Dingle’s Model-based EEG Peak Detection using a Rule-based Classifier

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Abstract

The employment of peak detection algorithm is prominent in several clinical applications such as diagnosis and treatment of epilepsy patients, assisting to determine patient syndrome, and guiding paralyzed patients to manage some devices. In this study, the performances of four different peak models of time domain approach which are Dumpala’s, Acir’s, Liu’s, and Dingle’s peak models are evaluated for electroencephalogram (EEG) signal peak detection algorithm. The algorithm is developed into three stages: peak candidate detection, feature extraction, and classification. Rule-based classifier with an estimation technique based on particle swarm optimization (PSO) is employed in the classification stage. The evaluation result shows that the best peak model is Dingle’s peak model with the highest test performance is 88.78%.

Keywords: Electroencephalogram (EEG) signal, Peak detection, Rule-based classifier, Particle swarm optimization (PSO), Biomedical applications.

1. Introduction

Electroencephalogram (EEG) signal is a microvolt electrical brain signal that is used for recording the brain activity of human behaviors. The most traceable signal pattern exists in the EEG signal is a peak point which signifies the brain activity on particular events or stimulus. The known peak point through the response of the brain can be translated into commands, for example, wheelchair movement.

Peak detection algorithm can be categorized based on four approaches which are time [1], frequency [2], time-frequency [3], and nonlinear [4] domains. In the time domain approach, the peaks are analyzed with respect to time. In frequency domain approach, the peaks are analyzed with respect to frequency. In time-frequency domain approach, the peaks are analyzed in both time and frequency domain. In nonlinear approach, some statistical parameters of the peaks are analyzed.

Several algorithms [1, 3, 5, 6] are designed by considering different peak models in the time domain approach which are Dumpala’s [5], Acir’s [6], Liu’s [3], and Dingle’s [1] peak models. Therefore, this study focuses on the employment on the different peak models into the proposed peak detection algorithm. The performances on the different peak models are evaluated and the best peak model is presented.

2. Methodology

Figure 1 shows the algorithm of the EEG signal peak detection using rule-based classifier. In the first stage, the detection of peak candidates is performed to differentiate

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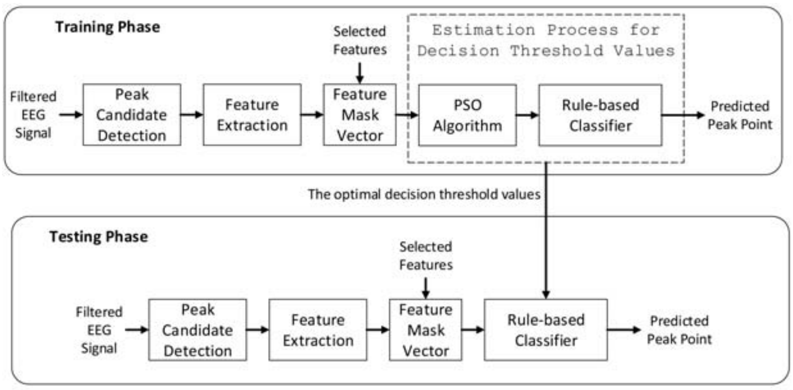

Fig. 1. The EEG signal peak detection algorithm

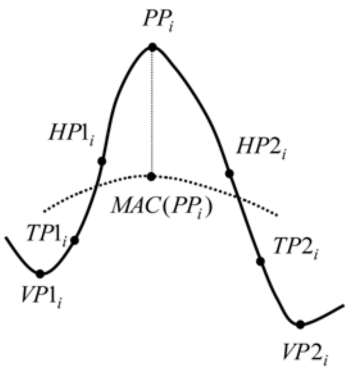

Fig. 2. Peak model parameters

Table 1. List of Different Peak Models and Sets of Feature

Peak Model	Set of Feature	Number of Features
Dumpala *et al*.	f_1, f_6, f_{11}, f_{12}	4
Acir *et al*.	$f_1, f_2, f_7, f_8, f_{13}, f_{14}$	6
Liu *et al*.	$f_1, f_2, f_3, f_4, f_6, f_9, f_{10}, f_{11}, f_{12}, f_{13}, f_{14}$	11
Dingle *et al*.	f_5, f_6, f_{11}, f_{12}	4

between a peak candidate and a non-peak point. The second stage is the extraction of peak candidate features. The selected features of all peak candidates based on different peak models are extracted in this stage. Then, the selected peak features of peak candidates act as input to the rule-based classifier. During the training, the decision threshold values are estimated to find the optimal value. The estimation process is done by using PSO algorithm. The optimal decision threshold values are then used during the testing phase. The final output of the training and testing phases is the predicted peak points and non-peak points of the identified peak candidates.

2.1. *Peak Candidate Detection*

A discrete-time signal, $x(I)$, of L points is considered in this stage. Next, the ith candidate peak point, PP_i, are identified using three-points sliding window method. Those three-points are denoted as, $x(I-1)$, $x(I)$, and $x(I+1)$ for $I = 1,2,3,\ldots,L$. A candidate peak point is identified when $x(PP_i - 1) < x(PP_i) > x(PP_i + 1)$ and two associated valley points, $VP1_i$ and $VP2_i$, are in between as shown in Fig. 2. Both valley points exist when $x(VP1_i - 1) > x(VP1_i) < x(VP1_i + 1)$ and $x(VP2_i - 1) > x(VP2_i) < x(VP2_i + 1)$. Another parameters of the ith peak location are a half point at first half wave ($HP1_i$), a half point at second half wave ($HP2_i$), a turning point at first half wave ($TP1_i$), a turning point at second half wave ($TP2_i$), and a moving average curve ($MAC(PP_i)$).

2.2. *Feature Extraction*

The peak features are calculated based on the eight parameters as shown in Fig. 2. The total peak features obtained from the existing peak models are 14 [7]. Those features are peak-to peak amplitude at the first half wave, f_1, peak-to peak amplitude at the second half wave, f_2, turning point amplitude at the first half wave, f_3, turning point amplitude at the second half wave, f_4, moving average amplitude, f_5, peak width, f_6, first half wave width, f_7, second half wave width, f_8, turning point width, f_9, half point width, f_{10}, peak slope at the first half wave, f_{11}, peak slope at the second half wave, f_{12}, 7urning point slope at the first half wave, f_{13}, and turning point slope at the second half wave, f_{14}. The list of peak models with their feature set is tabulated in Table 1.

2.3. *Rule-based Classifier*

A rule-based classifier is employed to distinguish either the candidate peak is a true peak or true non-peak from the extracted features. Each feature has a corresponding threshold value in the classification process. Given a set of features, a true peak only can be identified if all the feature values are greater or equal than the decision threshold values. The form of the rule is,

IF $f_1 \geq th_1$ AND $f_2 \geq th_2$ AND … AND $f_M \geq th_M$ THEN Candidate Peak is a True Peak

where f_i is denoted as selected peak features, th_i is the corresponding decision threshold value of f_i, M is total number of selected peak features, and true peak is predicted peak point.

Algorithm 1. PSO Algorithm

```
Initialization
while not stopping criteria do
    for each ith particle in a population do
        calculate fitness function
        update pbest and gbest
    end for
        for each particle in a population do
            update the ith particle's velocity and
            update the ith particle's position
        end for
end while
```

Table 2. Representation of Particle Position

Particle	Decision Thresholds			
	1	2	…	F
s_i^k	$x_{i,1}^k$	$x_{i,2}^k$	…	$x_{i,d}^k$

2.4. *Parameters Estimation using Particle Swarm Optimization*

Fundamentally, the PSO algorithm follows several steps as described in Algorithm 1.

In PSO, particles search for the best solution and update the position information among each other iteration to iteration. Each particle in the population consists of a vector position and vector velocity in d dimension. The position of particle i at iteration k is denoted as $s_i^k = \{x_{i,1}^k, x_{i,2}^k, x_{i,3}^k, \ldots, x_{i,d}^k\}$. To obtain the updated position of a particle, s_i^{k+1}, each particle changes its velocity as the following:

$$v_i^{k+1} = \omega v_i^k + c_1 r_1 \left(p_i^k - x_i^k\right) + c_2 r_2 \left(p_g^k - x_i^k\right) \quad (1)$$

where c_1 is a cognitive coefficient, c_2 is a social coefficient, r_1 and r_2 are random values [0,1], and ω is a decrease inertial weight calculated as follows:

$$\omega = \omega_{\max} - \left(\frac{\omega_{\max} - \omega_{\min}}{k_{\max}}\right) \times k \quad (2)$$

where $\omega_{\max}$ and $\omega_{\min}$ denote the maximum and minimum values of inertia weight, respectively, and $k_{\max}$ is the maximum iteration. Then, the particle's position is updated based on Eq. (3).

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (3)$$

Table 2 illustrates the representation of particle position. The ith particle at iteration k, $x_i(k)$, in represents continuous type of dimension, $s_i^k = \{x_{i,1}^k, x_{i,2}^k, x_{i,3}^k, \ldots, x_{i,d}^k\}$. The $d = 1,2,3,\ldots,F$ is a dth dimension. F is the total number of decision thresholds. The total number of decision thresholds is equal of the total number of peak features.

Table 3. Parameters Setting of PSO Algorithm

Parameters	Value
Decrease inertia weight, ω	0.9 ~ 0.4
Cognitive component, c_1	2
Social component, c_2	2
Random value, r_1 and r_2	Random [0,1]
Velocity vector for each particle	0
Initial pbest score for each particle	0
Initial gbest score	0
Range of search space for F=1 to F=5	[0 30]
Range of search space for F=6 to F=10	[0 781.25]
Range of search space for F=11 to F=14	[0 24.16]

3. Experimental Setup

The experiment for each peak model is conducted in 10 independent runs. In PSO, 30 particles are used. For each particle, the total number of dimensions is depending on the number of features in a feature set. The maximum iteration was set to 1000. The parameters setting of PSO algorithm are tabulated in Table 3. The fitness function used in this study is geometric mean (*Gmean*).

3.1. *Experimental Protocols*

The EEG signal recording was conducted using the g.MOBIlab portable signal acquisition system. The EEG signal was recorded from C4 channel. The EEG signal of channel CZ was used as a reference. The ground electrode was located on the forehead. The electrode was placed using the 10-20 international electrode placement system. The sampling frequency was set to 256-Hz.

The filtered EEG signal is shown in Figure 3. The total length of EEG recording is 40-second. 40 locations of true peak points are highlighted in the red circle. The next process is to prepare the training and testing data.

From the data collection, 40 true peak points have been identified. In 40-second signal there are 10280 sampling points, $x(I)$. There are only 40 peak points and the remaining of 10240 sampling points are the non-peak points. For preparing the training and testing signal, the training signal is selected from 1 to 5140 sampling points while the remaining EEG signal is used for testing signal.

4. Results and Discussions

Four peak models are employed for evaluating those peak model performances in the proposed algorithm. The training and testing performance based on those four different measures for each model is shown in Table 4.

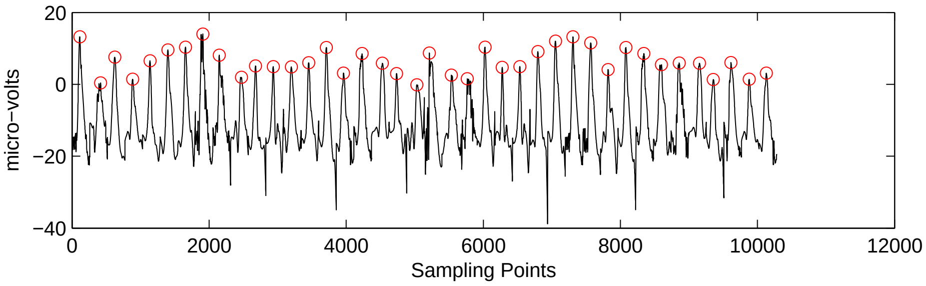

Fig. 3. Filtered EEG Signal

The testing performance for average, maximum, minimum, and STD is 81.22%, 91.83%, 74.15%, 9.13 for Dumpala *et al.*'s peak model; 68.59%, 77.43%, 54.77%, 6.97 for Acir et al.'s peak model; and 88.78%, 94.75%, 77.44%, 7.98 for Dingle *et al.*'s peak model, respectively. Compared to the test average performance of the peak models, the highest performance is obtained by Dingle *et al.*'s peak model, which is 88.78%.

For the Liu *et al.*'s peak model, will give 0% performance for training and testing phase. This result indicates that the limitation of rule-based classifier when dealing with this feature sets. During the training process on this feature sets, the particles in the PSO algorithm does not meet the optimum decision threshold values and the particles might also be trapped at local optima. Based on the preceding rule, a true peak only can be identified if all the feature values are greater or equal than the decision threshold values. So, if one of the feature values do not satisfy the decision threshold value, the classifier will decide the peak candidate as a non-peak point. When this happens to all peak candidates, *Gmean* will give 0% performance.

5. Conclusions

In this study, a rule-based classifier with PSO-based estimation technique was employed in the proposed algorithm of EEG signal peak detection. The four different peak models that consist of different feature sets are used in the feature extraction stage. The best peak model is Dingle *et al.*'s peak model with highest performance obtained is 88.78%.

Acknowledgement

This project is funded by the Ministry of Education Malaysia (UM.C/HIR/MOHE/ENG/16 Account code: D000016-16001). The first author would like to thank the Ministry of Education Malaysia for awarded him MyPhD scholarship.

Table 4. Training and Testing Performance of Peak Detection for each Peak Model

Peak Model	Training (%)				Testing (%)			
	Avg	Max	Min	STD	Avg	Max	Min	STD
Dumpala *et al.*	84.01	89.15	80.58	4.43	81.22	91.83	74.15	9.13
Acir *et al.*	74.4	80.59	67.08	3.71	68.59	77.43	54.77	6.97
Liu *et al.*	0	0	0	0	0	0	0	0
Dingle et al.	*90.98*	*94.76*	*83.66*	*5.1*	*88.78*	*94.75*	*77.44*	*7.98*

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