Journal of **Software Engineering**

ISSN 1819-4311

Academic
Journals Inc.

www.academicjournals.com

OPEN ACCESS Journal of Software Engineering

ISSN 1819-4311
DOI: 10.3923/jse.2017.54.59

Research Article
Classification of Single Trial EEG During Automatic Correction of Finger Movement

[1,2]Yalin Song, [1]Yaoru Sun, [1]Zijian Wang and [1,3]Hong Zhang

[1]Department of Computer Science and Technology, Tongji University, 201804 Shanghai, China
[2]School of Software, Henan University, 475001 Kaifeng Henan, China
[3]Department of Mathematics, Taiyuan Normal University, 030012 Taiyuan Shanxi, China

Abstract
Background: The automatic correction mechanism plays an important role in both planning and execution of visually guided movements in daily life and it could be also as the effective therapy for upper limb motor rehabilitation. **Materials and Methods:** In this study, a novel classification method of single trial EEG signals was put forward to recognize automatic correction of finger movement. **Results:** The average accuracy of event related potentials (ERP) based feature extraction method for automatic corrections was 80.41%, improved by about 8% compared with the common method. **Conclusion:** The novel classification method of automatic correction of finger movement was effective and it could be applied to neuro-rehabilitation with severe brain injury.

Key words: Automatic correction, single trial, feature extraction, activity recognition, event-related potentials components

Received: April 03, 2016 Accepted: July 19, 2016 Published: December 15, 2016

Citation: Yalin Song, Yaoru Sun, Zijian Wang and Hong Zhang, 2017. Classification of single trial EEG during automatic correction of finger movement. J. Software Eng., 11: 54-59.

Corresponding Author: Yaoru Sun, Department of Computer Science and Technology, Tongji University, 201804 Shanghai, China

Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

The automatic correction mechanism allows human to quickly and involuntarily adjust ongoing hand movements in response to the unexpected change of the target's properties (e.g., location). Some recent studies[1-3] suggested that automatic correction is mainly mediated by the dorsal visual pathway and associated with Posterior Parietal Cortex (PPC). Rehabilitation method based automatic correction mechanism is worthwhile for helping patients relearn sensorimotor capabilities by exploiting the plasticity of the neuromuscular system. Activity recognition as a key step in the rehabilitation system is commonly investigated by using wearable sensors (e.g., accelerometer) and somatosensory devices (e.g., Nintendo Wii, Microsoft Kinect camera)[4,5]. The EEG-based activity recognition is suitable for testing automatic correction of finger movement because EEG signals could be seriously affected by hand movement. Thus, EEG-based activity recognition is more important for rehabilitation system due to the fact that wearable sensors and somatosensory devices are not suitable for patients with severe brain injury (e.g., stroke) and losing an arm movement.

Classification of EEG signals is a relatively difficult task, especially the classification is performed on a single trial EEG[6,7]. Currently, classification of EEG signals commonly relied on some feature extractions, such as mean value, energy and autoregressive (AR) model method etc[8,9]. However, information (e.g., latency and peak voltage) of event-related potential in the EEG signals are commonly ignored in the classification system. In addition, although the research results of EEG signals had been fruitful in brain-computer interface, it is unclear whether automatic correction can be recognized accurately. In this study, a method based on features of event-related potential is used for the classification of single trial EEG during automatic correction of finger movement. A higher classification accuracy was achieved compare to the common method for EEG signals.

MATERIALS AND METHODS

Data collection: The finger movements were performed by eleven normal participants, sat in a dimly lit room with their chin resting on a chin-rest. The classic double-step paradigm[1,10,11] was adopted in the experiment in which participants were explicitly instructed to move the right hand-cursor to point to the targets through the right thumb-stick of a gamepad as quickly as they could. The experiment consists of 200 trials. In each trial, a target randomly appeared in one of the two lateral positions, located left or right of the vertical meridian of the display. On 25% of the trials, the target changed its position to the second target position at the finger movement initiation (jump trial). On the remaining 75% trials, the target remained at its original location (static trial).

During this process of experiment, EEG data were recorded using a 64-channel brain products. The EEG data were sampled at 500 Hz and band-pass filtered between 0.5 and 40 Hz. Eye movements were monitored by additional bipolar horizontal (hEOG) and vertical EOG (vEOG) electrodes. A trial started with a 1st period during which a gray background was presented at the monitor. Then the duration between the first target presentation and a black square starting point with a hand-cursor presentation randomly varied between 1000 and 1500 msec. Moreover, trigger marker of the first target presentation was recorded. Then, within a limited time window ($\leq$300 msec), participants were asked to quickly control hand-cursor to point to the second position using right thumb-stick in jump trials (Fig. 1b), whereas they need to control hand-cursor to point to the first position in static trials (Fig. 1a).

Data preprocessing: According to some recent researches of automatic correction, it is associated with the posterior Parietal Cortex (PPC). Then, three important electrodes (i.e., Cz, CPz and Pz) were selected to analyze and recognize the EEG signals of automatic correction. The data from three channels were filtered between 0.5-40 Hz. The EEG signal was corrected for ocular artifacts with both hEOG and vEOG recordings.

Feature computation: Extracting features as a fairly effective way that can represent the characteristics of different class signals have been widely used in all kinds of classification systems. In classification of EEG signals, some feature extractions are commonly selected, such as Mean (M), Standard Deviation (SD), coefficient of variation (SD/M, CV), Energy (E) and autoregressive coefficient model (AR) etc.

The Mean (M) is the mean value of the frequency domain over a trial of finger movement. Standard Deviation (SD) indicates the amplitude variability of a finger movement.

The Energy (E) feature could show the data periodicity of automatic correction of finger movement. Then, it was selected to discriminate the class of automatic correction. It is obtained that:

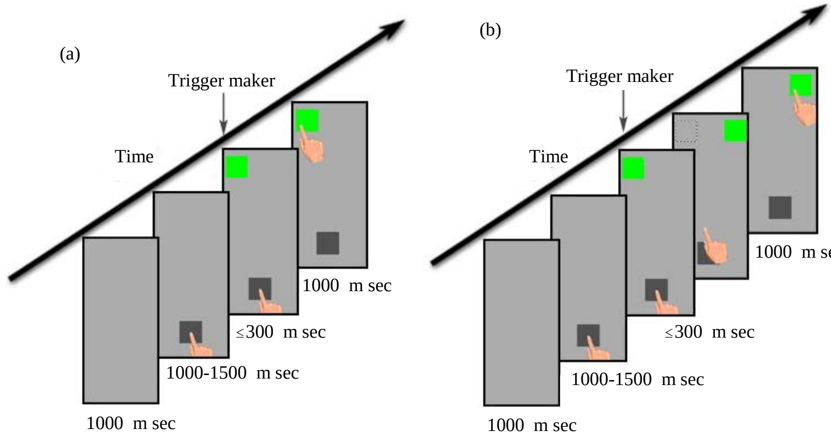

Fig. 1(a-b): Experimental paradigm for automatic correction

$$X(i) = DFT\left[x(n)\right] = \sum_{n=0}^{N-1} x(n)\, W_N^{ni}\; 0 \le i \le N-1 \tag{1}$$

Where:

$$W_N = e^{-j\frac{2\pi}{N}}$$

The Energy (E) would be:

$$E = \frac{Sum\left(\left|X(i)^2\right|\right)}{N}\; i = \{1, 2\ldots N\} \tag{2}$$

Autoregressive (AR) models are used to model the EEG signal and its parameters also used for identification EEG signals in some researches[12,13]. The AR model was used to describe EEG features of finger movements in the study. The following AR model AR(p) is established for each acceleration component y(i):

$$y(i) + \sum_{j=1}^{p} a_j . y(i-j) = e(i) \tag{3}$$

where, a_j ($j = 1,2,\cdots,p$), p are the model parameters and model order of the AR model and e(i) is a white-noises sequence. The 4-order AR coefficients were extracted from each of the three electrodes of EEG signals in the study.

The correlations between electrodes are especially useful for discriminating the class of EEG signals of finger movements. They are calculated between each pair of electrodes and a covariance between the two electrodes (e.g., Cz and CPz) can be given by:

$$C = \frac{\sum x.y - \left(\sum x.\sum y\right)/N}{\sqrt{\sum x^2 - \left(\sum x\right)^2/N}\, .\sqrt{\sum y^2 - \left(\sum y\right)^2/N}} \tag{4}$$

Feature extractions of event-related potential: Event-related potential (ERP) is a stereotyped electrophysiological response to a specific cognitive event (e.g., attention and action) and it could be reliably measured using electroencephalography (EEG)[14,15]. The ERP waveforms were commonly described by peak amplitudes and peak latencies and it is not usually visible in the EEG recording of a single trial (Fig. 2). To see the brain's response to a stimulus (i.e., ERP), random brain activity (i.e., EEG signals) of many trials must be averaged and, the relevant ERP waveform are calculated. Then, it is suggested that the relative features of ERP of automatic correction are important for the classification of single trial EEG signals.

Given that it is difficult to directly test the automatic correction of hand movement and to remove the effect of head and hand movements, relative ERP components of automatic correction were seldom reported. Thus, ERP components of automatic correction of finger movement were first computed. According to some recent studies of automatic correction, ERP components were analyzed from a cluster of electrodes located at parietal sites (C1, C2, C3, C4, C5, C6, Cz, CP1, CP2, CP3, CP4, CP5, CP6, CPz, P1, P2, P3, P4, P5, P6 and Pz) (Fig. 3a). Figure 3b show the grand-averaged ERP waveforms for each trial type (jump and static) from the parietal electrodes in the experiment. The results showed that N1 and P300 components were found in jump trials and P300 was not appeared in static trials (Fig. 3b). Two ERP components were in the following time windows post-stimulus: N1 (100-200 msec) and P300 (200-400 msec).

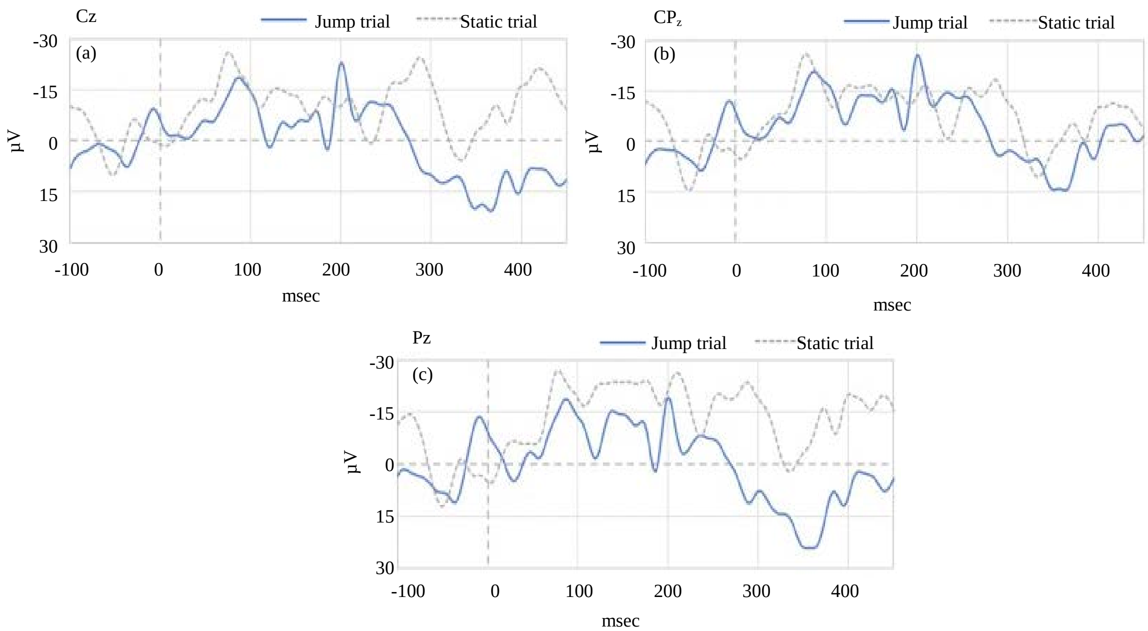

Fig. 2(a-c): Three electrodes of one trial EEG of finger movement

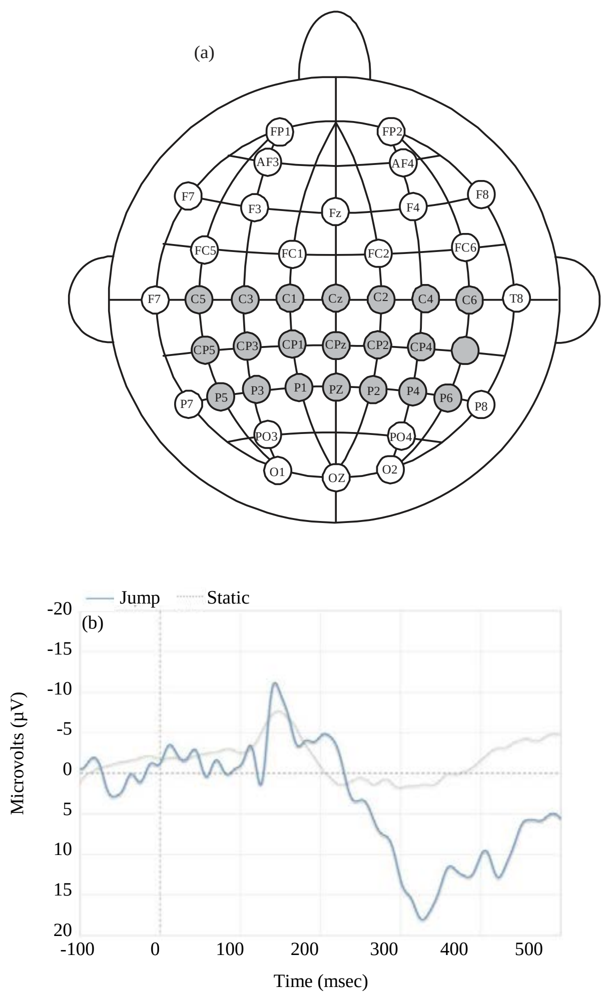

Fig. 3(a-b): Electrodes used for calculating ERP of automatic correction

Thus, for each trial, the peak amplitudes (μV) and peak latencies (msec) in N1's time window (100-200 msec) and in P300's time window (200-400 msec) were extracted, respectively from the three electrodes (Cz, CPz and Pz) as the important features of EEG signals.

In sum, features Mean (M), Standard Deviation (SD), Energy (E), correlation between axes (C), autoregressive coefficient model (AR) and feature of event-related potential (fERP) were combined as a feature-type set F to describe a single finger movement:

$$F = \{M, SD, E, C, AR, fERP\} \quad (5)$$

Classification: According to the design paradigm of our experiment, two classes of finger movement (i.e., "Static" class and "Jump" class) were included in the study. Given that support vector machine (SVM) is well known for its high recognition performance in binary classes and it is a small sample size method based on statistic learning theory[16], the authors used the Support Vector Machine (SVM) to classify the single trial EEG signal of finger movement. The SVM is originally designed for binary classification in which it aims at finding the maximum-margin hyperplane using a transformation that mapping the data from input space to feature space.

The feature-type sets (F) of finger movements were calculated and input into the SVM classifier in order to train and test the classifications of automatic correction. The same number of samples in the two-class data ("Jump" and "Static") was selected using the SVM classifier. The 80% total samples of EEG signals were randomly selected to train the SVM classifier and the remains were used to test. The classifier was built five times. The cross-validated classification result is the average of the five testing results.

In order to compare the performance of the method of ERP-based features against the common feature extraction method, feature-type sets with ERP-based features (i.e., {M, SD, E, C, AR, fERP}) and one without ERP-based features (i.e., {M, SD, E, C, AR}) were operated respectively by the same steps. Two methods of feature extractions would be compared through recognition rate.

RESULTS

Classification accuracy was used to evaluate classification performance of two type feature sets. The data of behavioral results without completing automatic correction and those of bad EEG signal data were removed. The 368 samples (single trial EEG signal) of finger movement data in jump trials and the same number of samples in static trials were selected. The data of feature-type sets with ERP-based features and that without ERP-based features were calculated to check respectively the recognition performance of SVM. In each of feature-type sets, 295 samples (i.e., 80% of total samples) of the two classes ("Static" and "Jump") were randomly selected to train the SVM classifier and the remaining 20% data were used to test. The SVM classifier was built five times in the data of the two feature-type sets. The classification results, averaged five testing results are listed in Table 1. An average accuracy of 80.41% was obtained for single trial EEG signals using the method of feature-type sets with ERP-based features, whereas one of 71.51% was obtained using the method of feature-type sets without ERP-based features. Namely, the average recognition rate of single trial EEG signals improved by about 8% through the novel feature extraction.

Table 1: Accuracy of recognition of single trial EEG

	Recognition rate (%)	
Times	ERP-based features (%)	Common features (%)
1	80.82	71.23
2	77.40	72.60
3	82.88	74.66
4	79.45	68.49
5	81.51	70.55
Average accuracy	80.41	71.51

DISCUSSION

Compare the common method and ERP-based feature extraction method for recognizing automatic correction of finger movement in the study. Classification of EEG signals commonly relied on some common feature extractions (e.g., mean value, energy and autoregressive (AR) model method) at present[8,9]. In this study, the recognition rate of automatic correction for finger movement is 71.51% with the common feature extractions method. However, an average accuracy of 80.41% was obtained with ERP-based features method for the same finger movement. One possible reason for the higher classification accuracy is that the feature-type sets with ERP-based features included some more effective features discriminating the two classes ("Static" and "Jump") of finger movements compared to the common method. The results suggested that feature-type sets with ERP-based features might be used to build a robust and noninvasive Brain Computer Interface (BCI) system and it could be as a feedback control signal of the rehabilitation system for patients with severe brain injury (e.g., stroke).

CONCLUSION

A classification method of single trial EEG during automatic correction of finger movement has been presented in the study. The EEG data of experiments with double-step paradigm was recorded by Brain Products system. Feature extraction with ERP-based features, according to the results of our experiment by ERP components analyzing and one without ERP-based features were operated respectively by using the same processing procedure. The average accuracy of classification for the single trial EEG signals of automatic correction was 80.41% using ERP-based feature extractions, which improved by about 8%. The results indicated that the new classification method of automatic correction of finger movement was effective and could be applied to neuro-rehabilitation with severe brain injury.

ACKNOWLEDGMENTS

This study was supported by the Grants from the National Natural Science Foundation of China (61173116) and the Doctoral Fund of Ministry of Education of China (20110072110014).

REFERENCES

1. Pisella, L., H. Grea, C. Tilikete, A. Vighetto and M. Desmurget *et al*., 2000. An 'automatic pilot' for the hand in human posterior parietal cortex: Toward reinterpreting optic ataxia. Nat. Neurosci., 3: 729-736.
2. Blangero, A., V. Gaveau, J. Luaute, G. Rode and R. Salemme *et al*., 2008. A hand and a field effect in on-line motor control in unilateral optic ataxia. Cortex, 44: 560-568.
3. Desmurget, M., C.M. Epstein, R.S. Turner, C. Prablanc, G.E. Alexander and S.T. Grafton, 1999. Role of the posterior parietal cortex in updating reaching movements to a visual target. Nat. Neurosci., 2: 563-567.
4. Saposnik, G., R. Teasell, M. Mamdani, J. Hall and W. McIlroy *et al*., 2010. Effectiveness of virtual reality using Wii gaming technology in stroke rehabilitation: A pilot randomized clinical trial and proof of principle. Stroke, 41: 1477-1484.
5. Clark, R.A., Y.H. Pua, K. Fortin, C. Ritchie, K.E. Webster, L. Denehy and A.L. Bryant, 2012. Validity of the Microsoft Kinect for assessment of postural control. Gait Posture, 36: 372-377.
6. Hsu, W.Y., 2012. Enhanced active segment selection for single-trial EEG classification. Clin. EEG Neurosci., 43: 87-96.
7. Jia, W., X. Zhao, H. Liu, X. Gao, S. Gao and F. Yang, 2004. Classification of single trial EEG during motor imagery based on ERD. Proceedings of the 26th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Volume 1, September 1-5, 2004, San Francisco, CA., pp: 5-8.
8. Dornhege, G., B. Blankertz, G. Curio and K.R. Muller, 2004. Boosting bit rates in noninvasive EEG single-trial classifications by feature combination and multiclass paradigms. IEEE Trans. Biomed. Eng., 51: 993-1002.
9. Jahankhani, P., V. Kodogiannis and K. Revett, 2006. EEG signal classification using wavelet feature extraction and neural networks. Proceedings of the IEEE John Vincent Atanasoff 2006 International Symposium on Modern Computing, October 3-6, 2006, Sofia, pp: 120-124.
10. Cressman, E.K., I.M. Franks, J.T. Enns and R. Chua, 2006. No automatic pilot for visually guided aiming based on colour. Exp. Brain Res., 171: 174-183.
11. McIntosh, R.D., A. Mulroue and J.R. Brockmole, 2010. How automatic is the hand's automatic pilot? Evidence from dual-task studies. Exp. Brain Res., 206: 257-269.
12. Mohammadi, G., P. Shoushtari, B.M. Ardekani and M.B. Shamsollahi, 2006. Person identification by using AR model for EEG signals. Proc. World Acad. Sci. Eng. Technol., 11: 281-285.
13. Poulos, M., M. Rangoussi, V. Chrissikopoulos and A. Evangelou, 1999. 1999Person identification based on parametric processing of the EEG. Proceedings of the 6th IEEE International Conference on Electronics, Circuits and Systems, Volume 1, September 5-8, 1999, Paphos, Cyprus, pp: 283-286.
14. Friedman, D. and R. Johnson Jr., 2000. Event-Related Potential (ERP) studies of memory encoding and retrieval: A selective review. Microsc. Res. Tech., 51: 6-28.
15. Luck, S.J., 2005. An Introduction to the Event-Related Potential Technique. 1st Edn., The MIT Press, Cambridge, MA., ISBN-13: 978-0262621960, Pages: 374.
16. Garcia, G.N., T. Ebrahimi and J.M. Vesin, 2003. Support vector EEG classification in the Fourier and time-frequency correlation domains. Proceedings of the 1st International IEEE EMBS Conference on Neural Engineering, March 20-22, 2003, Capri Island, Italy, pp: 591-594.