

## A Novel Epileptic Seizure Detection Algorithm Based on Analysis of EEG and ECG Signals Using Probabilistic Neural Network

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**Abstract:** In this paper, we present a novel epileptic seizure detection algorithm based on analysis of electroencephalogram (EEG) and electrocardiogram (ECG) signals to detect seizure onsets that are not associated with rhythmic EEG activity. In this algorithm, spectral and spatial features are extracted from seizure and non-seizure EEG signals by Gabor functions and combined with four extracted features of ECG signals to form feature vector. Then a probabilistic neural network (PNN) classifier is used to determine an optimal nonlinear decision boundary. This proposed algorithm can automatically detect the presence of seizures which can be important advance facilitating timely medical intervention. Our algorithm is evaluated on 12 records of physionet database. The obtained results indicate that the proposed algorithm can recognize 98.25% of seizures with a false detection rate of 12.47%.

**Key words:** Gabor functions, seizure detection, epilepsy, EEG, ECG, probabilistic neural network (PNN).

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### INTRODUCTION

Epilepsy is a chronic disorder of central nervous system that predisposes individuals to experiencing recurrent seizures (A.J. Casson *et al.*, 2007). A seizure is a sudden, transient aberration in the brain's electrical activity that produces disruptive symptoms. These symptoms range between a lapse in attention, a sensory hallucination, or a whole-body convulsion (N. Verma *et al.*, 2010). In new therapeutic systems, a local electrical stimulator such as Vagus Nerve Stimulator (VNS) is used to halts the progression of a seizure prior to the development of clinical symptoms (C.M. DeGiorgio *et al.*, 2006). In this system, brain activities (EEG signals) of patient are recorded and monitoring by portable (Chung-Ping Young *et al.*, 2011) or wearable (A. Casson *et al.*, 2010) devices. When the onset of a seizure is recognized, the magnetic field is generated by implanted electromagnet triggers to initiate on-demand stimulation of the vagus nerve prior to the development of debilitating symptoms.

There are different algorithms to detect the seizure onset based on analysis of EEG signals such as Gotman (J. Gotman, 1990), Celka (P. Celka and P. Colditz, 2002) and (P. Colditz, 2010). These algorithms can be patient non-specific (A. Yazdani *et al.*, 2009) or patient-specific (W.A. Chaovaitwongse *et al.*, 2011), but since the cerebral origin, spread of seizures and the spectral content of rhythmic activities vary across individuals, so the patient-specific algorithms have a better performance (W.A. Shouyi Wang and S. Wong, 2010). To design a seizure detector, the features are extracted from the seizure and non-seizure EEG signals of patient and are classified at two classes. For example, Shoeb establish a patient-specific seizure onset detection algorithm (A.H. Shoeb, 2009). It extracts the eight features from 0-25HZ frequency band by means of a 3 HZ bandwidth filter and a support vector machine (SVM) classifier is used to classify the feature vectors. But the latency was large for some patients that can be arisen from large similarity of seizure and non-seizure signals. This issue can be solved by a suitable classifier that set an accurate curve of decision boundary.

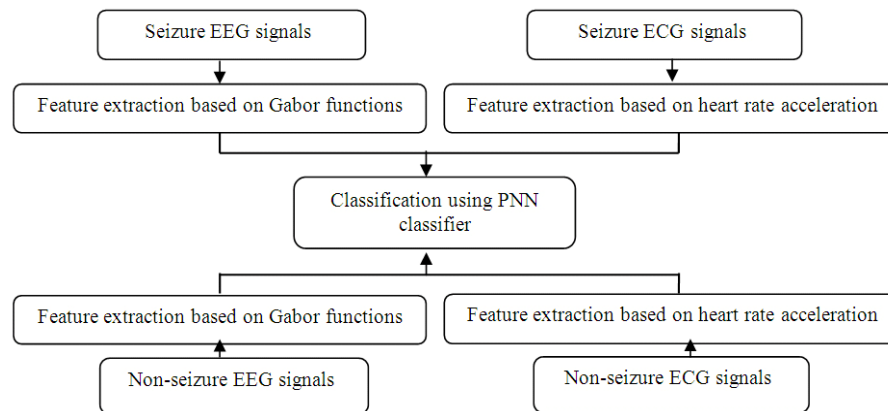
In some patients, once the entrained neural mass is large enough, rhythmic activity reflective of neuronal hyper synchrony becomes manifest within the scalp EEG. Detecting seizures of this kind using the scalp EEG is challenging since the EEG changes observed following seizure onset are also seen routinely during non-seizure states. In order to detect those types of seizures a detector requires information beyond that within the scalp EEG to ascertain whether or not a seizure is taking place. The additional information can be derived using a second physiologic signal whose dynamics are influenced by the seizure. The second physiologic signal and the scalp EEG will complement each other and improve seizure onset detection. For example, seizures resulting in repetitive motor activity may become readily detectable if scalp EEG data is supplemented with accelerometer sensor data (B.R. Greene, 2006). For other types of seizures, especially those originating within or spreading to the temporal lobes, seizures are associated with ECG changes. The most common ECG change associated with seizures is heart rate acceleration (tachycardia) (H. Khamis *et al.*, 2009).

To design a seizure onset detector based on analysis of EEG and ECG signals, the features are extracted from the seizure and non-seizure EEG signals of patient and combined with the extracted features from ECG

signals, simultaneously. The spectral and spatial features can be obtained from spectrum energy of each EEG channel. Also, the mean heart rate and the instantaneous heart rate can be extracted from ECG signals. For example, Barry present a seizure onset detection algorithm based on EEG and ECG signals (B.R. Greene *et al.*, 2006). It extracts the six features (dominant spectral peak, power ratio, bandwidth of dominant spectral peak, nonlinear energy, spectral entropy and line length) from EEG signals and six features (mean R-R interval, std. dev. R-R intervals, mean R-R interval spectral entropy, mean change in the R-R interval, interval coefficient of variation, interval power spectral density) from ECG signals. The R-R interval is defined as the time in seconds between adjacent R-wave maximum points that described by (D. Benitez *et al.*, 2001). It could recognize 617 of 633 expert-labelled seizures with a false detection rate of 13.18%.

In this paper, we propose a seizure onset detection algorithm based on analysis of EEG-ECG signals. In this algorithm, seizure and non-seizure EEG signals is decomposed by Gabor functions and spectral and spatial features are extracted from them. To reduce the computational cast of the Gabor function, we introduce three simplified Gabor function representations. Each representation is obtained by filtering the EEG-ECG signals with a certain sum of Gabor functions. The three EEG-ECG representations are: the sum over directions of Gabor function (GaborD), the sum over scales of Gabor function (GaborS), the sum over scales and direction of Gabor of function (GaborSD). We also extract the four features from ECG signals, synchrony. Furthermore, we develop a probabilistic neural network (PNN) classifier as a fast training classifier that have six advantages relative to other classifiers such as back propagation and SVM: 1) training samples can be added or removed without extensive retraining, 2) guaranteed to converge to an optimal classifier as the size of the representative training set increases (Bayes' optimal decision surface), 3) an inherently parallel structure (making parallel implementation a natural progression), 4) estimate the probability density function for each class based on the training samples. 5) Relatively simple implementation, 6) robustness to noise and self-learning ability.

The rest of the paper is organized as follows. The proposed seizure onset algorithm including the feature extraction and classification are presented in section II. In section III, the performance of algorithm is obtained based on six measures (accuracy, sensitivity, specificity, latency, false detection rate and good detection rate) and the best results compared with other algorithms. Finally, some conclusion is discussed in section IV.



**Fig. 1:** Outline of the proposed seizure detection algorithm.

#### ***The Proposed Seizure Onset Detection Algorithm:***

Block diagram of the proposed seizure onset detection algorithm is shown in Fig.1. In this algorithm, firstly, L-second epochs from seizure and non-seizure EEG signals are decomposed by Gabor functions and represented in the spatial, spectral and temporal domain. Secondly, five features such as the number of zero coefficients, the smallest and largest coefficients, the mean and standard deviation of coefficients are extracted from each sub-representation. Synchronously, four features such as the mean heart rate, instantaneous heart rate, power ratio and spectral entropy are extracted from L-second ECG epochs. Finally, a probabilistic neural network classifier is employed to train on the extracted features from seizure and non-seizure EEG-ECG signals of each patient for determination of optimal nonlinear decision boundary.

#### ***Feature Extraction:***

Gabor noted that communication theory was based on two distinct methods of signal analysis: one method describes the signal as a function of time, the other in terms of its frequency content (S. Challa *et al.*, 2007). Gabor's theory considered a new representation for the processing of information which could take account of

both the time and frequency domains (K. Okajima, 1998). The time-domain representation defines the amplitude of a signal at each instant in time, while the frequency-domain representation uses infinitely-long pure sinusoids, defined only by their frequency, amplitude and phase. A Gabor function is defined as:

$$g(t) = e^{-\alpha^2(t-t_o)^2} \cdot (\cos[2\pi f(t-t_o) + \phi] + i \sin[2\pi f(t-t_o) + \phi]) \quad (1)$$

where  $\alpha$  is the constant of the Gaussian modulating probability function and is inversely proportional to the width of the function,  $t_o$  defines the centre of the Gaussian function.  $f$  is the frequency of the oscillation,  $\phi$  is the phase of the harmonic oscillation (relative to the center of the Gaussian modulating function). In our application, we use Gabor functions with two different scales ( $t_o = 0,1$ ) and four different orientations ( $\phi = \pi d / 4$  for  $d = 0,1,2,3$ ) and  $f = 2$ .

If  $X_{c,w}$  be the L-second epoch at channel  $c$  and time  $w$ , the Gabor function representation is obtained by convolving the Gabor function with  $X_{c,w}$ . The result is a 3th order tensor in  $R^{N_1, N_2, N_3}$  which give the spatial, spectral and temporal domain. Although this method for representation is powerful, its computational costs both for recognition and calculation for representation are high. We use three representations of the  $X_{c,w}$ . These are the sum over directions of Gabor functions based representation (GaborD), the sum over scales of Gabor functions based representation (GaborS) and the sum over scales and directions of Gabor functions based representation (GaborSD) (Karlheinz Gröchenig, 2011). The most important benefit of these new representation is that the cost of computing them is low. GaborD is the magnitude part of the output generated by convolving an  $X_{c,w}$  with the sum of Gabor functions over the four directions with the fixed scale as:

$$GaborD(c, f, t) = \left\| \sum_d X_{c,w} * g(t) \right\| = \left\| X_{c,w} * \sum_d g(t) \right\| \quad (2)$$

$GaborD(c, f, t)$  is the output of the GaborD method for representation. Therefore, we have four different outputs to represent the  $X_{c,w}$  in GaborD decomposition. GaborS is the magnitude part of the outputs generated by convolving an  $X_{c,w}$  with the sum of Gabor functions over the two scales with the fixed direction as:

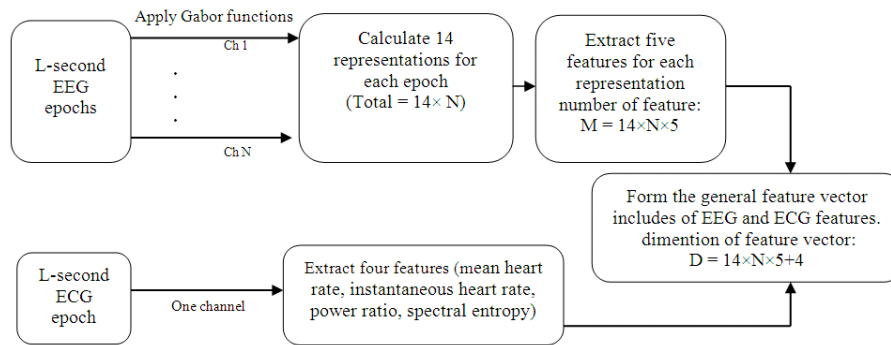


Fig. 2: The process of feature extraction.

$$GaborS(c, f, t) = \left\| \sum_{t_o} X_{c,w} * g(t) \right\| = \left\| X_{c,w} * \sum_{t_o} g(t) \right\| \quad (3)$$

$GaborS(c, f, t)$  is the output of the GaborS method for representation. Therefore, we have six different outputs to represent the original  $X_{c,w}$  in the GaborS decomposition. GaborSD is the magnitude part of the output generated by convolving an  $X_{c,w}$  with the sum of all eight Gabor functions as:

$$GaborSD(c, f, t) = \left\| \sum_{t_0} \sum_d X_{c,w} * g(t) \right\| = \left\| X_{c,w} * \sum_{t_0} \sum_d g(t) \right\| \quad (4)$$

Therefore, 14 represent is calculated by GaborD, GaborS and GaborSD for each EEG epoch channel. We extracted five features such as the number of zero coefficients, the smallest and largest coefficients, the mean and standard deviation of coefficients from each sub-representation form L-second EEG epochs. So feature vector containing  $M = 14 \times N \times 5$  features from  $N$  channels. We also extract four features such as the mean heart rate, instantaneous heart rate, power ratio and spectral entropy from L-second ECG epochs, synchronously. Fig.2 shows the process of feature extraction and forming of the feature vector.

**Classification Using PNN:**

In this paper a probabilistic neural network (PNN) (M. Kh. Hazrati and A. Erfanian, 2010) classifier is used to classify the selected features from seizure and non-seizure EEG and ECG signals. The PNN is introduced by Specht (D.F. Specht, 1991) and are characterized by fast training and convergence to Bayes-optimal decision surface. It estimates Parzen or a similar probability density function for each class based on the training samples that is capable of realizing or approximating the Bayes classifier as:

$$c(x) = \arg(\max_{1 \leq j \leq M} \{p_j f_j(x)\}) \quad (5)$$

where  $x \in R^d$  is a  $d$ -dimensional feature vector,  $c(x)$  denotes the estimated class of pattern  $x$ .  $p_j$  is the prior probability of class  $j$ , and the conditional probability density function of class  $j$  is  $f_j$ . The goal of the PNN is to estimate the values of  $f_j$  by equation (6).

$$\hat{f}_{n_j}(x) = \frac{1}{n_j} \sum_{i=1}^{n_j} K_{n_j}(x, X_i^{(i)}) \quad (6)$$

where  $X = \{X_i, Y_i\}$  is the set of  $n$  observations, each  $X_i \in x_i^d$  is a feature vector, and  $Y_i$  is a label indicating the class of pattern  $X_i$ . The sequence  $K_n$  is Parzen kernel which is defined as:

$$K_n(x, u) = h_n^{-d} K\left(\frac{x-u}{h_n}\right) \quad (7)$$

where  $K$  is an appropriately selected function and  $h_n$  is a certain sequence of numbers. The function  $K$  can be presented as:

$$K(x) = \prod_{i=1}^d H(x^{(i)}) \quad (8)$$

Then, sequence is expressed by means equation (9).

$$K_n(x, u) = h_n^{-d} (2\pi)^{-1/2} \prod_{i=1}^d e^{-\frac{x^{(i)} - u^{(i)}}{h_n}} \quad (9)$$

The prior probabilities  $p_j$  are estimated as:

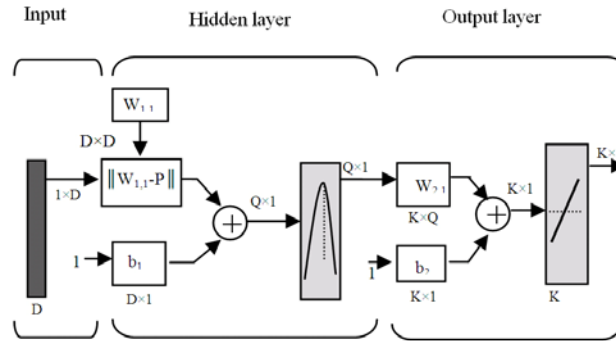
$$\hat{p}_j(x) = \frac{n_j}{n} \quad (10)$$

where  $n_j$  is the number of observation from class  $j$ . we get the following discriminant function estimate by combining equation (5), (6) and (10).

$$\hat{d}_{j,n}(x) = \frac{1}{n_j} \sum_{i=1}^{n_j} k_{n_j}(x, X_i^{(j)}) \tag{11}$$

Assign input pattern  $x$  to class  $m$  in moment  $n$  if

$$\hat{d}_{m,n}(x) \hat{d}_{i,n}(x) > 0 \tag{12}$$

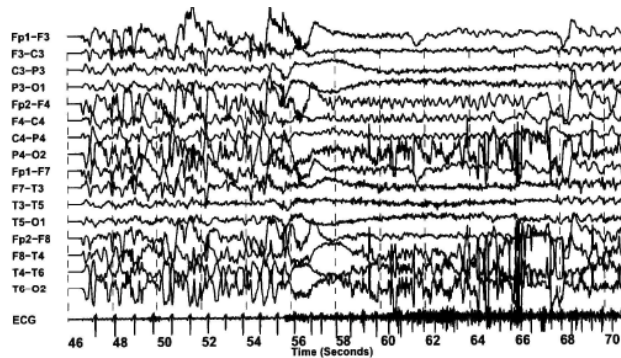


**Fig. 3:** PNN structure. D: number of features. Q: number of training samples, K: number of classes (K=2). The three layers are input layer, radial basis layer and competitive layer.

In this paper, we use a feed forward networks built with three layers. This network structure is shown in Fig.3. The input layer is fully connected to the hidden layer. Feature vectors are normalized and are used as inputs of this network. The hidden layer has a node for each classification. Each hidden node calculates the dot product of the input vector with a test vector subtracts 1 from it and divides the result by the standard deviation squared. Three nodes in output are represented by unit vector seizure = [1 0], non-seizure = [0 1].

**Experimental Results:**

In this section, we evaluate the performance of our seizure onset detector algorithm. First, the used dataset is introduced. Then, the evaluation measures are introduced. Finally, the results of algorithm are compared with other algorithms.



**Fig. 4:** example of a multi-channel electrographic seizure. Seizure begins at 56 seconds.

**EEG and ECG Dataset:**

A dataset of 12 records from 10 term neonates containing 633 labeled seizure events, with mean seizure duration of 4.60 min, were recorded and analyzed. The records had a mean duration of 12.84 h. Each record contained 7-12 channels of EEG and one channel of simultaneously acquired ECG. Ten records, sampled at 256 Hz, were made in the neonatal intensive care units of the Unified Maternity Hospitals in Cork, Ireland, using the Viasys NicOne video-EEG system. The remaining recording, sampled at 200 Hz, was recorded at Kings College Hospital, London, on a Tele factor Beehive video-EEG system. A total of 154.1 h of EEG and ECG were analyzed. Table 1 shows the number of seizure events per record, the duration of each record and the mean seizure duration for each record. Further information about this data is available in (EEG and ECG Database).

Fig. 4 shows an example of an electrographic seizure. The seizure, which begins at 56 seconds, involves a 12 second period of low-amplitude EEG activity across most EEG channels. At the same time, the patient's heart rate accelerates. Later, at 68 seconds, 1-2 HZ generalized rhythmic activity develops.

**Evaluation Measures:**

We evaluated the performance of our detector based on five measures:

**Accuracy:** The classification accuracy is defined as the percentage of epochs correctly classified by detector.

**Sensitivity:** The sensitivity is defined as the percentage of seizure epochs (as labelled by an expert in neonatal EEG and ECG) correctly identified as seizure epochs by detector.

- **Specificity:** The specificity is defined as the percentage of labelled non-seizure epochs correctly classified as non-seizure by detector.
- **Latency:** the delay between the expert-marked seizure onsets within the EEG detector declaration of seizure activity.
- **FDR:** The false detection rate is defined as the percentage of non-seizure epochs incorrectly identified as seizure epochs is equivalent to 100-specificity (%).
- **GDR:** The seizure sensitivity or good detection rate (GDR) is defined as the percentage of electrographic seizure events as labelled by an expert in neonatal EEG and ECG correctly identified by the detector.

**Table 1:** Database characteristics for each record: Number of seizure events, duration of recording, mean seizure duration.

Record	No. of seizure events	Record duration (h)	Mean seizure duration (min)
1	90	10.01	2.77
2	22	10.42	7.33
3	21	24.53	5.41
4	60	14.25	1.56
5	35	14.40	10.02
6	29	10.01	2.15
7	155	24.04	5.28
8	56	13.17	1.99
9	60	5.20	1.05
10	41	5.69	1.16
11	50	17.33	4.88
12	14	5.05	11.64
Total	633	Total 154.10	Mean 4.60

**Seizure Detection Results:**

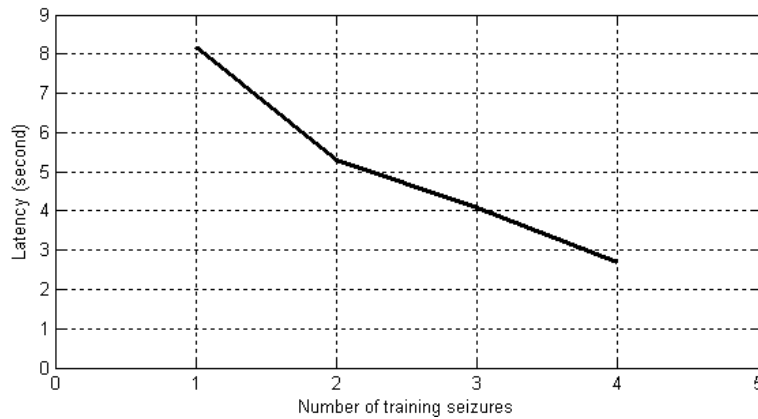
The proposed algorithm is an epoch-based detector so it makes intuitive sense to quantify its performance in term of accuracy measure. From a clinical viewpoint, the most important measure of the clinical utility of a seizure prediction algorithm is the percentage of seizure events correctly detections, because it increases the capability of detector to recognize the seizure in order to initiate the just in time therapy methods. We use the MATLAB to implement our algorithm. The used data in the experiments is labelled as seizure or non-seizure.

To evaluate the utility of the combining EEG and ECG information, we compare the performance of two detectors. One detector classifies a synthesized feature vector using EEG and ECG, the other classifies a synthesized feature vector using EEG features. Both detector are trained on 20 seconds following the onset of the electro decrement with training seizures, and both detectors process L = 2 second epochs. When the detector uses the ECG-EEG information, the mean GDR was found to be 98.25% with an FDR of 12.47%. The classification had a mean classification accuracy of 86.31% with the associated sensitivity and specificity of 79.66% and 87.79%, respectively. When the detector use only EEG information, the mean GDR, FDR and accuracy have been reduced while, the specificity has been increased. The result illustrates that the ECG is suitable in its own right for use in seizure detection algorithms. The combination of two signals supplies the neonatal seizure detection algorithm with a broader seizure-specific information base, offering potentially superior seizure detection performance. Table 2 shows the obtained result by our detector which is comparison with Barry's algorithm (B.R. Greene *et al.*, 2006). Our detector exhibits a shorter FDR, a higher sensitivity and accuracy and a comparable specificity relative to Barry's algorithm. The high sensitivity increase the capability of detector to recognize the seizures in order to initiate the just in time therapy methods.

Our detector could detect the 54% of 633 seizures within 3.7 seconds delay. Fig. 5 illustrates the effect of increasing of the training seizures samples on the mean latency. When a training seizure sample is used, the detector will obtain latency greater than 8 seconds for test seizures. The detector obtains latency close to 4 and 3 seconds for three and four training seizures, respectively. So the detector performance is improved as more seizure EEG signals are included in the training dataset.

**Table 2:** Results of the proposed algorithm in comparison with Barry's algorithm.

	Our algorithm		Barry's algorithm (B.R. Greene <i>et al.</i> , 2006)	
	EEG	EEG-ECG	EEG	EEG-ECG
Accuracy (%)	84.57	86.31	84.55	84.66
Sensitivity (%)	73.41	79.66	71.02	74.08
Specificity (%)	88.37	87.81	88.53	86.82
FDR (%)	11.15	12.47	11.47	13.18
GDR (%)	94.38	98.25	93.64	97.52



**Fig. 5:** Increasing the number of the training seizures decreases the detection delay.

**Conclusion:**

We presented an algorithm for seizure detection which uses the extracted information from physiologic EEG and ECG signals. In this algorithm, seizure and non-seizure EEG signals are decomposed by Gabor functions (GaborS, GaborD, GaborSD) and are represented in spectral, spatial and temporal domain. Then, five features are obtained from each representation. Furthermore, four features based on heart rate acceleration are extracted from ECG signals, synchronously. Finally a PNN classifier is used to determine an optimal nonlinear decision boundary. The used PNN classifier has an inherently parallel structure and prevents the premature convergence which can increase the sensitivity of seizure onset detector. The algorithm was evaluated using a large data-set containing ECG and multi-channel EEG. The obtained result showed when ECG and EEG signals simultaneously was used for seizure detection, the sensitivity and specificity was better relative to when only EEG signals was used. Average accuracy rate of 86.31% obtained when EEG and ECG signals were synchronously used.

**REFERENCES**

Benitez, D., P.A. Gaydecki, A. Zaidi and A.P. Fitzpatrick, 2001. "The use of the Hilbert transform in ECG signal analysis," *Computers in Biology and Medicine*, 31(5): 399-406.

Casson, A., D. Yates, S. Smith, J. Duncan and E. Rodriguez-Villegas, 2010. "Wearable Electroencephalography," *IEEE Engineering in Medicine and Biology Magazine*, 29(3): 44.

Casson, A.J., D.C. Yates, S. Patel and E. Rodriguez-Villegas, 2007. "Algorithm for AEEG data selection leading to wireless and long term epilepsy monitoring," 29<sup>th</sup> Annual Inter. Conf. IEEE Eng. in Medicine and Biology Society, EMBS, Lyon, pp: 2456.

Celka, P. and P. Colditz, 2002. "A computer-aided detection of EEG seizures in infants: a singular-spectrum approach and performance comparison," *IEEE Transactions on Biomedical Engineering*, 49(5): 455 - 462.

Challa S. Sastry, M. Ravindranath, Arun K. Pujari and B.L. Deekshatulu, 2007. "A modified Gabor function for content based image retrieval," *Pattern Recognition Letters*, 28(2): 293-300.

Chaovalitwongse, W.A., R.S. Pottenger and 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*, (99): 1.

Chung-Ping Young, Sheng-Fu Liang, Da-Wei Chang, Yi-Cheng Liao, Fu-Zen Shaw and Chao-Hsien Hsieh, 2011. "A Portable Wireless Online Closed-Loop Seizure Controller in Freely Moving Rats," *IEEE Trans. on Instrumentation and Measurement*, 60(2): 513.

Colditz, P.B., 2010. "Signal processing applications in clinical newborn medicine to improve health outcomes," 10th International Conference on Information Sciences Signal Processing and their Applications (ISSPA), pp: 819-823.

DeGiorgio, C.M., A. Shewmon, D. Murray and T. Whitehurst, 2006. "Pilot study of trigeminal nerve stimulation (TNS) for epilepsy: a proof-of concept trial," *Epilepsia*, 47(7): 1213-1215.

EEG and ECG Database, <http://www.physionet.org/pn6/chbmit>.

Gotman, J., 1990. "Automatic seizure detection: improvements and evaluation," *Electroencephalography and Clinical Neurophysiology*, 76(4): 317-324.

Greene, B.R., G.B. Boylan, R.B. Reilly, P. de Chazal and S. Connolly, 2006. "P16.1 Neonatal seizure detection using a combination of EEG and ECG analysis," *Clinical Neurophysiology*, 117(1): 200.

Greene, B.R., G.B. Boylan, R.B. Reilly, P. de Chazal and S. Connolly, 2006. "Neonatal seizure detection using a combination of EEG and ECG analysis," *Clinical Neurophysiology*, 117(1): 200.

Karlheinz Gröchenig, 2001. "Multivariate Gabor frames and sampling of entire functions of several variables," *Applied and Computational Harmonic Analysis*, 31(2): 218-227.

Kh. Hazrati, M. and A. Erfanian, 2010. "An online EEG-based brain-computer interface for controlling hand grasp using an adaptive probabilistic neural network," *Medical Engineering & Physics*, 32(7): 730-739.

Khamis, H., A. Mohamed and S. Simpson, 2009. "Seizure state detection of temporal lobe seizures by autoregressive spectral analysis of scalp EEG," *Clinical Neurophysiology*, 120(8): 1479-1488.

Okajima, K., 1998. "The Gabor function extracts the maximum information from input local signals," *Neural Networks*, 11(3): 435-439.

Shoeb, A.H., 2009. "Application of machine learning to epileptic seizure onset detection and treatment," Ph.D. dissertation, Dept. Electrical Eng., MIT. USA.

Shouyi Wang, W.A. and S. Wong, 2010. "A novel reinforcement learning framework for online adaptive seizure prediction," *IEEE Inter. Conf. on Bioinformatics and Biomedicine (BIBM)*, pp: 499.

Specht, D.F., 1991. "A general regression neural network," *IEEE Transactions on Neural Networks*, 2(6): 568-576.

Verma, N., A. Shoeb, J. Bohorquez, J. Dawson, J. Gutttag and A.P. Chandrakasan, 2010. "A Micro-Power EEG Acquisition SoC With Integrated Feature Extraction Processor for a Chronic Seizure Detection System," *IEEE Journal of Solid-State Circuits*, 45(4): 804-816.

Yazdani, A., T. Ebrahimi and 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.