Classification of Motor Imagery for Ear-EEG based Brain-Computer Interface

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Abstract— **Brain-computer interface (BCI) researchers have shown an increased interest in the development of ear-electroencephalography (EEG), which is a method for measuring EEG signals in the ear or around the outer ear, to provide a more convenient BCI system to users. However, the ear-EEG studies have researched mostly targeting on a visual/auditory stimuli-based BCI system or a drowsiness detection system. To the best of our knowledge, there is no study on a motor-imagery (MI) detection system based on ear-EEG. MI is one of the mostly used paradigms in BCI because it does not need any external stimuli. MI that associated with ear-EEG could facilitate useful BCI applications in real-world. Hence, in this study, we aim to investigate a feasibility of the MI classification using ear-around EEG signals. We proposed a common spatial pattern (CSP)-based frequency-band optimization algorithm and compared it with three existing methods. The best classification results for two datasets are 71.8% and 68.07%, respectively, using the ear-around EEG signals (cf. 92.40% and 91.64% using motor-area EEG signals).**

Keywords-brain-computer interface; ear-EEG; motor imagery

I. INTRODUCTION

The past twenty years have seen increasingly rapid advances in the field of brain-computer interface (BCI). BCI technology allows its users to interact with the external environment through a direct connection between the brain and an output device using brain signals. The brain signals can be acquired through various modalities such as electro-encephalography (EEG), functional near-infrared spectroscopy (fNIRS), magneto-encephalography (MEG) and so on.

EEG is one of the most widely used methods due to its economic efficiency and high-temporal resolution. However, conventional EEG-based BCIs are still uncomfortable to accomplish practical applications owing to lots of EEG electrodes, wearing an EEG-cap, need of skilled-assistants etc. Hence, ear-EEG-based BCIs have been researched for the more convenient BCI (Note that ear-EEG can be divided into measuring EEG signals 'around the outer ear' or 'in the ear'). Previous study demonstrated that the quality of the ear-EEG signals is enough to extract brain activities [1] using the various BCI paradigms (e.g., P300-based event-related potentials (ERP), steady-state visual evoked potentials (SSVEP) and alpha attenuation).

However, previous studies did not deal with the motor imagery (MI) in the ear-EEG. MI stands for a mental simulation for a given action without overt movement, which is one of the most used paradigms in the BCI. And the MI is more suitable for the practical applications than other exogenous-BCIs because of the advantage that it does not need external stimuli [2].

This study, therefore, set out to assess the performance of the MI-classification using the ear-around EEG signals. Also we propose a common-spatial pattern (CSP)-based optimal frequency band search algorithm for classification MI task based on ear-EEG. And we compared the classification performance with that of three existing methods (i.e., CSP [3], common spatio-spectral pattern (CSSP) [4], filter bank CSP (FBSCP) [5]) on two datasets. Our results show a possibility of MI classification based on the ear-EEG for the practical BCI applications.

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II. METHOD

A. Data Acquisition

Two datasets were used for evaluating the proposed method. *Dataset1* was obtained through our experiment and *Dataset2* was the BCI Competition III dataset IVa.

1) Dataset1: Five subjects participated in the experiment. Right hand, left hand, and foot MI tasks were performed in random order (50 times per class) following the manner: A blank screen was displayed for 0~3 s. And then, a fixation cross appeared at the center of the monitor for 3~6 s after a warning sound was given. After that, a visual cue (right, left, down arrow) corresponding to each class was randomly assigned for 6~10 s. During the 4 s, the subjects performed the MI. The experiment was conducted for approximately 30 minutes. EEG signals were recorded from 70 Ag/AgCl scalp electrodes following the international 10-20 system (Easy cap, BrainProduct) referenced to the nose tip. AFz electrode served as ground (Fig. 1) and the data were sampled at 1,000 Hz.

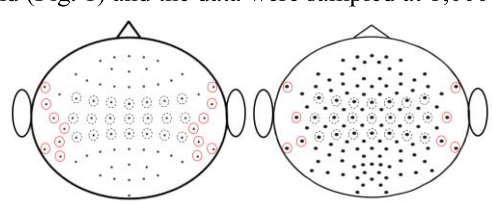

Figure 1. Electrode montage for dataset1 (left) and dataset2 (right). Solid red-line means ear-around channels and dotted black-line means motor-area channels used for the classification.

TABLE II. PERFORMANCE [%] FOR DATASET1

Method	Area	Subject					Avg.	Ear/Motor
		1	2	3	4	5		
CSP	Motor	84	88	80	86	93	86.20	66.13
	Motor+Ear	83	86	76	87	92	84.80	
	Ear	56	58	44	66	61	57.00	
CSSP	Motor	89	93	87	84	93	89.20	74.66
	Motor+Ear	85	92	87	81	96	88.20	
	Ear	63	67	57	73	73	66.60	
FBCSP	Motor	81	92	72	90	88	84.60	72.10
	Motor+Ear	75	93	70	82	89	81.80	
	Ear	60	61	59	60	65	61.00	
Proposed	Motor	92	94	90	91	95	92.40	77.71
	Motor+Ear	91	93	87	82	96	89.80	
	Ear	67	71	67	77	77	71.80	

TABLE I. PERFORMANCE [%] FOR DATASET2

Method	Area	Subject					Avg.	Ear/Motor
		aa	al	av	aw	ay		
CSP	Motor	86	96	74	90	95	88.21	67.69
	Motor+Ear	84	96	73	90	94	88.00	
	Ear	54	63	53	60	68	59.71	
CSSP	Motor	92	97	75	98	96	91.57	71.69
	Motor+Ear	90	98	77	97	95	91.29	
	Ear	60	67	64	65	73	65.65	
FBCSP	Motor	91	97	71	92	94	89.00	68.94
	Motor+Ear	89	97	74	90	95	88.86	
	Ear	56	61	58	61	71	61.36	
Proposed	Motor	93	97	76	97	96	91.64	74.28
	Motor+Ear	91	97	78	97	95	91.64	
	Ear	63	69	66	66	76	68.07	

2) *Dataset2:* We used the BCI Competition III dataset IVa. Five healthy subjects (aa, al, av, aw, ay) participated in the experiment. 118 electrodes were used to record the EEG signals based on 10-20 system and sampled at 250 Hz. Each subject performed 140 trials per each MI task respectively [6].

B. Pre-processing and Parameter Setting

All EEG data were down-sampled to 100 Hz. And the channels from around the ear (*Dataset1*: 14, *Dataset2*: 8) and motor area (*Dataset1*: 21, *Dataset2*: 21) were selected for the classification. The EEG data were band-pass filtered between 8 Hz and 30 Hz. For the FBCSP, nine band-pass filter banks were used (see details in [5]). Time-delayed embedding varied from 1 to 15 in the CSSP and the proposed method. All EEG data were processed using OpenBMI, which is a Matlab-based open source toolbox [7].

C. EEG Data Processing

In MI classification, frequency-band optimization is one of the most critical issues. So far, we determined the frequency-band of the time delay embedding signals through the spectral filter by the 5-fold cross-validation. First, low-bound of the frequency-band was fixed based on the performance of the time delay embedding method [4]. The low-bound started at 5 Hz and moved to a higher frequency if the current performance was lower than that of the higher frequency. If not, the frequency was fixed as the low-bound of the frequency-band. Then, upper-bound was determined oppositely. The upper-bound started at 35 Hz because 5 to 35 Hz frequency-band includes both the Mu (8-14 Hz) and Beta (14-30 Hz) rhythm known as the most significant frequency-bands to classify the MI. A spatial filter was calculated by CSP. Then, we classified log-variance features using a regularized linear discriminant analysis (RLDA) classifier.

III. RESULTS

We presented MI classification performance (right vs. foot) of the four methods for each dataset in TABLE I and II. In the classification performance using the EEG signals around the ear, the proposed method showed accuracy of 71.80% and 68.07% in each dataset. And, we computed the p-values using a paired t-test to assess whether the differences in classification accuracies between proposed method and other methods are at a significant level on each dataset. The p-values on each dataset is as follows: p=0.0027, 0.0029 (CSP), p=0.0123, 0.0042 (CSSP), p=0.0037, 0.0006 (FBCSP). Note that the classification performance was evaluated by the 5-fold cross-validation and the same training/test partitions were used in the cross-validation for a fair comparison among the competing methods.

IV. DISCUSSION AND CONCLUSION

In this paper, we classified the 2-class MI tasks using the ear-around EEG. And, the performance was compared with that of the motor area to verify the feasibility of the motor imagery classification in the ear-EEG. The proposed method showed better performance than the other methods by finding the optimal frequency-band through the spectral and the temporal filter. However, as expected, ear-EEG based MI classification showed lower accuracies compared with using motor area EEG signals. Note that the performance of the 'Ear' with the 'Motor', it showed 77.71% and 74.28%, respectively (Table I and II). In this study, we used conventional EEG electrodes attaching around the ear far away approximately 1.5 cm from the ear. However, in future work, we will evaluate the proposed method using ear-EEG electrodes that more close to the ear.

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