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REVIEW PAPER

A Review on Time-domain Peak Detection and Classification Algorithms for Electroencephalogram Signals

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ABSTRACT – In this paper, the developments in the field of EEG signals peaks detection and classification methods based on time-domain analysis have been discussed. The use of peak classification algorithm has end up the most significant approach in several applications. Generally, the peaks detection and classification algorithm is a first step in detecting any event-related for the variation of signals. A review based on the variety of peak models on their respective classification methods and applications have been investigated. In addition, this paper also discusses on the existing feature selection algorithms in the field of peaks classification.

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Introduction

Electroencephalogram (EEG) is physiological signals that contain of the non-invasively recorded electrical activity of the human brain. Specific EEG electrodes are used to acquire the signals which are placed based on the international standard protocol of the 10-20 electrode placement system [1]. The electrical activity that is arrised in EEG recording represents various signal patterns of the brain response including the celebral and human activities. The celebral activities including event-related desynchronization, mental task, slow cortical potential, and evoke potential. Example of human activities are eye blinks, horizontal eye movements, left and right movements, finger movements, and head movements.

The area of research in EEG signals, nowadays, is moving toward real-time, continous, and complex applications such as continuous monitoring critically ill patients in coma [7], brain-computer interface (BCI) [2], diagnosing stroke patients [5], human-machine interface (HMI) [3], diagnosing and monitoring epilepsy [4], and tracking eye gaze [6]. The physical impared people require personal assisstance and support to survive in their everyday life especially for communication and movements. These difficulties can be assisted by the implementation of HMI, BCI, and tracking eye gaze applications. Those particular applications, however, still require some researches for improvement in term of efficiency and reability by utilizing various advanced processing methods.

The use of peak detection and classification algorithma have end up the most significant approach in several applications for physiological signals such as the detection of epileptic EEG signals [4][8], the detection of P300 response in the EEG signals [9], photoplethysmogram (PPG) signals monitoring [10], electrocardiogram (ECG) signals monitoring [11-13], the analysis of gastric electrical activity (ECA) [14], and the detection of eye gaze direction applications [6]. Typically, in those applications consist of two major processes including peaks and event-related classifications. Means, the peaks that have been classified are used as input to classify particular event-related of EEG signals application. In epilepsy detection application, as an instance, epilepsy of EEG signals can be diagnosed whilst frequent peaks are detected during a given time interval by any immediately identifiable cause. A similar concept that is involved the both classification processes is for the horizontal eye gaze direction detection application. In this application, a classified true peak represents the horizontal eye gaze event. For example, on one occasion a true peak is identified, a subject at the particular time may have shift their eye once to the left or right direction. Another example, such as P300 response, triggers a peak in the EEG signals, as well. P300 is a kind of brain response that measured by electrodes covering the parietal lobe in the presence of visual and auditory stimuli. On the other hand, peak

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classification algorithm is also employed in PPG signals monitoring for the estimation of blood presure and glucose level. The classified peaks of PPG signals are also can be further utilised for the analysis of heart rate variability in evaluating vascular effects. For the ECG signals, peaks detection are typically used at the first stage to detect a QRS complex. The QRS complex is defined as a peak model for ECG signals including Q-peak point, R-peak point, and S-peak points. Another essential peak points in ECG signals are P-peak and T-peak points. The detection of the QRS complex is a critical part in numerous ECG signals processing system.

Note that, the peaks classification is just a first step in detecting any event-related for the variation of signals such as PPG, EEG, ECG, and ECA. The main aim of event-related detection is to determine the particular event, not the whole peaks. Therefore, the classification performances of the highlighted applications are not the performance of interest of peak detection research.

The Definition of a Peak in the EEG Signals

In general, a peak point in a signal holds the highest value located at a specific time and location. A peak point can exist in the signals as the response of brain on human activities or noise. Some examples of the response of brain on human activities that triggers a peak in the signals are epilepsy, eye blink, and the horizontal and vertical eye movements. Some researchers focused on research to define the characteristics of a peak in the EEG signals. For example, in the epileptic EEG signals point of view, Gloor [15], has defined a peak as follows: (1) a restricted triangular transient clearly distinguishable from background activity, (2) having an amplitude of at least twice that of the preceding five seconds of background activity in any channel of EEG signals, and (3) a peak signals have a duration of lower and equal than 200ms. From the response of eye blink and eye movements in the EEG signals, Iwasaki *et al.* [16], have pointed out that the amplitude of peak points are different from one subject to another and it can vary from 600μV to 1100μV. Another research work by Sovierzoski *et al.* [17], have analyzed the electrical behavior of EEG eye blink events. The research work has recorded the minimum, maximum, and the average of the peak amplitude. The minimum value of amplitude was 55μV. The maximum value of amplitude was 533μV. The average of peak amplitude was 170μV. These findings showed that the peak amplitude can vary from 55μV up to 533μV and it depends on subjects. Sometimes, the amplitude is higher than usual due to various noises. From the various definition of a peak in EEG signals, it can be understood that a peak definition is not similar to different events. Also, different subjects often do not produce the same peaks. As such, this kind of knowledge has to be considered in the further research works.

Overview of Peak Classification Algorithms

To date, variety approaches of peak classification algorithms have been introduced. The algorithms can be categorized into four main approaches based on time domain [14][18-19][20-25], frequency domain [26], time-frequency domain [22][27], and nonlinear [28]. In time domain approach, the peaks are analyzed against time. In frequency domain approach, the peaks are analyzed against 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.

In general, the algorithm for peak classification usually involves several processes which are signal pre-processing, peak candidate detection, feature extraction, and classification. Various signal pre-processing methods have been employed such as data compression [29], wavelet transform [30], Kalman filter [31], and Hilbert transform [24]. Two methods for peak candidate identification have been used which are three points sliding window method [14] and k-point nonlinear energy operator (k-NEO) method [8]. Various feature extraction techniques have been proposed which are model-based [8] wavelet analysis [32], template matching [33], and power spectra analysis [34]. The classification approaches that have frequently been used for EEG signals peak detection consist of rule-based [14][21][35], AdaBoost [22], radial basis function [19], support vector machine [8], radial basis support vector machine [19], artificial neural network [22], and expert system [21-22].

Dumpala *et al.* [14] have introduced the utilization of three points sliding window and threshold-based classification. Theoritically, the maxima and minima concept using three-point sliding window technique has been employed to identify a candidate peak. Two algorithms of peak detection have been proposed, as well. A predicted peak can be classified once the feature values are satisfied the decision threshold values. The authors claimed that the proposed peak classification algorithm can be used to other physiological signals. Dingle *et al.* [21], use two-threshold systems to detect a candidate peak. An expert system which considered both spatial and temporal contextual information has been used to reject the artifacts and classify the transient events.

Another method such as Wavelet transform has been used in peaks classification algorithm to decompose the EEG signals by Liu *et al.* [22]. The decomposed signals are used to extract seven different features for a peak. Next the process is continued by employing these features for ANN classification. By considering that all the artifacts in EEG signals have to be removed, an expert system with spatial and temporal contextual information has been proposed in the algorithm. To distinguish the type of artifact, several heuristic rules have been employed. After all artifacts are recognized ad rejected, the decision will be made to classify the epileptic events.

Acir *et al*. [19] have introduced a three stages procedure based on ANN for the detection of epileptic peaks. The EEG signal is transformed into the time-derivative signals. To detect a peak candidate several rules have been employed. Two discrete perceptron classifiers are used to classify between three groups: 1) definite peak, 2) definite non-peak, and 3) possible non-peak. Next, the peak that belongs in the third group is going further process by nonlinear classifier. Different peak detection algorithm based on a modified radial basis function network (RBFN) and discrete perceptron classifiers has also been invented by Acir et. al. for the detection of epileptic spikes [19]. k-NEO method has also been used by Liu *et al*. to detect a candidate peak [8]. The peak features are calculated and then used as the input of the AdaBoost classifier.

Peak Models based on the Time Domain Analysis

The first conventional peak model in the time domain analysis has been introduced in Dumpala's peak detection research [14]. The defined peak model comprises of four features, which are (1) the amplitude of the magnitude of peak point and the magnitude of valley point at the first half wave, (2) the width between valley point of first half point and valley point at second half wave, (3) and (4) two slopes between a peak point and valley point in the first half wave and second half 35 wave. A peak point is a point that holds the maximum value located at a specific time and location on the signals. However, a valley point is a vice versa a peak point. A similar definition of the peak amplitude and slopes are also been used in [18][19][25].

An additional feature of peak amplitude and two features of the peak width have been introduced by Acir *et al*. [19] to detect a peak of EEG epileptic signals. The additional peak amplitude is the amplitude of the magnitude of peak point and the magnitude of valley point of the second half wave. The peak widths are the width between peak point and valley point of first half wave and second half wave. The total features that are introduced by are six features. Acir *et al*. [19] did not use the width feature that was introduced by Dumpala *et al*. [14]. A similar definition of the peak amplitudes, widths, and slopes are also been used in [8]. In [8], an additional peak feature is added to a set of feature that is introduced in [18][19], which is the area of the peak. However, the definition of area integration is not presented in the paper.

Also, Liu *et al*. [22] have introduced 11 peak features. The peak model consists of four amplitudes; (1) the amplitude of the magnitude of peak point and the magnitude of valley point at the first half wave, (2) the amplitude of the magnitude of peak point and the magnitude of valley point of the second half wave, (3) the amplitude of the magnitude of peak and the magnitude of turning point at the first half wave, and (4) the amplitude of the magnitude of peak and the magnitude of turning point at the second half wave. The turning point is defined as the point where the slope 36 decreases more than 50 percent as compared to the slope of the preceding point. The model also consists of three widths; (1) the width between valley point at first half point and valley point at second half wave, (2) the width between turning point at first half wave and turning point at second half wave, and (3) the width between half point at first half wave and half point at second half wave. Four slopes are also measured; (1) and (2) two slopes between a peak point and valley point in the first half wave and second half wave, (3) and (4) two slopes between peak point and turning point at first half wave and second half wave.

Another peak model consists of four features, which has been introduced by Dingle *et al*. [21]. The peak amplitude is the difference between the peak point and the floating mean. The floating mean is the average EEG that is centered at the peak point that is also called moving average curve (MAC) [23]. The width is calculated based on the difference between the valley point at the first half wave and the valley point at the second half wave. The two slopes are the slopes between a peak point and valley point in the first half wave and second half wave. Recently, Elgendi *et al*. [10] also used MAC in his study to detect systolic peak for heart rate analysis. Based on the literature study of peak detection, almost all researchers focus on the problem of an epileptic EEG signal. A review of peak detection algorithms that is employed to the epileptic EEG signal is presented by Wilson *et al*. [36] and Webber *et al*. [37]. Details of the different peak detection algorithms on different peak models are tabulated in Table 1. Note that, the detection performances of the highlighted applications are not the performance of interest of peak detection research. The detection performance is just to show that the utilization of peak detection algorithm in the events classification has provided the best performance.

Feature Selection Methods Using Optimization Algorithms for EEG Signals Peak Classification

One approach for improving the peak classification performance is to identify the best combination of peak features. Previously, several authors have defined a variant of peak models based on the characteristic of the peak of EEG signals in the time domain analysis. In one peak of EEG signals, there are several signal parameters including different amplitudes, widths, and slopes. A variety of peak features can be calculated based on those signal parameters. For instance, the peak-to-peak amplitude of the first and second half waves, peak width, ascending peak slopes at the first half wave, and descending peak slope at the second half wave. All these features are used as inputs to the classification process to differentiate between the peak and non-peak of the signals. To the best of our knowledge, there are very reports a few studies have used feature selection method to find the best peak model for EEG signals peak detection application. Two methods that have been found in the literature are particle swarm optimization [6] and gravitational search algorithm [38]. Both of the methods use the same classification approach which is a rule-based classifier. There are a limitation has been pointed out, which the classifier tend to have poor performance with peak models defining many peak features. The classification performance declined to nil when the classifier employed all 11 features from Liu model [6].

An adequate solution was achieved in a shorter time by utilizing population-based metaheuristic optimization algorithms. Many complicated real-world issues can be ironed out by using these algorithms. These algorithms can also be practiced to solve almost any optimization problems [39]. There are a variety of population-based metaheuristic optimization algorithms which have been created such as genetic algorithm [40], simulated annealing [41], particle swarm optimization [42], ant colony optimization [43], big bang-big crunch optimization [44], intelligent water drops algorithm [45], honey bee mating optimization [46], firefly algorithm [47], gravitational search algorithm [48], harmonic search optimization [49], bat algorithm [50], and black hole algorithm [51]. Thus far, these optimization algorithms have been widely applied in fields such as power system [52], manufacturing [53], and medical [6][54] as a practical technique for feature selection. 39 A new metaheuristic optimization algorithm was introduced by Ibrahim *et al*. [55] and this algorithm was inspired by the state estimation process of Kalman filter. The new optimizer is entitled simulated Kalman filter (SKF) algorithm. There are three main processes in the principle of Kalman filter which are states prediction, state measurement, and state estimation. Each agent acts as an individual Kalman filter and holds a vector state in the SKF algorithm. New states are predicted and new locations of agents are revised from the prediction, measurement, and estimation state processes. The processes are iteratively looped until the maximum iteration is achieved. The SKF algorithm has the capability to find the most optimal solution efficiently while the performance is comparable to gravitational search algorithm and black hole algorithm for unimodal optimization problems based on the final experimental results in [55]. The original SKF algorithm, however, cannot be used for solving discrete optimization problems. In order to eradicate this problem, various binary-based SKF algorithms were introduced such as Angle modulated SKF (AMSKF) [56], Binary SKF (BSKF) [57], Local Optimum Distance evaluated SKF (LocalDESKF) [58], and Global Distance Evaluated SKF (GlobalDESKF) [59] algorithms. Based on the capability of the Binary-based SKF algorithms, they have potential to be developed as a feature selection method [61][62].

Conclusions

The existing peak classification algorithms have all been used successfully in various applications. However, almost no comparisons of these algorithms have been performed so far. For that reason, it appears as difficult to choose which one the best. To address this difficulty, the similarity of these algorithms in the time domain analysis point of view are observed. As presented in the previous section, a group of researchers have used a different style of frameworks but similar processes, for example, there are a variety of methods in signal pre-processing, peak candidate identification, feature extraction, and classification. This is the reason why this study focused on the similar processes.

The review also showed that every existing algorithm employed a different peak model in specific event-related EEG signals. The selection of these peak models with the associated features are based on the characteristics of the EEG signals. Consequently, a good performance of peak classification is obtained in the past work. However, the utilization of the existing peak models not guaranteed to achieve higher performance in other event-related EEG signals peak classification.

Moreover, to the best of our knowledge, none of the techniques based on experimental exploration to find the best model have been performed so far. This motivated this research explores a good experimental technique that can produce the best and generalized peak model for any event-related EEG signals peak classification. The best approach so far is feature selection.

Table 1. Summary of the previous research works using various types of peak detection algorithms on different peak models for various applications.

Peak Model	Input Signals	Event	Classification Method	Accuracy Test of Events (%)
M. Elgendi *et al.* [10]	PPG	Heart rate analysis	Thresholds, Rule based	Sensitivity: 99.89 Selectivity: 99.84
Y. C. Liu *et al.* [8]	EEG	Epilepsy	AdaBoost	93.5
Acir [4]	EEG	Epilepsy	Radial basis function network (RBFN)	Sensitivity: 91.1 Selectivity: 89.2
Acir *et al.* [19]	EEG	Epilepsy	Radial basis support vector machine (RB-SVM)	Sensitivity: 91.1 Selectivity: 89.2
H. S. Liu *et al.* [22]	EEG	Epilepsy	ANN, Expert system	90
Dingle *et al.* [21]	EEG	Epilepsy	Thresholds, Rule based, Expert System	80
Dumpala *et al.* [14]	ECA	Gastric activity	Thresholds, Rule based	100

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