A Hybrid Grasshopper Optimization Algorithm and Nonparallel Support Vector Machines For Epileptic Seizure Classification

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***Abstract*—Electroencephalography (EEG) signal are significant for automatic classification and detection of epileptic seizures. This paper introduces a hybrid classification approach based on nonparallel support vector machine (NPSVM) and grasshopper optimization algorithm (GOA) for epileptic seizure detection in EEG signal termed GOA-NPSVM approach. Furthermore, the discrete wavelet transform (DWT) was used to decompose the EEG signal and hence the extracted features were employed to train and test the NPSVM with radial basis function (RBF). To evaluate the performance of the proposed approach, five well-known algorithms such as genetic algorithm (GA) with NPSVM (GA-NPSVM), particle swarm optimization (PSO) with NPSVM (PSO-NPSVM), NPSVM, traditional support vector machine (SVM) and twin support vector machine (TWSVM) using RBF have been compared. Therefore, the experimental results revealed that the proposed GOA-NPSVM approach is able to enhance the diagnosis of epilepsy (normal versus epileptic) with accuracy 100%.**

Keywords*—*Electroencephalogram; Classification; Epilepsy; Discrete wavelet transform; Nonparallel support vector machine; Grasshopper optimization algorithm.

I. INTRODUCTION

Seizures prediction is a major challenging task due to the little knowledge about the seizure onset mechanism [2]. However, the brain activities are keeping under observation through EEG signals to diagnose and predict epileptic seizures clinically [3]. Hence, developing an efficient technique based on human signals for automatic diseases detection and prediction is an ongoing work [4], [5]. The process of recording the electrical activity called Electroencephalography (EEG) [6] signals with several electrodes are used at the scalp which including a lot of significant information including the numerous physiological processes to conclude the brain disease, such as epilepsy [7]. Two cases of abnormal activities called interictal (seizure free) and ictal (seizure) are detected from EEG signals of epileptic patient [8]–[11]. According to the large amount of EEG data contained in the long-term EEG recording of the patient with epilepsy, the detection of epileptic activity is a very difficult task and required a detailed analysis of EEG data. Therefore, a computer-aided detection (CAD) is used to overcome these limitations [12].

Various algorithms for epileptic seizure detection and prediction in EEG signal have been developed such as, a genetic programming (GP) is applied for automatic feature extraction to improve both of K-nearest neighbor (KNN) performance and feature reduction has been presented by Guo et al., [13]. Also, in [14], an epileptic seizure detection approach using k-Nearest Neighbour (KNN) has been proposed. In this approach, wavelet packet coefficients is applied to extract the features. Furthermore, Supriya et al., [15], presented an approach based on the least square SVM (LS-SVM) for EEG classification. In general, support vector machines (SVMs) [16] is regarded as a supervised learning technique that analyzes data used for classification and regression analysis in the domain of machine learning and biomedical science. Recently, a nonparallel support vector machine (NPSVM) [17] regarding as a new extension of SVM is extremely based on the following; 1) much numbers of parameters and 2) the well setting of these parameters. In order to proposes a novel seizure detection in EEG signals, this paper introduces a hybrid classification approach based on Grasshopper Optimization Algorithm (GOA) [18] and NPSVM called GOA-NPSVM approach. The GOA is employed for features selection as well as optimizing the NPSVM parameters simultaneously.

The rest of this paper is drawn as; Section II presents the materials and methods used in this paper. Then, the proposed classification approach for EEG including preprocessing of EEG, extracting features, classification, and feature optimization are discussed in Section III. The results obtained from the experiments are exposed in Section IV. In Section V, the conclusion and future work are introduced.

II. METHODS AND MATERIALS

This section will introduces the benchmark dataset and methods used in this paper.

A. Dataset Description

Department of Epileptology at University of Bonn, has been presented the EEG benchmark dataset was used in this paper [19]. This benchmark dataset consists of five subsets named A, B, C, D and E, which derived from this dataset. Each subset contains 100 segments with a sampling rate of 173.6 Hz and 23.6 seconds Length as well as each segment includes N = 4097 data points. Moreover, subsets A and B consists of segments extracted from healthy volunteers where the epileptic subjects are extracted from the subsets C, D and

E. All EEG signals have the spectral bandwidth which varies from 0.5 to 85 Hz.

B. Discrete Wavelet Transforms

The wavelet transform (WT) have been proposed and is regarded as a powerful rattling time-frequency method [20]. WT used the variable window size and revealed a significant results when applied to the signals for time-frequency resolution. Discrete wavelet transform (DWT) is the most well-known wavelet transform techniques in the domain of feature extraction. In this paper, due to the nature of non-stationary EEG signals, DWT is regarding as a suitable powerful technique in biomedical science such as epileptic seizure detection. Therefore, DWT is applied here for feature extraction due to the its efficiency for discarding all redundant information by employing a set of orthogonal basis functions and the required substantially fewer computations [20]. DWT is illustrated as follows:

$$DWT(j,k) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|2^j|}} \psi(\frac{t-2^j k}{2^j}) dt \tag{1}$$

DWT is employed in this paper to decompose the EEG signals into sub-band components similar the methodology in this study [21]. High-pass and low-pass filters are applied to decompose EEG data into multi-level. In the first decomposition level, high frequency (detailed signal) and low frequency (approximated signal) are obtained. Also, the approximate signals are further decomposed into detail and approximate signals in the second decomposition level this process can continue. Then, five EEG frequency namely the delta, theta, alpha, beta, and gamma sub-bands are obtained after the four decomposition level

C. Nonparallel Support Vector Machines

Three main parameters of NPSVM [17] such as; 1) $C_i \geq 0, i = 1, ..., 4$ representing the penalty constant, 2) ε is the insensitive loss function and 3) Kernel function parameters. In general speaking, NPSVM looks for two non-parallel hyperplanes as defined in the following equation:

$$f_+(x) = b_+ + (w_+ \cdot x) = 0 \; and \; f_-(x) = b_- + (w_- \cdot x) = 0 \tag{2}$$

NPSVM formulate the problem as a two convex quadratic programming problems (QPPs) as following [23]:

1) Problem 1:

$$min_{b_+, w_+, \xi_-, \eta_+^{(*)}} \frac{1}{2}||w_+||^2 + C_1 \sum_{i=1}^{n} (\eta_i + \eta_i^*) + C_2 \sum_{j=n+1}^{n+m} \xi_j \tag{3}$$

s.t. $b_+ + (w_+ \cdot x_i) \leq \eta_i + \varepsilon, \; i = 1, \cdots, n$

$-b_+ - (w_+ \cdot x_i) \leq \eta_i^* + \varepsilon, \; i = 1, \cdots, n$

$b_+ + (w_+ \cdot x_j) \leq \xi_j - 1, \; j = n+1, \cdots, n+m$

$\eta_i^*, \eta_i \geq 0, \; i = 1, \cdots, n$

$\xi_j \geq 0, \; j = n+1, \cdots, n+m$

2) Problem 2:

$$min_{b_-, w_-, \xi_+, \eta_-^{(*)}} \frac{1}{2}||w_-||^2 + C_3 \sum_{i=n+1}^{n+m} (\eta_i + \eta_i^*) + C_4 \sum_{j=1}^{n} \xi_j \tag{4}$$

s.t. $b_- + (w_- \cdot x_i) \leq \eta_i + \varepsilon, \; i = n+1, \cdots, n+m$

$-b_- - (w_- \cdot x_i) \leq \eta_i^* + \varepsilon, \; i = n+1, \cdots, n+m$

$b_- + (w_- \cdot x_j) \leq \xi_j + -1, \; j = 1, \cdots, n$

$\eta_i^*, \eta_i \geq 0, \; i = n+1, \cdots, n+m$

$\xi_j \geq 0, \; j = 1, \cdots, n$

Where $x_i, \; i = 1, \cdots, n$ are positive inputs and $x_i, \; i = n+1, \cdots, n+m$ are negative inputs, $C_i \geq 0, \; i = 1, \cdots, 4$ are penalty parameters.

To date, in the brain-computer interface researches, the most familiar kernel function is the radial basis function (RBF) that introduced in [23] and for more details [17].

D. Grasshopper Optimization Algorithm

Among meta-heuristic techniques [22], grasshopper optimization algorithm (GOA) mimics the behaviour of grasshopper swarms is a new swarm intelligence algorithm that was presented for solving optimized problems by Mirjalili et al. [18]. The search agents in the exploration phase are promoted to move in the search space for exploring various regions. In contrast, in the exploitation phase to enhance the current solutions, the search agents move locally. Mathematically, in order to simulate the GOA behavior, the following formulas are defined:

$$X_i = S_i + G_i + A_i \tag{5}$$

Where X_i defines the $i-th$ grasshopper position and S_i, G_i and A_i are represents the social interaction, gravity force and the wind advection respectively.

So, the S_i, G and A components for the number of grasshoppers N is defined in the following three Equations:

$$S_i = \sum_{j=1 \; j \neq i}^{N} s(d_{ij}) \widehat{d_{ij}} \tag{6}$$

Where d_{ij} is calculated as $d_i j = |X_j - X_i|$ to represent the distance between two grasshopper $i-th$ and $j-th$, and $\widehat{d_{ij}} = \frac{X_j - X_i}{d_i j}$ is the a unit vector from $i-th$ and $j-th$ grasshopper.

$$G_i = -g\widehat{e_g} \tag{7}$$

Where g refers to gravitational constant and $\widehat{e_g}$ represents the unity vector.

$$A_i = u\widehat{e_w} \tag{8}$$

Where u defined as a constant drift and $\widehat{e_w}$ refers to the unity vector.

In addition, substituting S, G, and A in Equation 5 will reformulated as follows:

$$X_i = \sum_{j=1\ j\neq i}^{N} s(|X_j - X_i|)\frac{X_j - X_i}{d_i j} - g\widehat{e_g} + u\widehat{e_w} \tag{9}$$

As mentioned in [18], the mathematical model presented in Equation 5 has been redefined as follows:

$$X_i^d = c\left(\sum_{j=1\ j\neq i}^{N} c\frac{ub_d - lb_d}{2} s(|X_j^d - X_i^d|)\frac{X_j - X_i}{d_i j}\right) + \widehat{T_d} \tag{10}$$

Where ub_d and lb_d is the upper limit and lower limit respectively. $\widehat{T_d}$ are the values of dimension D in the target and coefficient c is used to reduce the comfort zone.

III. The Proposed Classification Approach

This paper has been proposed a hybrid classification approach comprises of GOA and NPSVM termed GOA-NPSVM to set best values of the NPSVM parameters and selecting the optimal feature subset. In this approach each grasshopper reflects a number of accuracies (ten accuracy values) depend on cross-validation strategy. Therefore, all folds are averaged to obtain the fitness value as defined by the fitness function illustrated in Equation 11. Moreover, this approach consists of two main phases; 1) pre-processing and feature extraction, 2) feature selection and parameter optimization as illustrated in Figure 1.

$$f(g,t) = \sum_{k=1}^{N} acc_{g,t,k}/N \tag{11}$$

Where $f(g,t)$ refers to the fitness function, the number of folds selected is N and $acc_{g,t,k}$ is the accuracy resultant.

A. Feature extraction using DWT

In the pre-processing phase, five sub-band have been obtained based on DWT for each EEG subsets using four levels decomposition. Then, in feature extraction stage, five constitutive EEG sub-bands are decomposed using DWT. Therefore, five EEG bands called delta, theta, alpha, beta, and gamma are extracted used wavelet decomposition for EEG segments. The coefficients D1, D2, D3, D4 and A4 identical to 30-60 Hz, 15-30 Hz, 8-15 Hz, 4-8 Hz and 0-4 Hz respectively to extract the ten statistical useful features using DWT feature extractor.

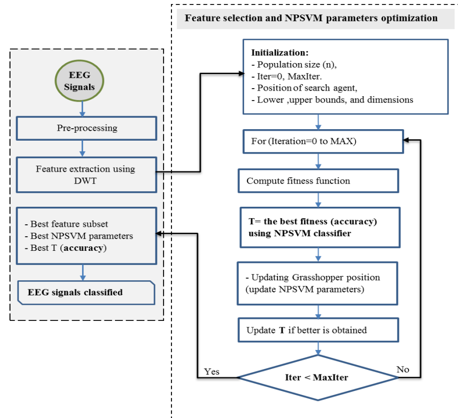

Fig. 1: The proposed GOA-NPSVM Classification approach framework.

TABLE I: Parameter setting for NPSVM and GOA.

NPSVM		GOA	
Parameter	**Value**	**Parameter**	**Value**
Kernel type	RBF	No of grasshoppers	30
Penalty C range	[1, 1000]	No of iterations	10
insensitivity parameter ε	0.1	cmax	1
Gamma γ range	[0, 100]	cmin	0.00004
Feature subset range	[0, 1]		

B. Parameters optimization and features selection using GOA

To select a significant features from EEG signals is critical task in which these features will help the NPSVM to achieve better performance. In order to realize that, GOA selects both of the optimal feature set as well as optimize the NPSVM parameters setting simultaneously. Whereas inappropriate NPSVM parameter values such as penalty C and γ for RBF need to be optimized carefully to avoid the poor classification results. Therefore, parameter optimization and feature selection was performed in two interior consecutive stages as; 1) fixed the feature set and applies NPSVM parameters optimization to obtain the highest average classification accuracy. 2) fixed the NPSVM parameters and applies feature set optimization to obtain the highest fitness value.

IV. Statistical Results and Discussion

Five well-known measures are used to evaluate the proposed approach. In addition, five different sub-signals (one approximation A4 and four details D1–D4 that correspond to delta (0-4 Hz), gamma (30-60 Hz), beta (13-30 Hz), alpha (8-13 Hz), and theta (4-8 Hz) respectively, are obtained as well as ten features are calculated similar to [10]. Also, K-fold cross-validation (CV) is used to divide a large amount of data into subsets for the training, testing and validation purpose. In this paper K is set to 10 (cross validation) and as mentioned in [24], this value is suitable for evaluating classification accuracy in biomedical signals. Table I shows the setting for NPSVM and GOA.

In order to assess the performance of the proposed approach several experiments were carried out. Table II illustrates the classification performance obtained for the proposed GOA-NPSVM approach for case 1 to case 4.

TABLE II: The experimental results obtained for the proposed GOA-NPSVM approach.

Cases	Performance Evaluation Measures				
	Acc (%)	Sens (%)	Spec (%)	Prec (%)	F (%)
Set A vs Set E	100	100	100	100	100
Set B vs Set E	100	100	100	100	100
Set C vs Set E	99.761	100	99.519	99.529	99.764
Set D vs Set E	98.93	100	97.735	98.015	98.998

Convergence curves illustrates the relation between the number of optimization iterations and the fitness value in this paper the classification accuracy. Figures 2a through 2d show the convergence of GOA-NPSVM for all the four cases respectively over all iterations. As can be observed, when the number of iteration was increased, the highest fitness value (best accuracy) was achieved.

Figures 3a to 3d demonstrates the obtained classification accuracy for the proposed GOA-NPSVM against those methods for RBF kernel function for case 1 to case 4 respectively. It is noticed from Figure 3a in case 1 that accuracy achieved by PSO-NPSVM is 98.713%, 99.761% using GA-NPSVM, 94.643% using SVM, 95.44% using TWSVM, 97.602% using NPSVM, while it has increased to 100% using GOA-NPSVM. For case 2 in Figure 3b, accuracy achieved with PSO-NPSVM is 98.075%, 98.857% using GA-NPSVM, 89.896% using SVM, 93.98% using TWSVM, 96.057% using NPSVM, while it has increased to 100% using GOA-NPSVM. Also, for case 3 in Figure 3c, accuracy achieved with PSO-NPSVM is 97.643%, 98.464% using GA-NPSVM, 86.594% using SVM, 91.21% using TWSVM, 92.196% using NPSVM, while it has increased to 99.761% using GOA-NPSVM. Finally, for case 4 in Figure 3d, accuracy achieved PSO-NPSVM is 96.083%, 98.031% using GA-NPSVM, 85% using SVM, 86.516% using TWSVM, 89.609% using NPSVM, while it has increased to 98.93% using GOA-NPSVM. Eventually, the proposed GOA-NPSVM achieved the highest results as illustrated in the experimental results.

V. Conclusion

This paper develops a hybrid approach called GOA-NPSVM based on GOA, and a powerful classifier referred to as NPSVM with DWT for automatic seizure detection into normal/epileptic in EEG signals. DWT is applied to decompose the EEG signals into different sub-bands then ten features from each sub-band have been extracted. To investigate the performance of the proposed approach, five well-known algorithms namely GA-NPSVM, PSO-NPSVM, NPSVM, TWSVM and the original SVM classification algorithms with RBF kernel function have been compared. According to the results, the proposed approach achieved 100% classification accuracies for case1 and case 2, 99.761% for case 3 as well as 98.93% for case 4. The obtained experimental results revealed that the proposed GOA-NPSVM approach has been achieved a significant classification accuracy for seizure detection. As future work, the proposed approach can be applied to a wide range of pattern recognition problems. Also, hybridization of machine learning classifiers is a line of research under investigation and a worthwhile research point.

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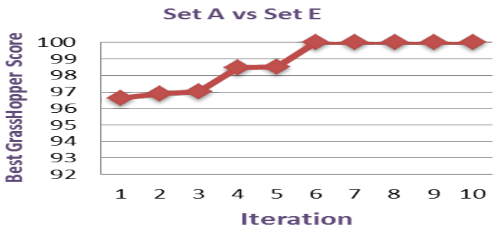
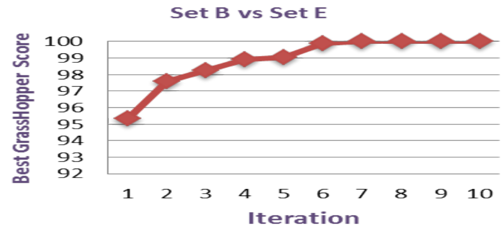
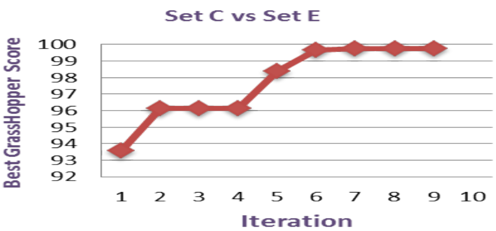


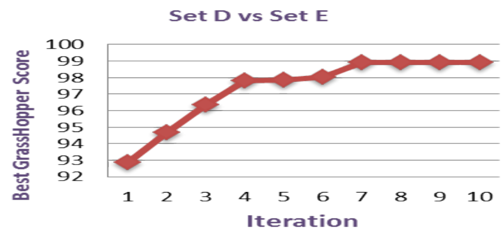
(a) Case 1 convergence.



(b) Case 2 convergence.

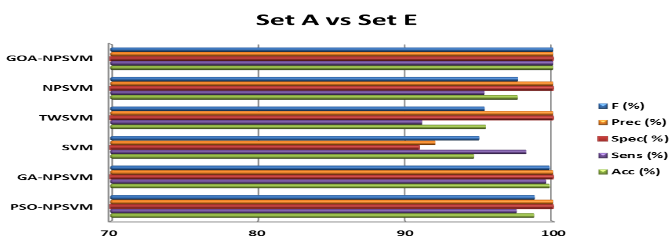


(c) Case 3 convergence.

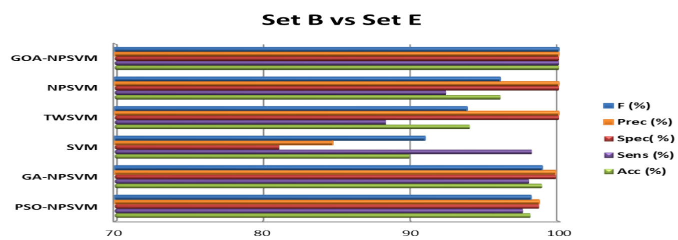


(d) Case 4 convergence.

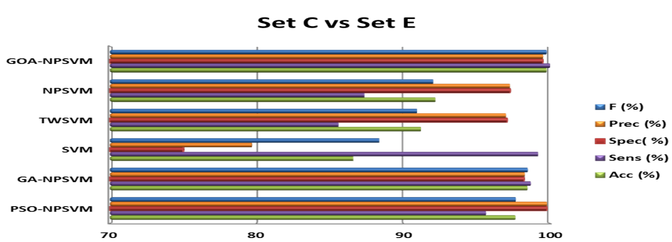
Fig. 2: The proposed GOA-NPSVM convergence curve.



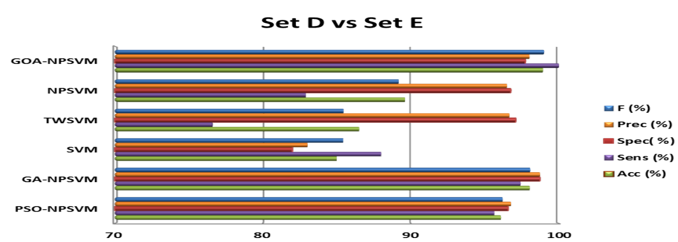
(a) Case 1 results.



(b) Case 2 results.



(c) Case 3 results.



(d) Case 4 results.

Fig. 3: The obtained comparative performance results.

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