EEG Signals Classification Using a Hybrid Method Based on Negative Selection and Particle Swarm Optimization

Nasser Omer Ba-Karait[1], Siti Mariyam Shamsuddin[1], and Rubita Sudirman[2]

[1] Soft Computing Research Group, Faculty of Computer Science and Information Systems
[2] Faculty of Electrical Engineering
[1,2] Universiti Teknologi Malaysia, 81310 Skudai, Johor Bahru, Malaysia
bakarait@yahoo.com, mariyam@utm.my, rubita@fke.utm.my

Abstract. The diagnosis of epilepsy from EEG signals by a human scorer is a very time consuming and costly task considering the large number of epileptic patients admitted to the hospitals and the large amount of data needs to be scored. In this paper, a hybrid method called adaptive particle swarm negative selection (APSNS) was introduced to automate the process of epileptic seizures detection in EEG signals. In the proposed method, an adaptive negative selection creates a set of artificial lymphocytes (ALCs) that are tolerant to normal patterns. However, the particle swarm optimization (PSO) algorithm forces these ALCs to explore the space of epileptic signals and maintain diversity and generality among them. The EEG signals were analyzed using discrete wavelet transform (DWT) to extract the most important information needed for decision making. The features extracted have been used to investigate the performance of the proposed APSNS algorithm in classifying the EEG signals. The Experimental results confirm effectiveness and stability of the proposed method. Its classification accuracy outperforms many of the methods in the literature.

Keywords: Electroencephalogram, epileptic seizure, discrete wavelet transform, machine learning, particle swarm optimization, artificial immune system.

1 Introduction

Brain activity can be measured in a variety of ways such as Magneto Encephalogram (MEG), optical images, and Electroencephalogram (EEG) signals. The EEG signal is a highly complex signal represents the electrical activity of the brain. In the last decades, the EEG has been intensively studied due to it conveys valuable clinical information used to study brain function and neurological disorders. Thus, the EEG has long been an important clinical tool in diagnosing, monitoring and managing neurological disorders, especially those related to epilepsy [1-3]. Epileptic seizures are caused by temporary electrical disturbance of the brain. Seizures may go unnoticed, depending on their presentation, but sometimes may be confused with other events, such as a stroke, which can also cause falls or migraines. The occurrence of a seizure seems unpredictable and its course of action is still very poorly understood. Research is needed for better understanding of the mechanisms causing epileptic disorders.

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Careful analysis of the EEG records could provide valuable insight into this widespread brain disorder [4, 5].

When diagnosed properly, many cases of epilepsy can be controlled effectively by medications or surgical treatments. In the case of surgical treatments, patients undergo long presurgical evaluations. During this period, large numbers of multi-channel EEG recordings are acquired for locating the epileptic part of the brain to be removed during the surgery [6, 7]. Clearly, analysis of the recorded EEG based on visual inspection is a very time consuming and costly task. In some other cases, individuals with epilepsy have seizures that are uncontrollable. Recently, methods have started being developed for medically resistant epilepsy. In these methods, a local therapy such as direct electrical stimulation or chemical infusions is delivered to the affected regions of the brain in order to avoid the onset of a seizure. Detection of seizures automatically forms an integral part of such methods [7, 8].

With the above premises, there is a great need for development of automated systems to recognize EEG changes. Therefore, tremendous effort has long been devoted by researchers for solving this problem and various methods have been presented in the literature. Mostly, these approaches coming from the area of artificial intelligence (AI) such as artificial neural networks [4-7, 9-11], adaptive neuro-fuzzy inference system [12-14] , support vector machine [3, 15-17] , decision tree [18, 19], and artificial immune system [20]. As it can be seen in above mentioned studies, the features that characterize the behavior of the EEG signals are extracted using techniques such as fourier transform, autoregressive, wavelet transform, and eigenvector methods.

However, algorithms involving artificial immune systems (AIS) have not been widely explored in the field of EEG-based medical diagnosis. Only few studies exists in the literature such as Polat and Güneş [20] in which artificial immune recognition system (AIRS) algorithm was applied for EEG signals classification. Therefore, investigating the performance of other AIS algorithms such as the negative selection algorithm (NSA) is of great importance. In this study, an adaptive NSA was hybridized with the particle swarm optimization (PSO) algorithm to introduce a novel method named adaptive particle swarm negative selection (APSNS) algorithm. The performance of the proposed algorithm in classifying the EEG signals was evaluated using features extracted by discrete wavelet transform (DWT).

2 Artificial Immune Systems

In the 1990s, artificial immune systems (AIS) emerged as a new computational research field inspired by the simulated biological behavior of the natural immune system (NIS). The NIS is a very complex biological network with rapid and effective mechanisms for defending the body against a specific foreign body material or a pathogenic material called antigen [21]. During the reactions, the adaptive immune system memorizes the characteristic of the encountered antigen by producing plasma or memory cells. The obtained memory promotes a rapid response of the adaptive immune system to future exposure to the same antigen [22]. In order to respond only to antigen, the immune system distinguishes between what is normal (self) and foreign

(non-self or antigen) in the body. The NIS is made up of lymphocytes, which are white blood cells circulate throughout the body, mainly of two types, namely B-cells and T-cells. These cells play the main role in the process of recognizing and destroying antigens [23].

Both T-cell and B-cell are created in the bone marrow and they have receptor molecules on their surfaces (the B-cell receptor molecule is also known as antibody). The way B-cells and T-cells can identify a specific antigen is called a key and key hole relationship as explained in Fig.1 [21]. In this case, the antigen and the receptor molecule have complementary shapes and so they can bind together with a certain binding strength, measured as affinity. After a binding between an antibody's paratope and an antigen's epitope, an antigen-antibody-complex is formed which results in deactivation of the antigen. The B-cell is already mature after creation in the bone marrow, whereas the T-cell first becomes mature in the thymus. A T-cell becomes mature if and only if it does not have receptors that bind with molecules that represent self cells. Consequently, it is very important that the T-cell can differentiate between self and non-self cells [24].

The AIS as defined by de Castro and Timmis [25] are: "Adaptive systems inspired by theoretical immunology and observed immune functions, principles and models, which are applied to problem solving". The AIS are one of many types of algorithms inspired by biological systems, such as neural networks, evolutionary algorithms and swarm intelligence. There are many different types of algorithms within AIS and research to date has focused primarily on the theories of immune networks, clonal selection and negative selection. These theories have been abstracted into various algorithms and applied to a wide variety of application areas such as anomaly detection, pattern recognition, learning, and robotics [26].

The negative selection algorithm (NSA) introduced by Forrest *et al*. in 1994 [27] inspired by the mature T-cells of the natural immune system; which are self-tolerant, that is mature T-cells have the ability to distinguish between self cells and foreign/non-self cells. The NSA uses a set of self patterns to train a set of artificial lymphocytes (ALCs) to be self-tolerant. These ALCs are applied as detectors to classify new data as self or non-self [25]. In NSA, any generated ALC is added to the self-tolerant set if the calculated affinity between the ALC and all self patterns is higher than a specified affinity threshold. The algorithm is summarized as in Alg.1.

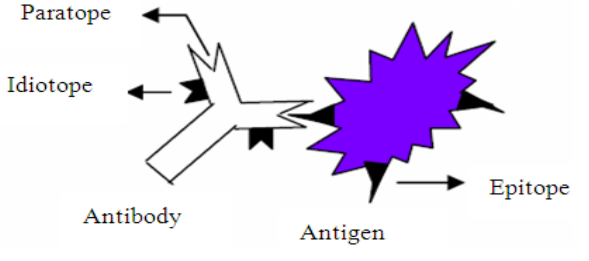

Fig. 1. Antibody-antigen complex

Alg.1. Negative selection algorithm

Create an empty set of self-tolerant ALCs as C;
Determine the training set of self patterns as Z_S;
Repeat
  Randomly generate an ALC, c_i;
  Calculate the affinity between c_i and each pattern in Z_S;
    If the calculated affinity with at least one pattern in Z_S is lower than the affinity threshold, then *reject* c_i;
    Otherwise *add* c_i to set C;
Until size of C equals some predefined number;

3 Particle Swarm optimization

The particle swarm optimization (PSO) algorithm was originally designed by Kennedy and Eberhart in 1995 [28]. The idea was inspired by the social behavior of flocking organisms. It belongs to the broad class of stochastic optimization algorithms that may be used to find optimal (or near optimal) solutions to numerical and qualitative problems. PSO uses a population (swarm) of individuals (particles) to probe promising regions of the search space. Each particle moves in the search space with a velocity that is dynamically adjusted according to its own flying experience and its companions flying experience and retains the best position it ever encountered in memory. The best position ever encountered by all particles of the swarm is also communicated to all particles [29].

The popular form of the PSO algorithm is defined as:

$$v_{id}(t+1) = w * v_{id}(t) + c_1 r_1 (pbest_{id}(t) - x_{id}(t)) + c_2 r_2 (gbest_d(t) - x_{id}(t)) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (2)$$

where v_{id} is the velocity of particle i along dimension d, x_{id} is the position of particle i in d, c_1 is a weight applied to the cognitive learning portion, and c_2 is a similar weight applied to the influence of the social learning portion. r_1 and r_2 are separately generated random number in the range of zero and one. $pbest_{id}$ is the previous best location of particle i. $gbest_d$ is the best location found by the entire population. w is the inertia weight. Velocity values must be within a range defined by two parameters $-v_{max}$ and v_{max}. The PSO with the inertia weight in the range (0.9, 1.2) on average have a better performance. To get a better searching pattern between global exploration and local exploitation, researchers recommended decreasing w over time from a maximal value w_{max} to a minimal value w_{min} linearly [30, 31].

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} * t \quad (3)$$

where, t_{max} is the maximum number of iterations allowed and t is the current iteration number.

4 Materials and Methods

4.1 EEG Data

The present work used the publicly available EEG data described by Andrzejak *et al.* [32]. In this dataset, all EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. The analog data were digitized at 173.61 samples per second by a 12 bit A/D resolution with band-pass filter settings of 0.53-40 Hz (12 dB/oct). The complete dataset contains five different sets (denoted A-E), each containing 100 single channel EEG segments of 23.6 sec. duration. These signals were selected and cut out from continuous multi-channel EEG recordings after removing artifacts caused due to eye movements, scalp muscular activity and power line interference.

Signals in sets A and B have been recorded from five healthy volunteers through external surface electrodes using the international 10–20 electrode placement scheme. The volunteers were relaxed in an awake state with eyes open (set A) and closed (set B). The EEG archive of presurgical diagnosis was used to originate sets C, D and E. EEG recordings taken from five patients using intracranial electrodes were selected. All patients had achieved complete seizure control after resection of one of the hippocampal formations, which was therefore correctly diagnosed to be the epileptogenic zone. Segments in sets C and D were measured in seizure free intervals from within the epileptogenic zone and opposite the epileptogenic zone of the brain, respectively. Set E were obtained from within the epileptogenic zone during seizure activity. Fig.2 shows typical EEG segments, one from each category.

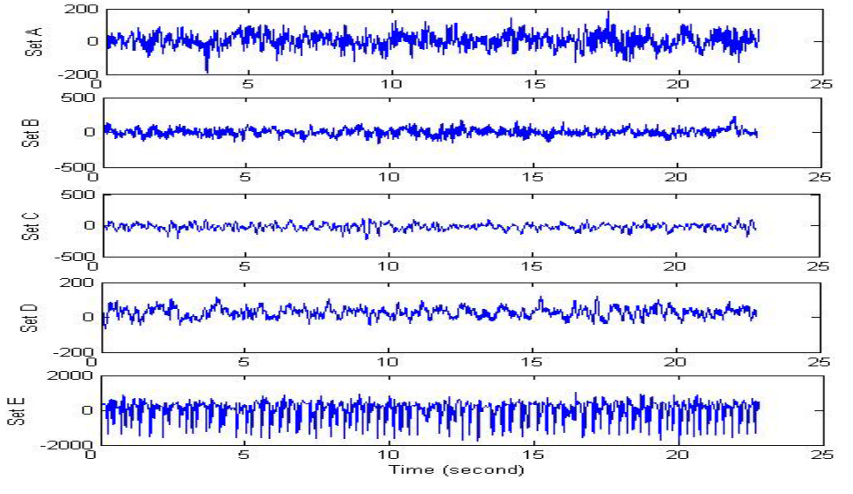

Fig. 2. Samples of five different sets of EEG data

4.2 Discrete Wavelet Transform: Feature Extraction

Discrete wavelet transform (DWT) has been particularly successful in the area of epileptic seizure detection due to its ability to capture transient features and localize them in both time and frequency domains accurately [9]. The DWT analyzes the signal $s(n)$ at different frequency bands by decomposing the signal into an approximation and detail information using two sets of functions known as scaling functions and wavelet functions, which are associated with low-pass $g(n)$ and high-pass $h(n)$ filters, respectively. Fig.3 shows the decomposition process of DWT.

When the DWT is used to analyze the signals, two important aspects should be considered: the number of decomposition levels and the type of wavelet. The decomposition levels number is selected based on the dominant frequency components of the signal. According to Subasi [10], the levels are selected such that those parts of the signal that correlate well with the frequencies required for the signal classification are retained in the wavelet coefficients. Therefore, level 4 wavelet decomposition was selected in the present study. Accordingly, the EEG signals have been decomposed into the details D1-D4 and one final approximation, A4. Table 1 shows the ranges of the various frequency bands of EEG data used. The smoothing feature of the Daubechies wavelet of order 2 (db2) made it more suitable to detect changes of EEG signals [12]. In this research, the db2 has been used to compute the wavelet coefficients of the EEG signals.

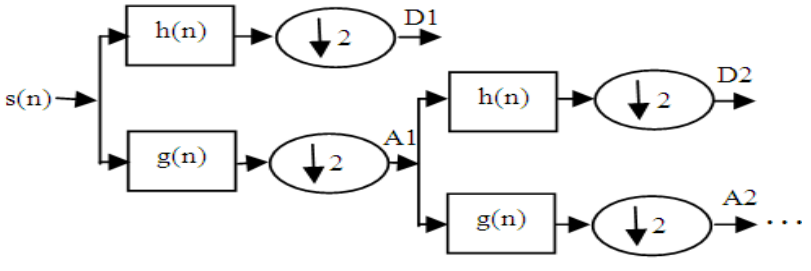

Fig. 3. Sub-band decomposition of DWT

Table 1. different decomposition levels Frequencies of db2 wavelet for the EEG dataset

Decomposed signal	Frequency range (Hz)
D1	43.4-86.8
D2	21.7-43.4
D3	10.8-21.7
D4	5.4-10.8
A4	0.0-05.4

The computed coefficients of discrete wavelet provide a compact representation that shows the energy distribution of the signal in time and frequency. In order to further decrease dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients are used [12]. The following statistical features were used

to represent the time-frequency distribution of the EEG signals: Maximum, Minimum, Mean, and Standard deviation of the wavelet coefficients in each sub-band.

4.3 Adaptive Particle Swarm Negative Selection: EEG Classification

Adaptive particle swarm negative selection (APSNS) algorithm is a hybrid method based on PSO and negative selection algorithms. It has been introduced in this research to classify EEG signals for diagnosis purposes. In APSNS, all patterns are represented in space as real-valued vector and Euclidean distance is used as the affinity measure. Each ALC has its own affinity threshold, *r*, to determine the matching with a non-self pattern. The steps of the algorithm are summarized in Alg.2.

An adaptive negative selection algorithm is proposed to evolve a set of ALCs to be self-tolerant, meaning they have the ability not to match any self pattern. Therefore, self patterns are used as the training set. The algorithm determines for each ALC its affinity threshold, *r*. To guarantee no overlap with the self, the *r* of the ALC is set to the closest self pattern. However if the value of *r* is equal to zero, the ALC is replaced by a new one. Otherwise, the ALC is considered self-tolerant, and it will classify any pattern as non-self if the distance between them is less than *r*.

Generally, self-tolerant ALCs do not cover all non-self space. In fact, only some of the non-self will be detected and only some of these ALCs will detect non-self patterns. Therefore, the PSO algorithm is used to promote the ALCs in self-tolerant set to new status called memory have a high ability to separate the non-self patterns from the self. In each run, PSO produces one optimal ALC which is added to the set of memory ALCs only if it detects new patterns in non-self training set.

The objectives of the PSO are to take the ALCs away from self patterns towards non-self space and to maintain diversity and generality among the ALCs. Hence, PSO needs to maximize: (1) the value of *r* for the evolved ALC, and (2) the distance between the new ALC and the ALCs in memory set. This guarantees the lowest average overlap between the memory ALCs and forces greater coverage of non-self space. To evaluate the quality of an ALC, c_i, fitness of i^{th} particle is calculated using the following function:

$$FitF(M, c_i) = \frac{1}{2}(r + DivF(M, c_i)) \tag{4}$$

where M is the set of memory ALCs, c_i is the ALC which the fitness must be calculated, and

$$DivF(M, c_i) = \frac{\sum_{j=1}^{|M|} Ed(m_j, c_i)}{|M|} \tag{5}$$

where m_j is the j^{th} ALC in the memory set and *Ed* returns Euclidean distance.

Alg.2. Adaptive particle swarm negative selection algorithm

1. Create an empty set of memory ALCs, *M*
2. Repeat
  (a) Initialize *N* particles, *X*
  (b) For t= 1 to t_{max}
    (i) Send *X* to adaptive negative selection to create self-tolerant ALCs set, *C*
    (ii) For each particle c_i
      (1) Calculate the fitness using Eq. (4)
      (2) Find personal best solution, *pbest*
    (iii) Find the global best solution, *gbest*
    (iv) Update each particle using Eq. (1) and (2)
  (c) If *gbest* detects new patterns then add it to the set *M*
3. Until non-self is covered or a maximum number of iterations is reached

5 Experimental Results

5.1 Performance Measures

In medical diagnosis tasks, the common performance measures are sensitivity, specificity and classification accuracy. The sensitivity is defined by the percentage of correctly detected epileptic EEG patterns to the total number of patterns in the epileptic EEG. On the other hand, specificity is defined by percentage of correctly detected normal EEG patterns to the total number of patterns in the normal EEG. Finally, the percentage of all correctly classified patterns to the total number of patterns in both normal and seizure EEG dataset represent the accuracy. Formally, the performance of a diagnostic system is measured as:

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{7}$$

where TP, TN, FP and FN denote true positives, true negatives, false positives and false negatives respectively.

$$Accuracy\,(Z_T) = \frac{\sum_{i=1}^{|Z_T|} Classify\,(z_{Ti})}{|Z_T|} \tag{8}$$

where, Z_T is the testing set, z_{Ti} is a pattern in Z_T to be classified, and *Classify* (z_{Ti}) returns one if z_{Ti} classified correctly by the algorithm and zero if not.

5.2 Results and Discussion

The APSNS algorithm was evaluated on the EEG data in order to investigate its performance in detecting the epileptic seizures. In the present study, the sets A and E were selected of the complete dataset to represent the normal and epileptic classes respectively. In each set of EEG data, there are 100 EEG signals of 4096 samples. Each signal is further divided by a rectangular window composed of 256 samples. Hence, the dataset was formed of 3200 patterns, i.e., each class has 1600 patterns. The DWT coefficients at the fourth level (D1-D3, D4 and A4) were computed for each pattern. The statistical features that were calculated over the set of wavelet coefficients reduced the dimensionality of feature vector to 20.

In machine learning field, it is common to partition the dataset into two separate sets: a training set and a testing set. Additionally, k-fold cross validation is often used by the researchers to evaluate the behavior of the algorithm in the bias associated with the random sampling of the training data. In this research, the EEG dataset (sets A and E) was randomly divided into training-testing as 50-50%, 60-40%, and with 10-fold cross validation. The class distribution of the patterns in the training and testing sets are summarized in Table 2.

Table 2. Class distribution of the patterns in the training and testing EEG datasets

Training-testing dataset partitions (%)		Class		Total
		Normal	Epileptic	
50-50	Training set	800	800	1600
	Testing set	800	800	1600
60-40	Training set	960	960	1920
	Testing set	640	640	1280
10-fold cross validation	Training set	1440	1440	2880
	Testing set	160	160	320

Ten particles (N=10) were trained for 200 iterations (t_{max}=200) to create the ALCs of the memory set. The values of other parameters of APSNS are the following: v_{max}=0.05, c_1=2.0, c_2=2.0, w_{max}=0.9, w_{min}=0.4. Consequentially, the ability of the generated memory ALCs is tested in order to assess effectiveness of the proposed method. Table 3 presents the results achieved by APSNS algorithm on the testing set with respect to sensitivity, specificity and accuracy in terms of average (Avg) and standard deviation (SD) of 10 runs. As it is seen from Table 3, the APSNS classified the EEG signals of training-test datasets partitions: 50-50%, 60-40%, and 10-fold cross validation with the accuracies of 99.44%, 99.60%, and 99.66% respectively. The results show good performance and stable behavior of the proposed method in recognizing epileptic and normal activities in the brain.

A comparison of the proposed algorithm with previous studies in the literature is shown in Table 4. Only the studies that used the same EEG dataset with the sets A and E are considered. Besides, all results illustrated in Table 4 are according to same training-test dataset partition and in terms of classification accuracy. The comparison proves the competitiveness of the APSNS algorithm for the epileptic seizures diagnosis in EEG signals.

Table 3. The values of Average, and SD for sensitivity, specificity, and accuracy of APSNS algorithm on EEG signals

Training-testing dataset partitions (%)	Performance measures (%)			
		Sensitivity	Specificity	Accuracy
50-50	Avg	99.69	99.19	99.44
	SD	0.21	0.55	0.23
60-40	Avg	99.73	99.47	99.60
	SD	0.28	0.45	0.26
10-fold cross validation	Avg	99.63	99.69	99.66
	SD	0.79	0.67	0.45

Table 4. Comparison of classification accuracy of the APSNS algorithm on EEG signals with methods in the literature

Study	Accuracy (%)	
	Previous study	This study
Kannathal *et al.* [13]	92.22	99.60
Polat and Güneş [18]	98.72	99.66
Subasi [4]	94.50	99.60
Polat and Güneş [20]	99.81	99.44
Chandaka *et al.* [17]	95.96	99.44
Übeyli [3]	99.56	99.44
Kumar *et al*. [11]	99.75	99.60
Wang *et al*. [33]	99.50	99.66
Nicolaou and Georgiou [16]	93.55	99.60

6 Conclusion

The present study introduced a hybrid detection system for automatic diagnosis of epileptic seizures in EEG signals. In this system, the diagnosis process is performed in two stages: feature extraction using discrete wavelet transform and decision maker using adaptive particle swarm negative selection. The ability of the proposed method has been evaluated on EEG dataset that have healthy and seizure signals. The results reveal that the APSNS shows promising performance for EEG signals discrimination compared to other methods in the literature. The proposed system could be an efficient tool to assist the experts by facilitating analysis of a patient's information and reducing the time and effort required to make accurate decisions on their patients.

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