A Hybrid EEG Signals Classification Approach Based on GWO Enhanced SVMs for Epileptic Detection

Asmaa Hamad Elsaied

Master Student, Faculty of Computers and Information, Mina University

Workshop: INTELLEGENT SYSTEMS AND APPLICATIONS.

http://www.egyptscience.net
Agenda

- Introduction
- Related Work
- Materials and Methods
  - EEG Data Acquisition
  - Discrete wavelet transforms (DWT)
  - Gray Wolf Optimization (GWO)
  - Support Vector Machine (SVM)
- Proposed Classification GWO-SVM Approach
- Experimental Results and Discussion
- Conclusion and future work
Epilepsy is one of the most common chronic neurological disorders of the brain that affect millions of the world’s populations.

It is characterized by recurrent seizures, which are physical reactions to sudden, usually brief, excessive electrical discharges in a group of brain cells. Hence, seizure identification has great importance in clinical therapy of epileptic patients.

According to WWW, around 50 million people worldwide has epilepsy and is suffering with this recurring and unpredictable seizure disorder. Therefore, diagnosing and predicting epileptic seizures precisely appear to be particularly important, which is able to fetch more effective prevention and treatment for the patients.
Electroencephalogram (EEG) is most commonly used in epilepsy detection since it includes precious physiological information of the brain.

The EEG signal is usually used for the purpose of recording the electrical activities of the brain signal that typically arises in the human brain.

The recording of the electrical activity is basically done by placing electrodes on the scalp, which measures the voltage fluctuations in the brain.
Introduction (cont’d).

- EEG contains lots of worthy information relating to the numerous physiological states of the brain and thus is a very useful tool for understanding the brain disease, such as epilepsy.

- EEG signals of epileptic patients exhibit two states of abnormal activities namely interictal or seizure free (in-between epileptic seizures) and ictal (in the course of an epileptic seizure).
The EEG signals are commonly decomposed into five EEG sub-bands:

- delta, theta, alpha, beta and gamma.

- GAMMA: Active Thought
- BETA: Alert, Working
- ALPHA: Relaxed, Reflective
- THETA: Drowsy, Meditative
- DELTA: Sleepy, Dreaming
Frequency range and amplitude for each type of waves

<table>
<thead>
<tr>
<th>Wave</th>
<th>Frequency range</th>
<th>Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delta band</td>
<td>0.5 – 4 Hz</td>
<td>High</td>
</tr>
<tr>
<td>Theta band</td>
<td>4 – 8 Hz</td>
<td>Low-medium</td>
</tr>
<tr>
<td>Alpha band</td>
<td>8 – 15 Hz</td>
<td>Low</td>
</tr>
<tr>
<td>Beta band</td>
<td>15 – 30 Hz</td>
<td>Very low</td>
</tr>
<tr>
<td>Gamma band</td>
<td>30 – 60 Hz</td>
<td>Smallest</td>
</tr>
</tbody>
</table>
## Related Work

<table>
<thead>
<tr>
<th>Ref.</th>
<th>Year</th>
<th>methods</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>[8]</td>
<td>2011</td>
<td>Wavelet packet entropy with KNN</td>
<td>proposed a hierarchical epileptic seizure detection approach. In this approach, the original EEG signals performed by wavelet packet coefficients and using basis-based wavelet packet entropy method to extract feature. In the training stage, hybrid the k-Nearest Neighbour (KNN) with the cross-validation (CV) methods are utilized, on the other hand, the top-ranked discriminative rules are used in the testing stage to compute the classification accuracy and rejection rate.</td>
</tr>
<tr>
<td>[9]</td>
<td>2012</td>
<td>Permutation Entropy with SVM</td>
<td>proposed automated epileptic seizure detection that used permutation entropy (PE) as a feature. SVM is used to classify segments of normal and epileptic EEG based on PE values. The proposed system uses the fact that the EEG during epileptic seizures is described by PE than normal EEG.</td>
</tr>
<tr>
<td>[10]</td>
<td>2010</td>
<td>Multiwavelet transform based approximate entropy feature with artificial neural networks</td>
<td>presented an automatic epileptic seizure detection method, which uses approximately entropy features derived from multiwavelet transform. Artificial neural network (ANN) is combined with entropy to classify the EEG signals regarding the existence or absence of a seizure.</td>
</tr>
<tr>
<td>[11]</td>
<td>2011</td>
<td>clustering technique-based least square support vector machine (CT-LS-SVM)</td>
<td>presented a clustering-based least square support vector machine approach for the classification of EEG signals. The proposed approach comprises the following two stages. In the first stage, clustering technique (CT) has been used to extract representative features of EEG data. In the second stage, least square support vector machine (LS-SVM) is applied to the extracted features to classify EEG signals.</td>
</tr>
<tr>
<td>[12]</td>
<td>2014</td>
<td>DWT based approximate entropy (ApEn) with Artificial neural network and SVM</td>
<td>authors developed a scheme for detecting epileptic seizures from EEG data recorded from epileptic patients and normal subjects. This scheme is based on DWT analysis and approximate entropy (ApEn) of EEG signals. SVM and (feedforward backpropagation neural network) FBNN are used for classification purpose.</td>
</tr>
</tbody>
</table>

*fewer previous research on the classification methods in EEG signals*
## Materials and Methods

### EEG Data Sets

- The experimental data used is publicly available
  - Bonn data set “Klinik für Epileptologie, Universität Bonn”.
- The dataset includes five different sets:

<table>
<thead>
<tr>
<th>Set</th>
<th>Details</th>
</tr>
</thead>
</table>
| A   | 5 awake healthy subjects with eyes open  
     | Surface EEG recording |
| B   | 5 awake healthy subjects with eyes closed  
     | Surface EEG recording |
| C   | Inter-ictal EEG from five epileptic patients  
     | Intracranial depth electrodes from hippocampal formation of opposite hemisphere the brain |
| D   | Inter-ictal EEG from five epileptic patients  
     | Intracranial depth electrodes from epileptogenic zone. |
| E   | Ictal EEG from five epileptic patients  
     | Depth and strip electrodes |
EEG Data Samples

- EEG signals of each dataset.
EEG Data Sets Characteristics

- Each set contains 100 single channel of 23.6s duration each.
- All EEG signals are recorded at
  - sampling rate of 173.61 Hz
  - 128-channel amplifier system with an average common reference
  - Band-pass filtered at 0.53–40 Hz.
- All channels are artifact-free
Discrete wavelet transforms (DWT)

A wavelet is a short wave, which has its energy intensified in time to give a tool for the analysis of transient, non-stationary signals or time-varying phenomena.

Wavelet transform method has been used to extract the individual EEG sub-bands and reconstruct the information accurately because the wavelet transform has the advantages of:

- time-frequency localization,
- multi-rate filtering, and scale-space analysis.
Materials and Methods (cont’d).

- **Gray Wolf Optimization (GWO)**
  - Grey wolf optimizer (GWO) is a new meta-heuristic technique.
  - In nature, The GWO algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves.
  - There are four types of grey wolves which are alpha, beta, delta and omega. Those four types can be used for simulating the leadership hierarchy.
Materials and Methods (cont’d).

Gray Wolf Optimization (GWO)

- Alpha is the best solution (Wolf that has best fitness), beta is the second best wolf, delta is the third best wolf. The omega wolves follow them these three wolves.

- The updating for the grey wolves positions is as in the following equation:

\[
\bar{X}(t + 1) = \frac{X_1 + X_2 + X_3}{3}
\]
**Support Vector Machine (SVM)**

- SVM is a supervised learning method, used for binary classification. It was introduced by Vladimir Vapnik and colleagues. The earliest mention was in, but the first main paper seems to be in 1995.

- SVM is a powerful classifier in the field of biomedical science for the detection of abnormalities from biomedical signals.

- SVM is an efficient classifier to classify two different sets of observations into their relevant class. It is capable of handling high-dimensional and non-linear data excellently.
Materials and Methods (cont’d).

*Support Vector Machine (SVM)*

The structural design of the SVM depends on the following: first, the regularization parameter, $C$, is used to control the trade-off between the maximization of margin and a number of misclassifications. Second, kernel functions of nonlinear SVMs are used for mapping of training data from an input space to a higher dimensional feature space. All kernel functions like linear,

![Diagram showing support vectors and margins for different values of C](image)

To date, the kernel generally used in Brain-Computer interface research was the Gaussian or radial basis function (RBF) kernel with width $\sigma$.
The Proposed Classification GWO-SVM Approach
Feature selection and SVM parameters optimization using GWO

Initialize GWO parameters:
- Population size (n), MaxIter.
- Iter=0, j=0,
- Lower and upper bounds, dominations
- Define fitness function as maximum

Randomly generate initial search space solutions (population): Each search agent position will be assigned based on the ranges of (C, σ and feature subset)

For each position of the search agent: Compute the fitness (classification accuracy) using SVM Classifier

- Optimal SVM parameters (C, σ and Feature subset)
- Best fitness (Accuracy)

Iter < MaxIter

Yes

Update the Position of the current wolf by eq: \( x(t + 1) = (x_1 + x_2 + x_3)/3 \)

SVM Parameters

- Calculate fitness of each search agent
- Update \( X_\alpha, X_\beta, \) and \( X_\delta \) positions

Set j = j+1

Set Iter = Iter+1

No

j < n

No

EEG signals classified
The Proposed Classification GWO-SVM Approach

- **Pre-processing and Feature Extraction using DWT**
  - Each EEG signal is decomposed into five constituent EEG sub-bands by discrete wavelet transform (DWT).
  
  - The EEG epochs were analyzed into various frequency bands by using fourth-order Daubechies (db4) wavelet function up to 4th-level of the decomposition. The statistical parameter like entropy, min, max, mean, median, standard deviation, variance, energy and Relative Wave Energy (RWE) were computed for feature extraction.
The Proposed Classification GWO-SVM Approach

- **Features selection and parameters optimization using GWO**
  - Better performance may be achieved by removing irrelevant and redundant data while maintaining the discriminating power of the data by feature selection.
  - Parameters setting of SVM have an important impact on its classification accuracy. Inappropriate parameter settings lead to poor classification results.
  - GWO has the potential to generate both the optimal feature subset and SVM parameters at the same time.

- The best position is **the optimal feature subset and optimal SVM parameters** which gives the highest fitness value.
The Proposed Classification GWO-SVM Approach

- **Classification**
  - the best values of SVM parameters (C, σ and feature subset) that are obtained from GWO swarm algorithms serve as input to the SVM and a training model is built to discriminate between seizure and no-seizure intervals.
  - The datasets are divided into two subsets namely training and test dataset. The training set is used to train the SVM, while the testing set is used to evaluate accuracy. This partition is done based K-fold cross-validation strategy (where k = 10).
The Proposed Classification GWO-SVM Approach

- **Fitness Function**

  - The optimization algorithm generally depends on its fitness function to obtain the best solution. In this paper, the classification accuracy is chosen as the solution qualifier through the search process. Each wolf (Search Agent) reflects a number of accuracies depend on cross-validation strategy. Moreover, each wolf reflects ten accuracy values for each fold and all accuracy values for all folds are averaged to return fitness value to the search algorithm as illustrated in the following equation.

  \[
  f(w, t) = \frac{\sum_{k=1}^{N} Acc_{w,t,k}}{N}
  \]

  - Where \( f(w, t) \) the fitness value for wolf \( w \) in iteration \( t \), \( N \) represents the number of folds selected for cross validation and \( Acc_{w,t,k} \) is the accuracy resultant.
Performance Evaluation Measurements

In this paper, the set A, B, C, and D are considered as positive class and set E is considered as the negative class respectively.

To evaluate the classification performance for different test cases in this paper, we have used five measures, which are:

1) Accuracy
2) Sensitivity
3) Specificity
4) Precision
5) F-Measure.
In this paper, the proposed technique is tested on the four different test cases as described in the following table.

<table>
<thead>
<tr>
<th>Case</th>
<th>Cases for seizure</th>
<th>Classification Problem Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>Set A vs Set E</td>
<td>Healthy Persons with eye open vs Epileptic patients during seizure activity</td>
</tr>
<tr>
<td>Case 2</td>
<td>Set B vs Set E</td>
<td>Healthy Persons with eye close vs Epileptic patients during seizure activity</td>
</tr>
<tr>
<td>Case 3</td>
<td>Set C vs Set E</td>
<td>Hippocampal seizure free vs Epileptic patients during seizure activity</td>
</tr>
<tr>
<td>Case 4</td>
<td>Set D vs Set E</td>
<td>Epileptic seizure free vs Epileptic patients during seizure activity</td>
</tr>
</tbody>
</table>
The parameter setting for the GWO algorithm is outlined in the following table. Same number of agents and same number of iterations are used for GA.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>No of wolves</td>
<td>30</td>
</tr>
<tr>
<td>No of iterations</td>
<td>10</td>
</tr>
<tr>
<td>Search domain</td>
<td>Penalty C range [1, 1000]</td>
</tr>
<tr>
<td></td>
<td>Kernel function parameters σ range [0, 100]</td>
</tr>
<tr>
<td></td>
<td>Feature subset range [0, 1]</td>
</tr>
</tbody>
</table>
Following figures show classification results obtained via applying the proposed GWO-SVM against traditional SVM classification approach and Genetic Algorithm (GA) with SVM for RBF kernel function for case 1 to case 4 respectively.
Comparative performance measures of case 1.
Experimental Results and Discussion

- Comparative performance measures of case 2.

Set B vs Set E

- Acc (%)
- Sens (%)
- Spec (%) 
- Prec (%) 
- F (%)

- SVM
- GA-SVM
- GWO-SVM
Experimental Results and Discussion

- Comparative performance measures of case 3.

![Graph comparing performance measures of Set C vs Set E](chart.png)
Experimental Results and Discussion

- Comparative performance measures of case 4.
As can be seen, the proposed GWO-SVM owns the highest results. Also GA-SVM is in second place and SVM is the worst one.
Conclusion

- In this paper, DWT is used for analysis of EEG to detect epilepsy. EEG signals are decomposed into different sub-bands through DWT to obtain ten features from each sub-band to classify EEG signal.

- This paper develops an approach using GWO for feature selection with SVM parameters optimization and the SVM classifier for automatic seizure detection in EEG signals.

- The 100% classification accuracies are obtained using GWO-SVM for case 1, 99.577% for case 2, 99.472% for case 3 and 99.232% for case 4.

- These results illustrate the effectiveness of using GWO and SVM classifier for seizure detection in EEG signals.

- Also, experimental results indicated that the proposed GWO-SVMs approach outperformed GA- SVM and the typical SVMs classification algorithm for RBF kernel function.
Future work

- As future work, we plan to conduct experiments with more robust classifiers for further investigation in this domain.
- It will be needed on the future work to evaluate many swarm optimization approaches versions and compare them with each other such as firefly, ant lion, social spider, cat, fish swarm ...etc.
- Also, it will be needed on the future work to use these optimization approaches for other purposes.
Thanks and Acknowledgement