Detection of movement-related cortical potentials associated with emergency and non-emergency tasks

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***Abstract*—This study focuses on a demonstration of differences between movement-related cortical potentials (MRCPs) during emergency and non-emergency situations. Two paradigms were designed for emergency and non-emergency situations. The necessary pre-processing and Laplacian spatial filter were used in the collected data. Then initial negative phase of MRCPs was extracted from scalp electroencephalogram (EEG) in non-emergency situation and compared with that in emergency situation. Based on the data of non-emergency, a matched filter (MF) algorithm was designed and was used to detect the motor intention in two paradigms. The result shows a significant difference of the initial negative phase of the MRCP in two cases. In addition, if the MF algorithm based on non-emergency situation was used for emergency situations directly, there was a large difference in accuracy. The true positive rate was 60.57±14.79% in non-emergency while 44.29±5.73% in emergency. The result indicates that additional consideration should be given to emergency situation when designing algorithms or collecting data. So, we designed a new algorithm to solve this problem, which works better compared to simple MF. The algorithm effectively improves the true positive rate and reduces the false positive per minute.**

***Index Terms*—electroencephalogram (EEG); movement-related cortical potential (MRCP); motor intention; emergency and non-emergency.**

I. Introduction

Brain Computer Interface (BCI) technology allows people to control external devices directly through EEG or other brain signals, which has attracted increasing attention in recent years. In early years, BCI research aims at helping paralysed people to be more independent. Therefore, the early application of BCI was mainly in medical field[1]. With the development of BCI technology, people saw its potential application in non-medical field. Recently, more and more attention has been paid to the application of BCI technology inin games, status detection and evaluation, and movement intention prediction for normal people[2][3].

The control of external devices depends largely on the user's movement intention, so the detection of the motion intention is the key to the normal operation of the related BCI equipment. So far, the research on the control of external equipment based on the detection of motion intentions, has been developed to predict the occurrence of braking action and to control quadcopter to capture targets[4][5]. MRCP is a slow cortical potential. Using MRCP is one of the most commonly used methods for the detection of motion intentions[6]. Methods of classification and detection of MRCP include Support Vector Machine (SVM)[7], Locality Preserving Projection-Linear Discriminant Analysis (LPP-LDA)[8], MF[9] and so on. The latest method is locality sensitive discriminant analysis with nearest-neighbor (LSDA-NN)[10], and some of the methods has been used for online system and has got a good effect. However, the current approaches are based on non-emergency data which is collected from the self-paced movement.

In real life, the situation where drivers braked sharply is commonly seen. If the MRCP has a large difference between emergency and non-emergency situations, the algorithms established in non-emergency situation will become not suited to an emergency. Thus, it is possible to have serious consequences if the movement intention of the emergency is not detected. However, few people pay attention to this aspect. It isn't easy to design the experimental paradigm that only changes the preparation time and set up the corresponding experimental environment. The intensity and speed of subjects may cause some interference. Therefore, the another challenge is to reasonably quantify the electromyography (EMG) signals in two situations and compare them.

We designed two scenarios, and all subjects needed to complete the emergency and non-emergency tasks. After using the same pretreatment and spatial filtering, we found that there was a significant difference in MRCP with two situations. The interval between the initial negative phase of the two is about 0.8s. We found that there wasn't significant difference between EMG singles in two cases (p=0.147). The change in MRCP was mainly due to the change of the preparation time. Then, we applied the MF algorithm which was based on the non-emergency data to the data collected in both tasks. The detection accuracy calculated as true positive rate (TPR) was 60.57±14.79% for non-emergency task, while 44.29±5.73 for the emergency case. The TPRs of all subjects were less accurate in the case of emergency (except for subject 5). Finally, we combined MF and SVM to detect the movement intention, and the recognition accuracy increased by 9.14% compared with the effect using the MF algorithm.

II. Materials and methods

A. Participants

Seven healthy, right-handed subjects (three females, average age 21.7±1.6 years), denoted by SUB1-SUB7, par-

Fig. 1: The virtual emvironment of non-emergency task. Subjects sit on the chair with right foot on the brake pedal and take actions according to what they saw on the screen in front of them. In this virtual environment, it displays a suburban road, with no traffic signs or traffic lights. The setting of the virtual environment is different between emergency and non-emergency tasks.

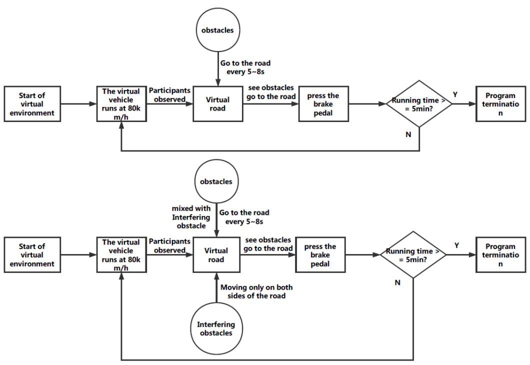


Fig. 2: Schematic diagram of the two tasks. The schematic diagram on the top represents a non-emergency task, while the below is for the emergency task. The time interval in which the obstacle appears is a random value between 5 and 8 seconds in two cases.The probability of obstacles on either side is the same, while the time required for the movement of obstacles from either side to the front of the vehicle is also the same.

ticipated in the experiment. Every subject had normal or corrected-to-normal vision, reported normal hearing and had no history of known neurological diseases. All subjects gave their informed consent before participation.

B. Virtual environment and experimental paradigm

The virtual environment displayed on the screen was developed using the Open Graphics Library (OpenGL) cross-platform graphical programming interface.

1) Non-emergency tasks: The road in the virtual environment will appear an obstacle every once in a while, and the obstacle will move to the front of the vehicle when the vertical distance between the vehicle and the obstacle is less than a certain distance. The subjects need to step on the brakes before the vehicle hits the object. Given that the subjects are able to detect obstacles in the distance and are ready to step on the brakes, they are thought to have completed a non-emergency mission when they step on the brake once.

2) Emergency tasks: In emergency tasks, other settings in the virtual environment are consistent with non-emergency settings. The only difference is that there are always obstacles on both sides of the road, but not all of obstacles will move to the front of the vehicle. Since the obstacle is suddenly moving from the pavement to the driveway, the subject has little time to prepare and will hit the brake as fast as he can. In this case the subject puts on the brakes once, and we think he has finished an emergency task.

At the experimental stage, each experiment was divided into five rounds, 5 minutes per round. The rest time between each two rounds is 2$\sim$3 minutes.

C. Data acquisition

A Brain Products GmbH BrainAmp Amplifier and an EasyCAP EEG cap were used to collected nine channels of EEG. The EMG signals were recorded from the tibialis anterior muscle of the right leg. According to the standard international 10-20 system, the EEG electrodes were placed on Fz, FC1, FC2, C3, Cz, C4, CP1, CP2 and Pz, while the ground electrode and reference electrode were placed on AFz and FCz. The impedances were below 15kΩ for EEG electrodes and below 50kΩ for EMG before data acquisition. The EEG and EMG were sampled at 5000Hz.

D. Signal analysis

The data we obtained was used in the form of a five-fold cross validation. That is, every time four of the five data sets was selected as the training set to extract the tracking template, and then the remaining one data sets were used as the test set to verify the effect. Data processing was in two steps. First was pre-processing, including the spatial filtering operation. The second step was to extract the detected template from the training set. With the extracted template, the motion intention would be detected in the test set by using the matching filter algorithm.

1) Pre-processing: First, we deleted the useless information from EEG signal and EMG signal we obtained. When the virtual environment ended, the background program is still recording the data. Besides, before the first obstacle appeared, some subjects had some unnecessary actions. So to avoid the interference of these useless data, we only intercepted data collected from when the first obstacle appeared to the time the virtual environment program ended. In addition, for EEG signals, the bandpass filter (second-order Chebyshev type II) was used for filtering with the frequency of 0.04-3Hz, and then down-sampled to 50Hz. The EMG signals were high-pass filtered (second-order Butterworth) with a cut-off frequency of 10Hz.

2) Definition of reference events: In order to compare with the final detection result, the reference movement onsets were supposed to be found. One-tenth of the maximum amplitude of the electromyography signals in the whole process of physical movement was considered as the threshold, and the time point of signal amplitude crossing threshold was approximated as the start time of the movement[11].

3) The comparison of EMG signals: After determining the time of movement, we extracted the EMG signals from three to three seconds before and after each movement and

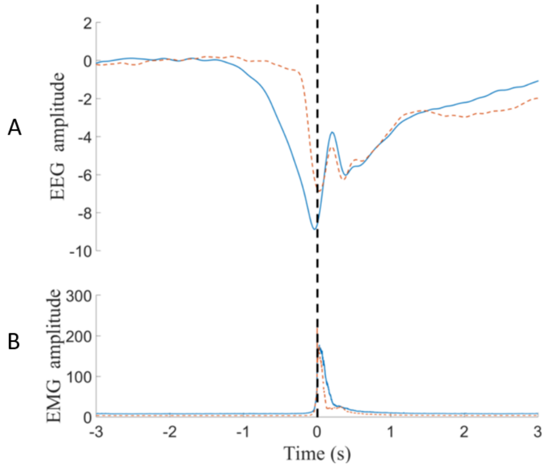


Fig. 3: (A)Average MRCP signals under emergency (dashed line) and non-emergency (solid line) tasks. It can be seen that, under emergency task, the descending curve of MRCP is in the position of -0.2s, while in the emergency task, the corresponding inflection point is at -1s. In cases, the initial negative phases of MRCP are significantly different. The initial negative phase of the signal under an emergency task is delayed, close to the movement onset.(B)Average EMG signals under emergency (dashed line) and non-emergency (solid line) tasks. The start time of movement corresponds to 0s in the figure.

calculate the average value of two tasks (See Fig.3(B)). Since EMG signals were mainly concentrated in the time period of 0∼0.25s, the root mean square (RMS) value of this period is used to represent the energy feature of the signals during exercise. We carried out paired-sample t-test for 7 pairs of RMS values, and the difference was not significant between them (p=0.147).

This result and Fig.3(B) can show that there is no significant difference between the EMG signals in the two cases, so the MRCP signals is only related to the length of the preparation time, which has nothing to do with the speed and intensity of stepping down the pedal.

4) Spatial filtering: Spatial filtering is a common method in MRCP signal processing and analysis, which can effectively increase the signal-to-noise ratio. Using Laplacian spatial filter (LSF) as the spatial filter, the formula is Cz - (FC1+FC2+CP1+CP2+PZ+FZ+C3+C4) /8. The sum of all coefficients is zero, so it can remove the spatial dc components. The surrogate Cz channel after LSF will be used for matched filter algorithm.

E. Matched filter algorithm

There are a number of effective classification and detection techniques, such as K-Nearest Neighbors(KNN), Support Vector Machine (SVM), Bayesian Classifiers (BC), Neural Network (NN), etc. However, Matched Filter (MF) is a method which can easily calculate the time interval between the detection point and the reference point. Besides, it can also be used for online system[8][9][11][12].

We can extract all the MRCPs in the training set and take the mean value as the template for the matching filter detection. But this method is not practical and not good enough. It can achieve better detection result with the part of the MRCP as the template for detection.

When conducting detection, we did the same preprocessing (remove the useless data, etc.) for the test set, and then used the template extracted from the training set to detect the motion intention. The true positive rate (TPR) and the number of false positive (FP) per minute were calculated as performance parameters for the MF algorithm evaluation.

F. MF-SVM

This algorithm combined matched filter and support vector machine. Each subject had ten data sets (five for emergency and five for non emergency). Each round we selected a data set as a test set, and then extracted two templates (emergency and non emergency) from the remaining data. The remaining data were processed by MF algorithm based on two templates, and the result was the training data for SVM. The test data of SVM was the selected test set with the same operation.

III. Result

A. The difference of full MRCPs in two cases

After the experiment finished, the data obtained was used to extract the MRCP template. Three seconds before and three seconds after of a reference point was seen as an MRCP segment. In two types of tasks, we got seven subjects' MRCPs. Then for each subject, we got an average MRCP in each task, which was used as his or her full MRCP template for the corresponding task. The final average MRCP template in a task, presented in Fig.3(A), was obtained by the accumulation of everyone's full MRCP template under the corresponding task divided by the number of subjects. We can see from the figure that the initial negative phase of MRCP was very different in two cases. We recorded three values of the average MRCP of each subject under two tasks. They were the minimum value of MRCP, the corresponding time, and the initial time of negative phase. The t-test was used to determine whether there was a significant difference between the MRCPs of the two tasks. The results showed that the initial time of negative phase were very different (p=0.002), but there was little difference between the other two values(p=0.765 for the minimum value of MRCP and p=0.487 for the time of corresponding minimum value). So even for the same person, the MRCP generated in an emergency is very different from the normal time.

B. Comparison of Non-emergency task and emergency task

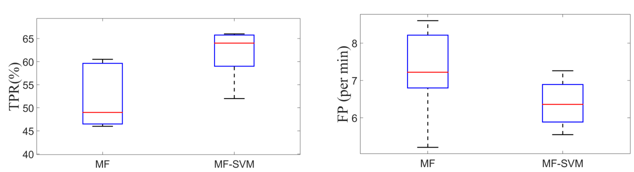
In order to further demonstrate that there are significant differences between emergency and non-emergency data, it is necessary to consider two cases separately, especially when using the algorithm such as MF, which requires a template. Therefore, we used the MF algorithm to detect movement

TABLE I: The result of all subjects in two tasks

	Non-emergency		Emergency	
SUB.ID	TPR(%)	FP(per min)	TPR(%)	FP(per min)
SUB.1	76	4.13	44	10.31
SUB.2	47	8.97	45	7.41
SUB.3	67	4.90	50	5.52
SUB.4	54	7.75	44	5.96
SUB.5	41	7.68	52	9.52
SUB.6	58	5.84	35	10.6
SUB.7	81	2.36	40	11.2
Avg	60.57±14.79	5.94±2.33	44.29±5.73	8.64±2.32

intention upon the data obtained from two tasks. In non-emergency situation, we took the [-1, 0]s before the peak negativity of full MRCP template as the detection template. In an emergency, we used the corresponding time point of each person in non-emergency situation to determine the detection template. Then we selected the turning point in the receiver operating characteristic curve as the threshold. The test sets were tested with these selected parameters.

The detection results of all subjects are shown in Table 1. In non-emergency situation, the TPR was 60.57±14.79%, and the number of FP was 5.94±2.33 per minute. In an emergency, the average TPR and FP per minute of all subjects were 44.29±5.73% and 8.64±2.32 respectively. T-test showed that the accuracy of the emergency was significantly lower than that of non-emergency situation (p=0.019). This is the result of using a time interval of each subject in a non-emergency situation to obtain a detection template of an emergency case without additional consideration.



(a) TPR of two methods (b) FP per minute of two methods

Fig. 4: The true positive ratio and the false positive of MF-SVM and MF.

C. Comparison of SVM-MF and MF

After using MF-SVM on the data, we can compare the result with before. It's obvious that MF-SVM is better than the simple MF (See Fig.4). Besides, the true positive rate of MF was 52.43±6.86% and the false positives per minute was 7.30±1.17, which was an average value of non-emergency and emergency tasks. However, the values were 61.57±5.19% and 6.41±0.93 for MF-SVM.

IV. Discussions

Whether there is a difference between MRCPs in emergency and non-emergency situations, determines whether emergency situation should be taken into account in designing algorithms and choosing parameters. We demonstrate that the MRCP of emergency situation differs greatly from that of non-emergency (see Fig.3(A)). This difference is only related to the preparation time by comparing the EMG signals of two tasks. In addition, if the emergency situation is not considered separately, and the parameters in the non-emergency situation are used directly in the emergency situation, it will lead to the loss of the accuracy of recognition and the increase of the FPR.

The MRCP-BCI technique is developing continuously in the field of detection of motor intention. Its effect is getting better, and the application of MRCP-BCI gradually extends from offline identification to online identification. User scope also extends from patients to healthy people. However, in these studies, the data obtained from the experiment was basically collected from the self-paced movement, which was collected in non-emergency situation. Conclusions and methods for non-emergency situation can be helpful for the rehabilitation of neurological diseases such as stroke.When applying brain-computer interface technology to people's daily life, emergency situation exists inevitably, but relatively rare. If emergency situation is not taken into account, algorithms will be designed based on non-emergency data completely. Finally, the probability of an error increases greatly in case of an emergency. If the equipment is always unable to respond properly in an emergency, the corresponding consequences will be serious.

The limitation of our work is that we only used the MF algorithm to prove the difference, and did not compare other algorithms such as SVM and LDA[8], which are commonly used for offline identification. Besids, the number of subjects was small in this experiment. Larger data will have a better effect on validation differences. And because of the limitation of the equipment, there was no online experiment to obtain real-time information. In addition, the detection of movement intention using the SVM-MF algorithm achieved the average accuracy of 61.57%, which was not good enough for urgent situations.

The future work is to recruit more subjects, and validate the conclusion on other algorithms. In addition, we are supposed to find a more efficient and accurate algorithm.

V. Conclusion

The study demonstrates that MRCPs are significantly different in emergency and non-emergency situations, and the lack of consideration of that can lead to low accuracy of movement recognition in emergency situation. This conclusion indicates that the emergency needs to be paid more attention to. So, we proposed a new algorithm based on MF and SVM. This work has certain significance to the detection of the movement intention through MRCP.

Acknowledgment

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