—194.
24 Vairavan Srinivasan, Chikkannan Eswaran, and Natarajan Sriraam, (2007) “Approximate Entropy-Based Epileptic EEG Detection Using Artificial Neural Networks” in IEEE Transaction on Information Technology in Biomedicine, vol. 11, no. 3.
25 V. Srinivasan and N. Sriraam,(2005) “Artificial Neural Network Based Epileptic Detection Using Time-Domain and Frequency-Domain Features” in Journal of Medical Systems, Vol. 29, No. 6.
26 Alexandros T. Tzallas, Markos G. Tsipouras, and Dimitrios I. Fotiadis, (2009) “Epileptic Seizure Detection in EEGs Using Time–Frequency Analysis” in IEEE Transaction on Information Technology in biomedicine, vol. 13, no. 5.
27 Hasan Ocak, (2009) “Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy”, in Expert Systems with Applications, vol. 36, pp. 2027–2036.
28 Y.U. Khan, J. Gotman*, (2003) “Wavelet based automatic seizure detection in intracerebral Electroencephalogram”, in Clinical Neurophysiology, vol. 114, pp. 898–908.