Comparative Analysis of Motor Imagery on Different Scales Based on Brain Computer Interface

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***Abstract*— The event-related brain oscillatory responses have a substantial role in motor imagery experiments. There are two patterns, i.e. event-related desynchronization (ERD) and event-related synchronization (ERS). In clinical applications and scientific experiments, an obvious event-related potential (ERP) is pivotal to achieve required tasks. Therefore, we explore how subjects generate the obvious ERP more easily. Eight healthy subjects participated in the experiments and completed motor imagery on two different scales (index finger versus arm). The results indicate that the motor imagery of arm reaches the better performance compared with the motor imagery of index finger. Furthermore, we make a comparative analysis in averaged power spectrum in order to reveal inherent phenomenon. The analysis of power spectrum further confirms that arm motor imagery has an advantage over index finger motor imagery.**

I. INTRODUCTION

Brain is the most precise and complex organ in human body. Thereby brain research, without a doubt, is a big challenge. Long-term effort is needed to explain how the brain works and neurons interact each other. Fortunately, a number of means can be adopted to study the brain. For instance, Ryuta Kawashima et al. observed which fields were activating in the brain during self-paced arm and finger movements by measurement of positron emission tomography (PET) [1]. The activated fields are related with movements. Iole Indovina and Jerome N. Sanes used functional magnetic resonance imaging (fMRI) to examine the representation pattern in the brain while participants were moving their fingers [2]. Besides the means mentioned above, electroencephalogram (EEG) measurement is another common way in brain research. EEG signals reflect overall effects of neuronal discharges in local area. The synchrony of neuronal population decreases when cortical areas is preparing to process or is executing a motor command in association with a cue. This phenomenon is called event-related desynchronization (ERD) [3-4]. The opposite phenomenon to ERD, event-related synchronization (ERS), is an increase in synchrony of neuronal population [5].

While subject is imagining arm or finger movement, the ERD phenomenon appears in the contra-lateral cortex. According to that principle, we can discriminate which side movement the subject is imagining. In this study, we investigate whether different scales affect the recognition[1] performance of motor imagery. Furthermore, we make a quantitative comparison of recognition accuracy between imaginary movement of index finger and imaginary movement of arm. At last, averaged power spectrum is analyzed between them.

II. METHODS

A. Data Acquisition

EEG signals were recorded from fourteen channels with a digital NeuroScan Synamps2 amplifier produced by NeuroScan, Inc.. All electrodes were mounted in a standard EEG cap according to the 10-20 international system. The electrodes used in our experiments are C5, C3, C1, CZ, C2, C4, C6, CP5, CP3, CP1, CPZ, CP2, CP4 and CP6. The EEG recordings were referenced to the electrodes which are attached to the mastoid bones behind each ear and grounded at the electrode of GND in the frontal area. Fourteen electrodes used for recording were placed on the region related to sensorimotor cortex. The impedances of all electrodes were kept below 5 kΩ in order to ensure good signals. EEG data were collected at the sampling rate of 250 Hz.

B. Subjects

The subjects participated in this study are eight adults without any sensory-motor diseases or history of psychological disorders. All subjects had attended related BCI experiments once previously. We gave them introduction about experimental process. Their age ranges from 23 to 27 years old and two of them are female. All subjects have given their written informed consent for this study.

C. Experimental Paradigm

The subjects sat still in a comfortable chair facing a 22-inch wide-screen monitor 1.2 meters away and were asked to remain motionless during sessions. Each subject completed five or six sessions for each of different scales (index finger and arm). There were two minutes for rest between successive sessions. Each session consisted of twelve trials separated by

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intervals of two seconds (see Fig. 1). The word 'Attention' was displayed on the screen for three seconds at the beginning of each session. A cue was presented to indicate which side movement the subject should imagined. The cues were presented in random order. Accuracy was displayed on the top of screen of computer monitor and updated after each trial. A trial was four seconds long and consisted of 25 sliding time windows. The width of sliding time window was 1000 ms.

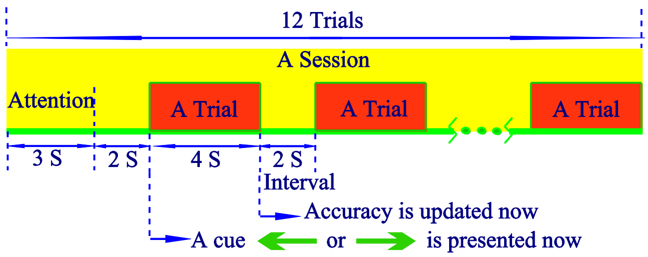

Fig. 1 The time arrangement of a session. At the beginning of each session, the word 'Attention' was displayed on the screen for three seconds in order to remind subjects. The interval between trials was 2 seconds. A cue 'arrow' is presented at the beginning of each trial. After each trial, accuracy is updated.

D. *Algorithm*

The recorded EEG signals were processed by a series of preprocessing methods. They include artifact removal, baseline calibration, band-pass filtering and so forth. The aim of preprocessing is to improve the signal-noise ratio and prepare for feature extraction. We employed common spatial patterns (CSP) to extract features of EEG signals which had been band-pass filtered between 8 and 30 Hz. The detailed explanation of CSP can be found in [6] and [7]. Those features obtained based on the optimal component separation property of CSP are optimal for discriminating two populations of EEG. And then, support vector machine (SVM) was used to classify features [8-9].

III. EXPERIMENTAL RESULTS

A. *Accuracy Comparison*

We made accuracy comparison between index finger motor imagery (IFMI) and arm motor imagery (AMI) in terms of trial and sliding time window. The experimental results show that the AMI performance surpasses the IFMI performance. The averaged classification accuracy in trials across all sessions of all subjects is 60.54% and 71.22% for IFMI and AMI respectively. The averaged accuracy in trials of each subject across all sessions is shown in the third and forth columns of table 1. As shown in table 1, NS is the number of sessions completed by each subject in the experiments. AT represents averaged recognition accuracy in trials across all sessions by percentage. AW represents averaged recognition accuracy in sliding time windows across all sessions by percentage. IF represents the index finger motor imagery. A represents the arm motor imagery. The overall mean averaged each column is shown in the last row of table 1. In terms of trial accuracy, every subject has a better performance under imagining arm movements compared to imagining index finger movements. Five of eight subjects improved more than 10 percentage points. In particular, subject 5 has a large improvement up to nearly 20 percentage points. In other

TABLE I
THE RECOGNITION ACCURACY FOR EACH SUBJECT AND THE NUMBER OF SESSIONS COMPLETED BY EACH SUBJECT

Subject	NS	AT(IF)	AT(A)	AW(IF)	AW(A)
1	5	48.2	60	47.54	57.01
2	6	54.17	61.17	52.64	54.38
3	5	69.8	83.4	66.32	72.92
4	6	59.67	76.33	61.32	69.08
5	6	54	73.5	53.94	64.33
6	6	94.5	98.67	82.64	91.9
7	6	54.17	65.17	50.76	57.91
8	6	49.83	51.5	54.75	53.33
Mean		60.54	71.22	58.74	65.11

words, the distance between red straight line and green straight line is long for subject 5 as shown in Fig. 2. In terms of sliding time window, the averaged classification accuracy across all sessions of all subjects is 58.74% and 65.11% for IFMI and AMI respectively. AMI outperforms IFMI again. The fifth and sixth columns show averaged classification accuracy across all sessions of each subject. The AMI accuracy of all subjects is higher than IFMI accuracy except subject 8. We assume that subject 8 didn't follow our instructions given before the experiments. He maybe imagined several fingers instead of index finger or something else like this.

B. *Power Spectrum Comparison*

In order to further reveal the differences between IFMI and AMI, Power spectrum comparison is done for showing inherent phenomenon. From the power spectrum comparison, we can understand more clearly why AMI outperforms IFMI. A projection matrix can be obtained based on CSP. Each row of projection matrix is an eigenvector. We select the eigenvector corresponding to the maximal eigenvalue because which contains maximal variance.

A segment of EEG data is projected into the space spanned by selected eigenvector as follows:

$$e = w^T * E . \tag{1}$$

Where E is a segment of EEG data, the length of a segment EEG used in this paper is one second. w is eigenvector corresponding to the maximal eigenvalue. And then, e is transformed by fast Fourier transform algorithm (FFT) to gain power spectrum P . After that, averaged power spectra is calculated as

$$P_{AVE} = \frac{1}{N}\sum_{i=1}^{N} P_i . \tag{2}$$

Where N is the number of segments. Fig. 3 shows the averaged power spectrum in the third session of subject 5.

The top panel in Fig. 3 is averaged power spectrum of AMI. The middle panel shows averaged power spectrum of IFMI. The bottom panel is the difference of averaged power spectrum between left motor imagery and right motor imagery. Consequently, the red dashed-dot line in the bottom panel indicates the difference values which are obtained through the values of red line minus the values of green line in the top panel. Similarly, the green dashed-dot line is the difference values for the middle panel. It's clear that averaged power spectrum is different for different motor imagery. Power spectrum of one class is high while that of the opposite class is low. Hence, classifier can be trained to recognize based on this principle. On the other hand, the bottom panel in Fig. 3 clearly shows the difference values of averaged power spectrum are larger when subjects imagine arm movements compared with index finger movements. This evidence illustrates AMI can induce larger difference in power spectrum. We further calculate averaged power spectrum of all sessions of subject 5 so as to show the whole difference. The results are drawn in Fig. 4. The AMI is better than the IFMI again.

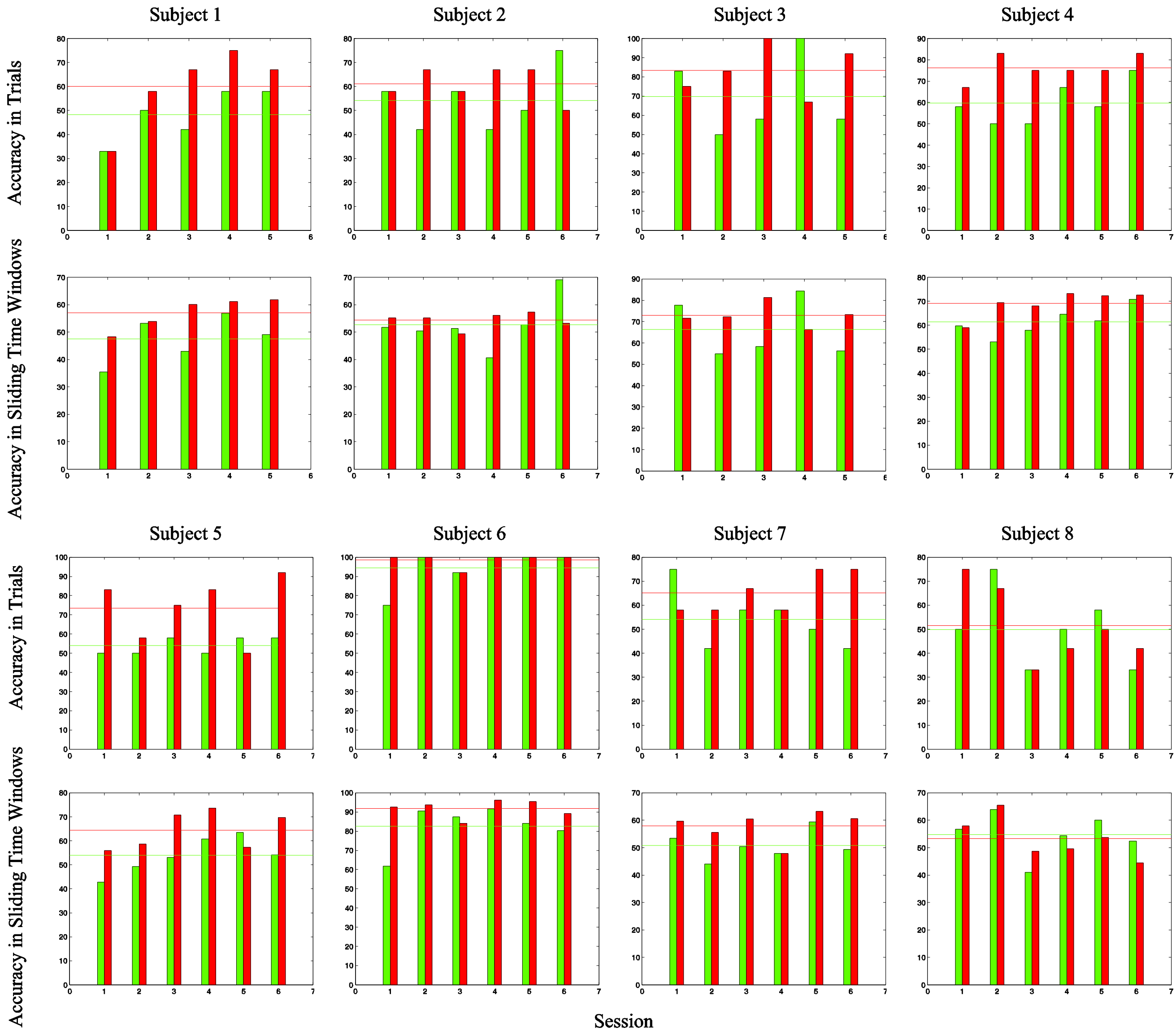

Fig. 2 A comparison in classification accuracy between motor imagery on different scales (index finger versus arm). Green bars represent classification accuracy of index finger motor imagery. In contrast, red bars represent classification accuracy of arm motor imagery. The straight lines drawn on the top of each subgraph indicate the mean of classification accuracy over all sessions (red line for arm and green line for index finger). The first and third rows show accuracy in trials for each subject. The second and fourth rows show accuracy in sliding time windows for each subject.

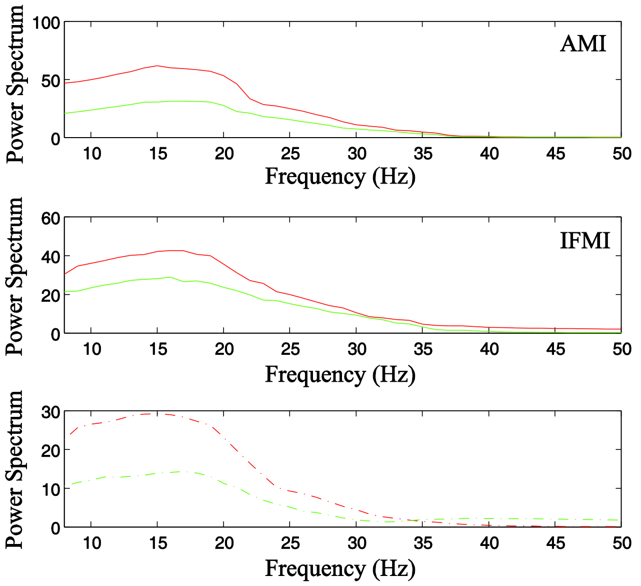

Fig. 3 Power spectrum comparison between arm motor imagery and index finger motor imagery. Averaged power spectrum is obtained by averaging all segments in the third session of subject 5.

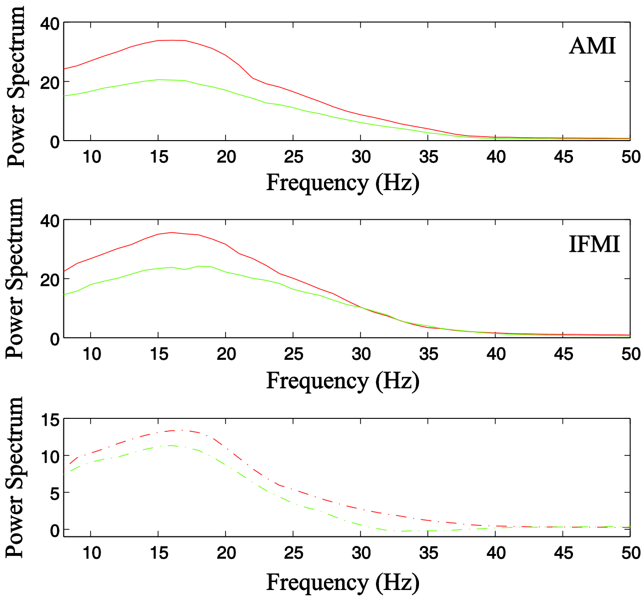

Fig. 4 Power spectrum comparison between arm motor imagery and index finger motor imagery. Averaged power spectrum is obtained by averaging all segments of all sessions of subject 5.

IV. Discussions and Conclusions

The aim of this work is to explore a mode which can induce event-related potential more easily. We expect to provide an experience for persons who engage in motor imagery experiments and make them more expediently select which motor imagery is used. In this paper, a comparison between arm motor imagery and index finger motor imagery is presented. The classification accuracy indicates the performance of AMI is better than the performance of IFMI. In terms of trail accuracy, the AMI for all subjects is higher than the IFMI. The same result is gained in terms of sliding time window accuracy except subject 8.

In addition, we analyze the performance in frequency domain. The results support AMI has the better performance. The difference of power spectrum is the larger while subjects are imagining arm movements. We assume the following reasons can to explain why the AMI outperforms the IFMI. In the first place, subjects are used to arm movements in daily life. People usually do arm movements every day and don’t usually do singular finger movements. In most cases, index finger moves along with other fingers. Moreover, large scale motor imagery is easily achieved because people can more easily focus attention on it. It can be imagined how difficult concentrating on small scale thing as an index finger. This is also confirmed by subjects’ responses to enquiry after the experiments.

We introduce the preliminary work here. Our further research is thorough comparative analysis. In addition, the relationship between performance and factors, such as movement frequency, movement extent, forms of visual feedback etc, is needed to determine.

Acknowledgment

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