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운동능력과 뇌편측성의 개인차에 따른 사지움직임예측을 위한 EEG 변수추출에 관한 연구

Research on EEG Parameters for Movement Prediction Based on Individual Difference of Athletic Ability and Lateral Asymmetry of Hemisphere

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ABSTRACT

Recently, EEG gains much interests due to its applicability for people to communicate directly with computers without detouring motor output. This study was designed to address this issue if EEG can be successfully used to predict limb movement. It was found that ordinary people appeared to show significant difference in brainwaves between right hand (foot) and left hand (foot) movement. Lateral asymmetry was also found to interact significantly with EEG. Further research is urged with this refined method to provide more useful insights into EEG-based BCI.

Keyword: BCI, EEG, lateral asymmetry

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1. Introduction

Although computer technology has been evolving at an astonishing speed, hands appear to be the most relied medium at present to interact with computers and some typical examples include keyboard and mouse. Recently, however, attempt has been made to allow other mediums to put forward user commands to computers. That is, rather than relying on users' motor output, it may be possible to utilize brainwaves to get what people think or wish to act transferred to computers (Keirn & Aunon, 1990b; Farwell & Donchin, 1988; Wolpaw et al., 1991; McFarland et al., 1993; Wolpaw & McFarland, 1994). This idea of so-called BCI (Brain Computer Interface) receives much attention and under research by some academics in such countries as America (Wolpaw et al., 1991), Japan (Hiraiwa et al., 1990), and Australia. BCI gains such attention due to its ability to provide "a communication channel directly connecting the brain to a computer or another electronic device"(Kalcher et al., 1996). This notion is founded on the fact that brainwaves contain information sufficiently enough to decode human thought and intended action and may well be translated into some commands in replacement of human limb movements. This study aims to explore the applicability of EEG in designing BCI (Brain Computer Interface). In a controlled lab setting, we collected EEG data and analyzed its characteristics in relation to limb movement. The result of this study indicated that athletic ability and lateral asymmetry should be taken into account in designing BCI. Next section discusses some relevant prior research with regards to EEG and BCI. Given this, we develop some research questions.

2. Literature Review

There have been a number of empirical studies in relation to BCI as seen in **Table 1** and the research methods appear to be remarkably different from each other. While most studies have been conducted in a controlled laboratory setting, some of the methodological issues are often related to (1) task contexts, (2) the characteristics of participants (e.g., right handed, sexuality) and (3) EEG measurement as seen in **Table 1**. Some studies investigated the applicability of EEG in the context of 'imagination': that is, participants are asked to imagine one of given tasks (e.g., figure rotation, Keirn & Aunon, 1990). Other studies examined the changes of EEG in relation to limb movement and people were typically asked to move their limbs during which EEG was recorded and put into analysis (Kalcher et al., 1996). More importantly, however, the way EEG is measured may be the one that plays a critical role in determining the applicability of BCI. Some of the focal issues may include electrode positions, the number of channels and analysis methods. **Table 1** shows that the central lobe area appear to be arguably the most common position of EEG measurement in relation to limb movement. The number of EEG channels appeared to be in the range between two (Wolpaw & McFarland, 1994) and rather comprehensively 64 (Pfurtscheller et al., 1996). What adds to complexity in brain research is the variety of mathematical models and their robustness. As seen in **Table 1**, a number of EEG analysis methods have been adopted in BCI studies. They include ERP P300 (Farwell & Donchin, 1988), asymmetry ratio (Keirn & Aunon, 1990), RP (Readiness Potential) (Pfurtscheller et al., 1993), μ(Wolpaw et al., 1991) and ERD (Event-Related Desynchronization) /ERS (Event-Related Synchronization) (Kalcher et al., 1996). We subsequently discuss accuracy and related issues that may play an important role in determining the applicability of BCI.

Accuracy may be greatly related, among others, to data measurement and preprocessing of measured data and mathematical models to analyze EEG. Over the decades, considerable research has been conducted on the robustness of mathematical models for the classification of EEG. The Fourier model has often been employed to analyze the power spectrum of physiological data (McFarland et al., 1993). The recent development of mathematics highlights the importance of such models as neural networks, Chaos and Wavelet that could recognize any changes in patterns contained in physiological data (Pfurtscheller et al., 1996). In consideration of the white noise effect on EEG (e.g., EEG attenuation due to skull), however, it may be practically impossible to achieve the perfect level of accuracy. As seen in **Table 1**, some empirical studies showed considerably high accuracy in predicting what people imagine. Among others, Hiraiwa et al. (1990) reported only one failure out of 24 trials in predicting directional joystick movement. Keirn and Aunon (1990) also showed 98% accuracy to detect what people imagine. On the other hand, some empirical studies showed accuracy only a little higher than a pure guess at the task of predicting 2-dimensional computer cursor paths and limb movements through brain waves (Pfurtscheller et al., 1996; Wolpaw & McFarland, 1994). Thus, further research

TABLE 1. Empirical Studies of EEG and BCI

Author(s)	Participant(s)	Task(s)	EEG measurement	No. Channel	Electrode locations	Training	Off-line Analysis	On-line Aanlysis	Accuracy (%)
Hiraiwa, Shimohara & Tokunaga (1990)	1	· task 1: syllable pronunciation(a, i, e, o, u) · task 2: joystick movement (up, down, right, left)	· RP · 0.5 15 Hz · measured 30 times	12	FP1, FP2, F7, F8, C3, C4, T5, T6, O1, O2, FZ, PZ	N	· averaged · NN (back-propagation) · 24 input layers (12 ch. x 2 averages (30 RPs each task)	· non-averaged · Y	· task 1: 16/30 correctly recognized (a: 5/6, i: 2/6, u: 5/6, e: 1/6, o: 3/6) · task 2: 23/24 correctly recognized · on-line: 10/10
Kalcher, Flotzinger, Neuper, Golly & Pfurstcheller (1996)	4 (1F, 3M), all right-handed, 23-27 yrs	· task 1: limb movement · task 2: limb moving imagination (4 limbs)	· ERD/ERS · For task 1, EEG recorded during movement prepara-tion	6 (bipolar)	C3/C3', CZ/CZ', C4/C4'	Y	· LVQ (5.3-35Hz or filtered (10-12 Hz, 20-24 Hz))	· LVQ (5.3-35Hz, 3250-4250ms	· 40 - 60% (online), 40 - 75% (offline)
Keirn & Aunon (1990)	5 (1F, 4M), 21-48 yrs	· multiplica-tion, figure rotation, letter composition, visual counting	· Asymmetry ratio	7 ch	O1, O2, P3, P4, C3, C4	-	· Bayes quadratic classifier, & W-K method	-	· 95 ~ 98% (2s & single), 82 ~95 % (2s & combined), 97 ~ 99% (0.25s & single) and 82 ~ 89% (0.25s & combined)
Keirn & Aunon (1990)	5 (1F, 4M), 21 - 48 yrs	· multiplica-tion, figure rotation, letter com-position, visual counting	· Asymmetry ratio	7 ch	O1, O2, P3, P4, C3, C4	-	· Bayes quadratic classifier, W-K method, Burg method (spectrum & AR coefficients)	-	· 95.5 ~ 98% (2s & single), 84.7 ~95 % (2s & combined), 96 ~ 98% (0.25s & single) & 82.3 ~ 89% (0.25s & combined)
Kuhlman (1978)	14 (8 normal & 6 epileptic patiens)	· Hand movement & visual stimulation	α, μ	8 ch	Cz, C3, F3, P3	-	· FFT	-	-
McFarland et al. (1993)	4	· cursor movement (up & down)	· μ rhythm	? (bipolar	anterior and posterior to C3	Y	· n/a	· FFT	· 39.1 ~ 75 (Hit ratio)
Pfurtscheller et al. (1994)	-	· Movement of hand, foot, & tongue	· ERD/ERS	56 ch	Post & precentral		· LVQ, Power time estimation, & topographical patterns	-	· In 2-class : · 75~83% (10~12Hz), 81~82% (38~40Hz) & 87 ~89% (all band) · in 4-class : · 51~59% (10~12Hz), 40~49%(38~40Hz), 62~70% (all bands)
Pfurtscheller, Flotzinger, Pregenzer, Wolpaw & McFarland (1996)	3	· cursor movement (up & down)	· ERD	64 ch	sensorimotor cortex	Y	· n/a	· Power spectra, DSLVQ, ERD maps & time courses	· 66.3 - 76.8%
Wolpaw, McFarland, Neat & Forneris (1991)	5 (1F, 4 M)	· cursor movement (up, down)	· μ rhythm	Unipolar	C3 or C4	Y	· n/a	· μ rhythm amplitude	· 80~95% (10 - 29 hits/min)
Wolpaw & McFarland (1994)	5 (2F, 3M)	· cursor movement (up, down, left, right)	· μ rhythm	2 ch (bipolar)	FC3/CP3, FC4/CP4	Y	· n/a	· FC-CP, FC-CP	· 40 - 70%

should be directed to under what contexts the mathematical models would perform well.

Individual differences should be taken into account in that EEG may not be necessarily consistent over individuals (e.g., age, right-handed) and thus, simple averaging of EEG may lead to incorrect interpretation as typically witnessed in mathematical analysis. It should also be noted that an individual might show different patterns of EEG signals over time. The former is referred to as inter-individual differences, whereas the latter, as intra-individual differences. Intra-individual differences suggest the importance of resting prior to data measurement and its timing. Variance would be larger for the intra-individual differences than for the inter-individual ones (Gasser et al., 1985) and thus, research may be needed to typify some homogenous groups of individuals who exhibit similar patterns in the changes of EEG. Despite the importance of individual difference, **Table 1** highlights very little research to address this issue. Given this, this study raises the following research questions with regards to EEG and limb movement.

- Does EEG exhibit different characteristics between athletics and non-athletics?
- Does lateral asymmetry influence EEG?

3. Research Methods

3.1 Participants

Participants in this study were 11 undergraduate students of whom 10 were male and the rest, female. It was ensured that they did not have any prior medical treatment in relation to brain and could freely move their limbs as required in this study. This study was designed to test the effect of athletic ability on EEG and thus, they were assigned to experimental conditions depending on athletic ability. Better performers were given corresponding positive feedback as the experiment proceeded (e.g., complementary remarks).

3.2 Design

This study is to observe different EEG characteristics between athletics and non-athletics and influence of asymmetry of brain in the condition of limb movement. A controlled lab design was opted for this study due to the easier control of variables of interest. All participants were assigned into the condition of athletic ability. The athletic group was four sportsmen and the non-athletic group, seven students of Information Systems major. At the task, they were required to complete four stages of experiment - (1) rest, (2) readiness, (3) action and (4) relaxation. Experimental stimuli were given at the second stage for the participants to get ready for limb movements. The limb movements were randomly selected and counterbalanced over participants among (1) right hand (RH), (2) right foot (RF), (3) left hand (LH) and (4) left foot (LF). At the third stage, they were asked to act as prompted by the system. Each movement was designed to last for 5 seconds. For the last stage, they were asked to relax for the next limb movement.

3.3 Procedure

Prior to the lab, the participants were briefed about the experimental requirements. Then, they were ushered into a small room and seated on a comfortable armchair. They were asked to rest while watching a computer screen located before them that led them through the experiments. For the subsequent stage of the experiment, the 'ready' sign was displayed twice to allow enough time for the participants to get ready for the limb movements. Then, the participants were guided to the second 'action' stage where human body was graphically displayed on the monitor to let the participants notice easily which part of their limbs to act. For example, the participants were asked to move their right hand soon after the right hand was highlighted. For the hand movement, they were asked to keep grabbing their hand as long as the sign was on. On the other hand, they were required to shake toes and rotate their foot until the sign went off. EEG was recorded during the action of their limb movements. They were told to move their limbs as fast and strong as possible to measure dominant EEG over motor cortex area. The task was repeated sixteen times and participants were required to imagine the action prompted to perform for the last repetition. Experiment was completed in one sitting and lasted for 680 seconds.

3.4 EEG recording

EEG was recorded with commercial Biopac (MP100) systems in this study. The systems had 16 bipolar/ monopolar channels and its minimum and maximum cut-off frequencies were 1 Hz and 30 Hz respectively. It had an 8 channel 12 bit resolution A/D converter and a 10MHz clock timer. Electrodes were attached at C3 and C4 that were presumed to be the most suitable locations to detect both hand and foot movements. Ground and reference were located on the posterior area of external ear. As data sampling frequency was 200Hz, 400 samples were digitized for each slot of two seconds.

3.5 Analysis method

Two seconds of EEG data were taken from each phase and put into FFT analysis. Area and maximum values were computed for ? rhythm in the frequency bandwidth of 12 – 20 Hz, 20 – 30 Hz and 13 – 35 and μ rhythm of 8 – 12 Hz. Then FFT values were used to compute ERD/ERS(Event-Related Desynchronization/Event-Related Synchronization) as follows:

$$ERD(\%) = 100 \times (R - \chi)/R$$

where R represents a power estimate in the reference interval of non-movement state and χ does movement state of each average power estimate. ERD was qualitative quantity of EEG activation based on reference state. ERD having positive value was ERS. Then t-tests were run to examine the effect of experimental variables on EEG. Since this study is explorative in nature, the significance level was set at 0.1. Post-hoc analysis was made on lateral asymmetry of EEG that divided participants into either right or left dominant group.

4. Results

4.1 Effect of Athletic Ability

The first research question was concerned with the effect of athletic ability on EEG. This study found that there was a significant difference between athletics and non-athletics over the stage of readiness. For non-athletics, ERD was significantly different in movement between RH and LH. ERD computed for 20 – 30 Hz β rhythm in the right hemisphere showed significant difference among limb movements as shown in Table 3. ERD of non-athletics for the RH movement was significantly less than that of the LH ($t(142)=-1.88$, $p<0.1$). Their ERD for the RF was significantly less than that of the LF ($t(166)=-2.27$, $p<0.1$). This was also found for both action and imagination. However, there was no significant difference of athletic movement between right and left movement of limbs.

4.2 Lateral Asymmetry

The second research question was related to the effect of lateral asymmetry on EEG. Lateral asymmetry between C3 and C4 was defined in relaxed state according to respective bandwidth such as 8-13Hz, 12-20Hz, 20-30Hz, and 13-35Hz in this study. Pair t-test showed that the right hemisphere at 20-30Hz($p<0.1$) and at 13-35 ($p<0.1$) showed significantly more dominant than the left. On the other hand, the reverse was true for the left hemisphere at 8-12 Hz($p<0.1$). Therefore, two groups such as right-hemisphere dominating group and left-hemisphere dominating group were classified according these results. The effect of lateral asymmetry on EEG was tested for classifying limb movements. ERS at 13-35Hz in right-hemisphere dominating group showed significant difference between movements of right and left hand ($t(142)=-2.62$, $p<0.01$) and between movements of right and left foot($t(142)=-1.66$, $p<0.1$) as shown in Table 2. ERD at 8-13Hz in left-hemisphere dominating group showed significant difference between movements of right and left hand($t(46)=2.02$, $p<0.05$) and between movements of right and left foot($t(46)=2.45$, $p<0.02$) as shown Table 3. These results were valid during movement plan. The same trend was shown during action and movement imagination.

Table 2. Experimental Procedure

Steps	10 sec	2 sec	5 sec	3 sec
	Rest	Ready	Action	Relax

Table 3. ERD by athletic ability at the second stage of readiness (20 - 30 Hz β rhythm)

Participants	Limb	Mean	Std	T	Df	Sig.
Non-athletics	RH	-10.7	56.3	-1.88	166	.06 ***
	LH	3.97	44.5			
	RF	-44.5	12.6	-2.27	166	.02 *
	LF	-9.03	68.4			
Athletics	RH	8.01	35.5	1.52	70	.13 **
	LH	-6.07	42.6			
	RF	7.76	37.2	1.11	70	.27 **
	LF	-2.09	38.4			

Table 4. ERD by lateral asymmetry at the second stage of readiness

Lateral Asymmetry	Limb	Mean	Std	T	Df	Sig.
Right (8 35 Hz ERS)	RH	-9.72	61.7	-2.62	142	.01 ***
	LH	10.9	25.8			
	RF	-1.79	38.6	-1.66	142	.1 *
	LF	7.54	28.3			
Left (8 13 Hz ERS)	RH	1.30	87.5	2.02	46	.05 **
	LH	-89.0	20.1			
	RF	11.8	72.0	2.45	46	.02 **
	LF	-71.8	15.1			

5. Conclusions and Discussion

This study explores EEG characteristics for the classification of limb movements. The parameters include movement duration, frequency bandwidth, athletic ability and lateral asymmetry that may possibly to associate with limb movements.

This study may conclude:

1. ERD at 20-30Hz could well be used as a classifier of left and right movement for both hand and foot movement. It should be noted that this was not found for the athletics.
2. Lateral asymmetry could classify left and right movement of respective hand and foot without consideration of athletic ability. ERS at 13-35Hz in right-hemisphere dominating group and ERD at 8-13(mu rhythm) in left-hemisphere dominating group were the parameters for classifying limb movements.

Athletic ability may require much training over longer periods. This study can suggest ERD at 20-30 Hz for classifying limb movement without any training. Inconvenience of training μ rhythm (Pfurtscheller et al., 1993) can be solved by this bandwidth for engineering application. However, the significance of the ERD at 20-30Hz might disappear with repetition of movement. In this case, the parameter should be mu rhythm for classifying movements.

More general parameters were specific bandwidth according to lateral asymmetry in this study. Defined asymmetry at relaxed state may play important role. ERS at 13-35Hz in right dominant group and ERD at 8-13 Hz in left dominant group might classify limb movements. Different bandwidth should be considered according to lateral asymmetry. Drake (1993) evoked relative difference of hemisphere activation using auditory stimuli and fined left activation exhibited more discounting of persuasive process. However, this study assumed asymmetry without direct measurement of activation level. This study defined asymmetry from direct measurement of potentials and suggested asymmetry related EEG parameters for movement classification.

Therefore, this study showed valuable parameters of EEG with full consideration of athletic ability and lateral asymmetry. Those can be applied to computer control and operation without any hand-oriented devices (keyboard and mouse), to robot control, and to rehabilitation of disabled people. This study did not control movement difficulty. Movement was free depending on a subject. Individual difference existed more in EEG since this uncontrolled. Normalizing process with ERD and ERS may overcome individual differences. The study controlling limb movement for solving inter-individual difference, for example finger bending by 90 degree with 100 psi, will be performed in the future. This study highlights more robust mathematical model in the design of BCI. It should be, however, noted that real-time analysis should take into account of time lag. Time lag refers to the amount of elapsed time for mathematical models to pick up any changes in the patterns of EEG signals. Depending upon the characteristics of mathematical models used, some level of time lag may be imperative. It is due to the fact that most models require some training sessions of data, which leads to a certain period of time delay. For example, neural networks require a set of training data in order to tune their layered mathematical architecture. This field is very promising and thus, further research is needed to find out more valid and timely EEG parameters and mathematical models.

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