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Discrimination of Motor Imagery Types by the Pattern of Brain Connectivity

뇌 연결성 패턴을 이용한 움직임 상상 유형의 구분 연구

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ABSTRACT

Discrimination of Motor Imagery Types by the Pattern of Brain Connectivity

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The motor imagery (MI) is a mental process reconstructing given motion and it is well known that the brain regions related to actual movement were activated. It has been demonstrated that MI has various types and strategies that can be induce different brain response. Particularly, kinesthetic motor imagery (KMI) and visual motor imagery (VMI) have difference even in the mainly activated brain regions. However, previous brain computer interface (BCI) studies had not designed the experiment concerning type of MI. We suggested that the absence of classification on types of MI is a main factor in BCI illiterate, which was found in ~30% of BCI users. It is necessary to instruct and guide the subject by classifying the type of MI. In our previous work, since the enhancement of functional connectivity was confirmed in state of planning motor, we expected that the states of subject can be classified using a pattern of functional connectivity. We regulated the most common states in BCI experiments as four states to classify. (e.g., motor execution (ME), kinesthetic motor imagery (KMI), visual motor imagery (VMI), and visual observation (VO)). The network was also established

with the consideration on the representative connectivity of brain areas in each state. Edges, which are components of the network, were proved suitable features for classification by ANOVA and permutation test. The naïve Bayes classifier applied these features could distinguish four states and it had significant higher accuracy than classifier using edges that is not part of the network. To examine the characteristics of KMI and VMI, the correlation coefficients were also calculated for the execution task (ME, VO) and each imagery task (KMI, VMI). Similar to previous studies investigating brain activity, functional connectivity pattern of KMI resembles that of ME but not of VMI. In particular, the accuracy of classifier produced by the data of two states, KMI and VMI, has important difference by subtracting V1-PPC edge in the features. In this study, four representative states containing KMI and VMI can be classified with the proposed functional connectivity network. It is possible to design future studies of BCI experiment considering the type of motor imagery if our classifier is applied to determine the state of subject objectively. We therefore assert that the conventionally reported problems could be addressed by using the classifying methods for the control and feedback related to modality of motor imagery to the subject in the research on BCI.

Key words: Kinesthetic motor imagery (KMI), Visual motor imagery (VMI), Functional connectivity, Brain network, Brain computer interface (BCI), Electroencephalography (EEG)

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CONTENTS

1. Introduction

Motor imagery (MI) is a mental process of resynthesizing given task without any movement or muscle tension. Brain computer interface (BCI), allowing human intentions to commands all the executions deals with sophisticated movement by utilizing MI. Especially for the disabilities, the MI based BCI is a remarkable technology as it helps to replace the partial body of the disabled by external device. Nevertheless, it has been shown that some of users failed to control in the range of 15–30% [1]. Moreover, studies having many participants reported that up to 50% of users have difficulty achieving an accuracy of more than 70% [2, 3]. There are a number of conjectures about the reason, and one of the reasonable explanation might be that a prediction algorithm does not work well owing to inconsistent types of MI on each occasion.

MI could be divided into various types: i) modality with visual or kinesthetic; ii) perspective as the first-person or the third-person; iii) object which subject control such as own body or alien body. This various types of motor imagery appear not only between subjects but also within subjects. As mentioned, the algorithm relying on ever-changing MI types can delay long time to create over a certain accuracy. The BCI process to build prediction algorithm consists of two main stages: i) training stage for creating decoder which transforms brain signal to real action of machine; ii) another is testing stage using decoder made by the previous stage. In the training stage, most of the BCI studies have used brain signals derived from performing imagery task without detailed instruction considering how to imagine movements so far.[4, 5]. Instructions for specific types of MI are necessary to reduce the time delay and to build the more precise decoder. In addition to detailed instruction, a constant type of imagery is required of users

while generating predict algorithm.

In order to meet the requirements, the experimenter need to identify the type of imagination by the subjects during performing the task and to provide appropriate guidance for precise feedback. Until now, the state of the subjects has been determined through questionnaire, behavioral investigation or verbal feedback, but these methods are subjective and sometimes unnecessary. Therefore, a specific technology measuring the state of the subject with only brain signals which naturally appear when the subject performs a task need to be preceded.

In this study, MI types has been distinguished by modality. The states of the subject observed using MI based BCI were condensed into four states as i) motor execution (ME), ii) kinesthetic motor imagery (KMI), iii) visual motor imagery (VMI), iv) visual observation (VO). It has been shown that most people use two strategies to perform the motor imagery: i) KMI and ii) VMI [6, 7]. KMI is an imagination that simultaneously imagines movement and sensation such as proprioception, perception of muscle and joints, pressure sense of hand and it is closely related with actual movement in activated brain region [8]. VMI, on the other hand, simply depends upon visual information so that it activates the brain regions less relevant to the real movements [9]. Expected artifacts in the imagery tasks are the VO state, which just looks at the target without using the motor related brain area, or the ME state which accompanied by muscle tension of the body corresponding to the task without recognizing it.

Motor cortex activity is considered as one of the reasonable features reflecting the movement-related activity. However, it has been observed even during the resting state. So it may produce false positive classification. Motor-related brain regions apart from the motor cortex are involved in during ME or MI

tasks. Therefore, functional connectivity within motor-related brain regions would be alternative feature. Our previous study also showed that functional connectivity in dorsolateral prefrontal cortex increased during movement planning [10]. There is possibility that the states including MI inducing change of cortical activity less than 25% of actual movement[11] were clearly classified by examining functional network. Functional connectivity refers statistical dependencies among signals from spatially separated brain areas [12]. Functional connectivity between brain areas can provide us with more direct evidence about exchanging information even if the activity of brain region does not increase compared to the baseline [13]. Not only relevant advantages, but also functional connectivity could possibly reflect the underlying structural organization of anatomical connections [14] by utilizing patterns of connectivity among brain regions that presented functional brain networks. Accordingly, many studies on memory [13], resting state [15, 16], cognitive impairments [17] have shown high functional connectivity even in case that cognitive function have been shown relatively weak activity.

We investigated edges that refer connectivity between one brain region and other brain region every state and revealed whether patterns of the edges were consistent with our hypothesis. In this study, we proposed that the classification of four states (ME, KMI, VMI, and VO) through the network represented by the connectivity pattern.

2. Methods

2.1. Participants

Eleven healthy volunteers aged 21-28(23.7±2.5) participated in this study (six females and five males). Except only one participant, all participants were right handed. Intrinsic abilities of two motor imagery types, i.e. KMI and VMI, in all participants were tested using Kinesthetic and Visual Imagery Questionnaire (KVIQ-10) [18] which translated Korean by experimenter (no validation in translated version of questionnaire). There were no excluded participants with KVIQ-10 depending on no difference between scores of each subject. All participants provided informed consent. This study was approved by the Institutional Review Board of Seoul National University Hospital (IRB number: 1605-136-765)

2.2. Data acquisition

Neural signal of all subjects was recorded using Ag/Cl sintered 64-channel EEG cap (Quik-CapEEG, Compumedics, Abbotsford, Victoria, Australia) and amplifier (Neuroscan synamps2, Compumedics, Abbotsford, Victoria, Australia). We acquired neural activities using 62 channels except channel number 33 and 43 for additional reference electrode. Reference electrode was attached to the mastoid which placed behind opposite ear of dominant hand of participant. Movement of arm was tracked by motion capture system with active optical marker (3D investigator, Northern Digital Inc., Waterloo, Ontario, Canada) during neural signal recording. EMG was also recorded from flexor of fingers and biceps for monitoring electric signal in these muscles while participants perform experiment. EEG, motion optic signal and EMG were acquired 2000Hz, 1000Hz and 2000Hz, respectively.

2.3. Experimental design

2.3.1. Instruction and tasks

Experiment begins after experimenter give full explanation about composition of tasks that the participants should do during recording whole signals. The participants wearing an EEG cap and 3D display device sat comfortably in a chair without armrests. Start posture was hands on thighs and the participants were asked to perform the all tasks using their dominant hand. All video for giving target or trajectory of arm according to each state was shown with 3D display device. The tasks for each state were consisted of motor execution (ME), kinesthetic motor imagery (VMI), visual motor imagery (VMI) and visual observation (VO). These tasks are representative samples among various states that can occur when people try to use BCI. ME task was to follow sequence of robot arm's movement from the video displayed on the 3D display device. Subjects were asked to synchronize with the action of robot arm in video and move as much as they can. In KMI task, the subject was instructed to imagine the same movements with their own arm as the movement sequence in the ME task. We emphasized that this task should involve imaging sensation felt before during the actual movement without muscle tension. VMI task had same way of visual imagination as KMI but subjects were asked to completely exclude sensory image. Lastly, subjects were instructed to keep watching the video without any thought and relaxing in VO task. To get better performance and good signals, experimenter shows participant how to perform, and practice with the participant until they can perform respective task on they own with confidence.

2.3.2. Block

Because it is hard to imagine movement without any preceded practical task, we established the block with the imagery task followed by the execution task to help imagination. Blocks are divided into two types of ME-KMI and VO-VMI,

but the ME-KMI block and the VO-VMI block give identical visual stimulation using the same video. In the video of the execution task that contains the ME trial and the VO trial, the robot arm sequentially acts with reaching-grasping-return-release for about 9 sec and rest for 4 sec. In the imagery task, which contains the KMI trial and the VMI trial, we showed video that only have target picture without robot arm during about 13sec. The reason of why we remove robot arm in the video is that robot arm's movement could disturb the motor imagery with their own arm. To reduce the effect of the EEG signal according to the direction, the targets in the video were placed in three directions of triangular shape. A block consisting of an execution trial and an imagery trial, each of which takes 13.3 seconds, requires about 27 seconds. One session is composed of identical 24 blocks that avoid repetition of the same direction right after and consists of total 48 trials required about 11 min. We run total Four sessions that two ME-KMI sessions and two VO-VMI sessions total 48 trials for each state.

2.4. Preprocessing

2.4.1. Resample

The sampling frequency of signals have different frequency depending on machines that Neuroscan for EEG signal and EMG and 3D investigator for tracking position of arm and fingers. All the data resampled to make same sampling frequency to 500Hz operating on MATLAB (R2016b, Math-Works, Natick, MA, USA).

2.4.2. Source analysis

Based on our hypothesis, we set up seven brain regions, DLPFC, PM, SMA, M1, S1, PPC, and V1, which were expected to be mainly involved in information transmission in ME, KMI, VMI and VO networks. We had source analysis from the resampled data according to determined region of interest (ROI)

using built-in function of discrete model probing in BESA research 6.0 (GmbH, Gräfelfing, Bavaria, Germany). The coordinate of ROI was cited from previous research in Table1. Each source was identically analyzed for all subjects by using equal mask.

2.4.3. Frequency band

We have filtered the ROI signal into four representative frequency bands in order to find out detailed characteristics of each frequency band and to improve accuracy of classifier. Each frequency band is defined as four bands: theta band (3~8Hz), alpha band (8~13 Hz), beta band (13~30 Hz) and gamma(32Hz~100Hz).

2.5. Signal processing

All process including signal post-processing and data analyses were conducted with MATLAB (R2016b, Math-Works, Natick, MA, USA).

2.5.1. Functional connectivity - Mutual information

Mutual information (MI) is appropriate for functional connectivity to measure both linear and nonlinear dependencies. This statistical measure was firstly suggested by Shannon's information theory [19] and indicate how two signal shared information in this study. MI of two random variables X and Y can be defined as:

$$\mathrm{MI} = \sum \frac{P(X,Y) * \ln(P(X,Y))}{P(X) * P(Y)}$$

Where $\mathrm{P(X,Y)}$ is the joint probability function of X and Y, and $\mathrm{P(X)}$ and $\mathrm{P(Y)}$ are the marginal probability distribution functions of X and Y, respectively. In this study, we prescribed X and Y as sample in signal, following

common usage in the area of signal processing. All value of mutual information was calculated by using function implemented in HERMES tool box [20].

2.5.2. ROI-ROI Mutual information

Source analyzed ROI signals were distributed in theta, alpha, beta, and gamma ranges by band-pass filter and the epoch duration was based on the onset time of the video. The movements of arm, which can be observed in ME trials by the signal of motion sensor, were investigated for each subject. Next, resting duration and task duration were determined on existence of movement in ME trials during same range of 500ms, respectively. Values of edge by mutual information were obtained with one ROI and the others in each set of resting and task durations. Finally, ROI-ROI mutual information matrix, edge matrix, of a trial was formed by subtracting the value of MI at task duration from the value of MI at resting duration as baseline.

2.5.3. Reject trial

To investigate the possibility of a subject that performs on KMI or VMI, there was the standard of exception for a subject who cannot imagine about their movement using KVIQ-10 before the experiments. However, it is necessary to select the trials strictly because the imaging is the mental process where concentration is easily broken by each trial. On this basis, we excluded the trials that is determined as outlier by comparing with MI values of all trials in an edge of the same state for each subject. We accept the threshold of outlier as follows:

$$[Q1 - k(Q3 - Q1), Q3 + k(Q3 - Q1)] \; or \; [Q1 - k * IQ, Q3 + k * IQ]$$

Q1and Q3is the lower and upper quartiles that denote as the 25th and 75th percentiles. The difference of lower and upper quartiles (Q3 - Q1) is called the interquartile range (IQ). k is constant, where k=1.5 indicates an ‘outlier’ that

proposed by John Tukey [21]. Any outside the range define an outlier. The number of excluded trials was about 15 and there were usually more than 30 trials per state.

2.6. Data analysis

2.6.1. ANOVA

We conducted ANOVA on the edge of each subject to examine that each state can be classified by the established edges based on our hypothesis. The MI values of all trial in each state across subjects, frequency and edge were collected, and it was used for data to perform analysis of variance (ANOVA). Then we obtained the number of subject that passed the criterion of ANOVA($p<0.05$) at each edge and produced the matrix using that number. The element of matrix was represented the number of subject who can classify at least one state of four with a single edge. To investigate how successfully network we applied, we summed all the matrix from each frequency band to create a total edge matrix. Then, we carried out the permutation test by dividing two groups of edges within the network and without the network. Averaged value of network group which composed of 7 edges was calculated and compared with averaged value of non-network group consist of other 14 edges.

2.6.2. Naïve Bayes classifier & Correlated coefficient

Naïve Bayes classifier based on Bayes' theorem is one of probabilistic classifiers[22]. The classifier assumed strong (naive) independence between the features and it makes simplicity. It requires less training data to estimate than other classifiers. The main reason why we selected Naïve Bayes classifier is because the probabilistic approach is empirically more suitable for our data than other approach such as linear discriminant analysis.

The correlation coefficient of KMI and VMI with the other stages were

compared with each other. All mutual information value of subjects in one edge was averaged for each frequency band, and the correlation coefficients were calculated after arranging averaged edges as a signal.

3. Results

3.1. Edges in functional network of hypothesis confirmed by ANOVA

Our ANOVA results corresponded to our hypothesis of the edges which were element of the network. We verified that value from selected edges have significant differences by permutation test ($p = 0.036$) (Fig1. a). The value indicated the number of subject that passed the criterion of ANOVA($p<0.05$) and its averaged value was 5.29. Although results in each frequency band contributed to different edge respectively, it seems to mostly overlap with the hypothesized edge (Fig1. b-e).

3.2. Comparison of classifier between within and without network edges

We can see that the classification accuracy varies depending on whether edges are included in the network or not. All edge, except for some edges who were considered unhelpful to classify the states in at least one subject by result of ANOVA, divided into two groups according to whether the edge belong to entire network or not. Naïve Bayes classifiers were then built using the edges in each group as features. The classifier that specifies the edges in the established network as features was able to distinguish the four states by an average of about 37 percent (Fig2. right). Comparing the graph on the front with the back showed that when the edges within the network were used as a feature, it is significantly more accurate than when the other edges are used as feature (Wilcoxon signed rank test, $n=11$, $p=0.0322$).

3.3. Correlation between each state

The correlation coefficient of KMI with ME was higher than that of VMI with ME in all frequency bands (Fig4. a). To investigate the similarity between each state, correlation coefficients between the states at whole edge were obtained in each frequency band (Fig3. a-d). VMI was more correlated with VO than ME, but at certain frequency bands, KMI was more similar to VO (Fig4. b).

3.4. Investigation of effective edges contributing to comparing KMI and VMI

According to the results, V1 and PPC was the most important edge that affects accuracy of classifier for distinguishing between KMI and VMI (Fig5). We have created a new naïve Bayes classifier that can classify KMI and VMI state with using edges in the network and evaluated accuracy of the new classifier. Then edge was subtracted one by one from the features and classifier was built again with remaining edges. Accuracies from each imperfect classifier were compared with accuracy from classifier using whole edges in the network in order to obtain the most effective edge when categorizing two state. As a result, not only the connectivity of V1-PPC significantly affected the classifier (uncorrected Wilcoxon signed rank test, $n=11$, $p=0.042$) but also all the other edges are affected.

4. Discussion

In this study, we aimed to demonstrate whether different states could be differentiated by the specific patterns from functional connectivity edges. We tried to classify four different states by using the network classifier. To achieve our goal, we selected seven different edges which were divided into two major parts; the one is the motor related signal pathways as such planning and sequencing movement consist of DLPFC-SMA, SMA-M1, and PM-M1 and the other is associated with the sensory information including visual and sensation consisting of M1-S1, S1-PPC, PPC-PM and PPC-V1. We presumed that each edge plays a specific role during each movement stage procedure such as motor planning, motor command, sensation and visual information.

To demonstrate a significant role of the selected edges in differentiating intra-individual four states, we compared the averaged value originated from selected edges along with non-selected edges. The very value indicates the number of the subject passing the criterion as analyzed by ANOVA. Therefore, the results indicate that seven selected edges could be used as a reasonable classifier.

We showed that the brain connectivity could distinguish between KMI and VMI. The brain network consisting of seven functional connectivity edges succeeded to reflect four states as a feature. We inferred from diverse combination of edges in each state in order to classify different states (Fig 2).

In this study, we expected that different functional connectivity among diverse

ROIs would be feasible according to the subjects' different states such as ME, KMI, VMI, and VO. In the ME state, in particular, we hypothesized the all edges to be activated since those actively communicates among ROIs along with enough information. In the KMI state, motor and sensation related pathways were found except PPC-V1 representing direct pathway of visual information from external stimuli. In other words, VMI mainly showed visual information flow expressed in PPC-V1 and also comprised of DLPFC-SMA and PM-PPC in the part of motor planning. Lastly, VO state had only PM-PPC and PPC-V1 on account of transmission of visual information without any motor processes.

We could not directly demonstrate that functional connectivity of all networks in each state were formed as we assumed. However, we focused on differentiating KMI and VMI since the limitations of previous studies such as delay to create decoder and BCI illiterate are generally comes from lack of awareness of the types of motor imagery. To control contamination factors other than modalities of motor imagery, we instructed participants to recognize the perspective and object as their own arm. As a result, we found that KMI and VMI showed the most significant differences in V1-PPC edge (Fig 5). We also found that sensory pathways, M1-S1, S1-PPC, and PM-M1, showed trend of differences between KMI and VMI. These results demonstrate our assumption of network properties.

In addition, we also investigated the relationship between ME and KMI by whole edge and found that KMI and ME showed similar patterns (Fig 3, Fig 4). Our result is in line with previous study that suggested KMI and ME uses similar brain areas [8, 11]. It is of note that previous studies used functional activation in their analysis since it is well known that ERD is observed during motor execution and KMI.

However, it is difficult to differentiate KMI from VMI at individual level by using ERD activities since there is great variability. Indeed, well-known previous study of KMI and VMI reported only 3 of 14 participants showed similar ERD activities [8]. Recent study used squat vertical jump for motion showed similar results of ours [23]. However, it also seems difficult to differentiate the different states of KMI and VMI simply by comparing the activation ratio in sensory-motor and parieto-occipital areas. Moreover, the possibilities that rather extreme motion enlarge the differences of KMI and VMI cannot be excluded. Therefore, functional connectivity, which can be calculated regardless of signal intensity, seems most suitable methods to investigate imagery task which generally showed the low signal intensity. Moreover, functional connectivity contains more structural information than the brain activity since it contains either direct or indirect structural connectivity.

In the present study, we adopted functional connectivity analysis to differentiate KMI from VMI. Although we differentiated KMI and VMI by using functional connectivity analysis, it still remains questionable whether each participant followed instruction properly. However, we excluded the false positive by taking questionnaire, detailed instruction, and extensive training before recording by the single investigator. Moreover, we also exclude the outlier of mutual information objectively within the same task to minimize the artifacts. We found that Subj 2 showed distinctive accuracy pattern changes apart from other subjects (Fig 2). It seems possible that Subj 2 can be BCI illiterate who thinks good at imagining himself. Thus, our criteria could not eliminate BCI illiterate who have illusion of well obeying the instruction. However, we can provide the possibility of differentiate BCI illiterates from comparing of accuracy featured in the network with outside network. The subject 2 could first candidate in our further study

applying the classifier with repetitive imagery training. Our classifier can also provide feedback to all the subject in a future MI-based BCI to use constant type of imagination. Therefore, our results are expected to be a solid foundation in reducing BCI illiterate rates. Finally, it would be possible to replace the body itself using KMI which shares an information pathway with ME, and the prosthesis which has capacity of sensory feedback together.

5. Conclusion

We believe that KMI, which transmitting information by the edges similar to ME, is the appropriate type of motor imagery because of using motor related areas in the most of MI based studies. The designed classifier provide opportunity to give guidance to subject how to imagine and to control state of subject at the same time

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LIST OF TABLES

#	ROIs	Talairach coordinate		
		x	y	z
1	Dorsolateral prefrontal cortex (DLPFC)	-17.82	46.13	29.01
2	Supplementary motor area (SMA)	-9.9	8.62	55.76
3	Premotor cortex (PM)	-37.3	-14.4	60.3
4	Primary motor cortex (M1)	-34.65	-20.40	58.13
5	Primary sensory cortex (S1)	-35.64	-32.07	57.80
6	Posterior parietal cortex (PPC)	-25.74	-54.35	58.91
7	Primary visual cortex (V1)	-9.9	-71.32	10.94

Table 1. The coordinate of ROIs. The coordinate of ROIs cited from previous research [24]. All subject follows this coordinate of each ROI except for one subject that have left-dominant hand. Coordinate of ROI transfer z to –z for the left-hander.

LIST OF FIGURES

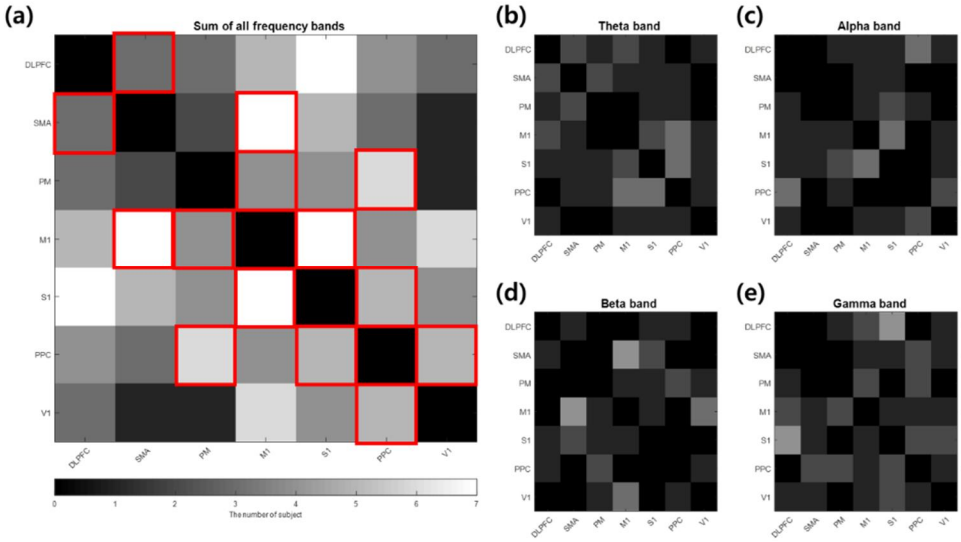

Figure 1. The results of ANOVA. (a) The summation of results for all frequency bands. Square highlighted in red is edges in network. (b-e) The results of ANOVA in each frequency band: (b) theta band, (c) alpha band, (d) beta band, and (e) gamma band.

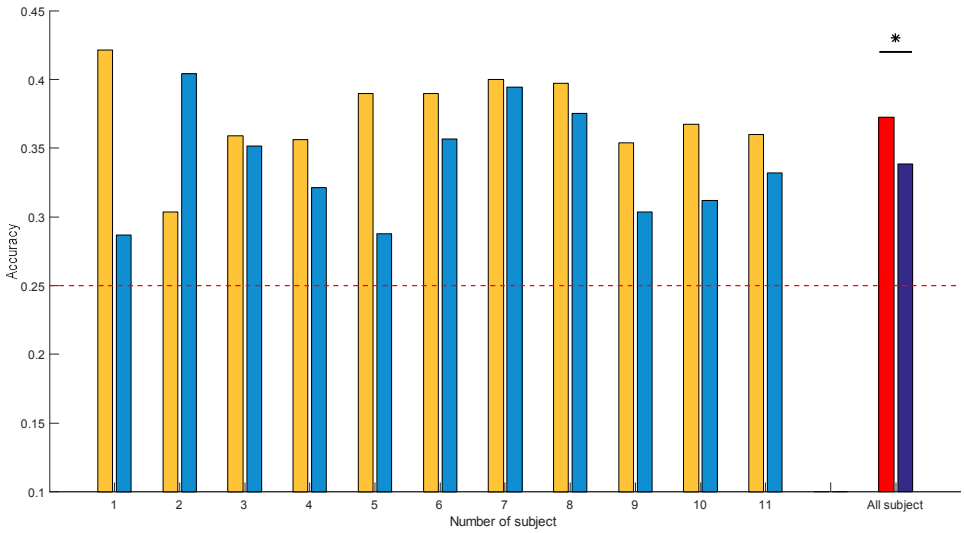

Figure 2. Accuracy of classifier using edges within and without network. (Left) Bar graph of all subjects within and without network. The classifier was generated by the selected edge based on the results of ANOVA. All subjects were compared with the classifier. (Right) Pair of bar indicates the averaged values on all subjects. The notation of star (i.e., *) indicates that the significant value (Wilcoxon signed rank test, $p<0.05$).

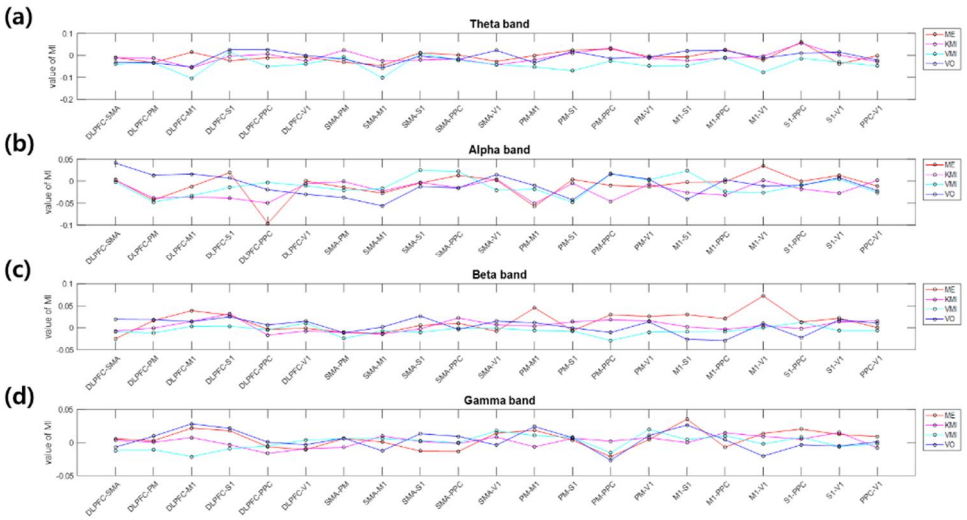

Figure 3. The plots of MI values in all edges. The plots of MI values as a function all edges, which can appear combination in 7 ROIs, with different frequency bands: (a) theta band, (b) alpha band, (c) beta band, (d) gamma band. Each line indicates different states.

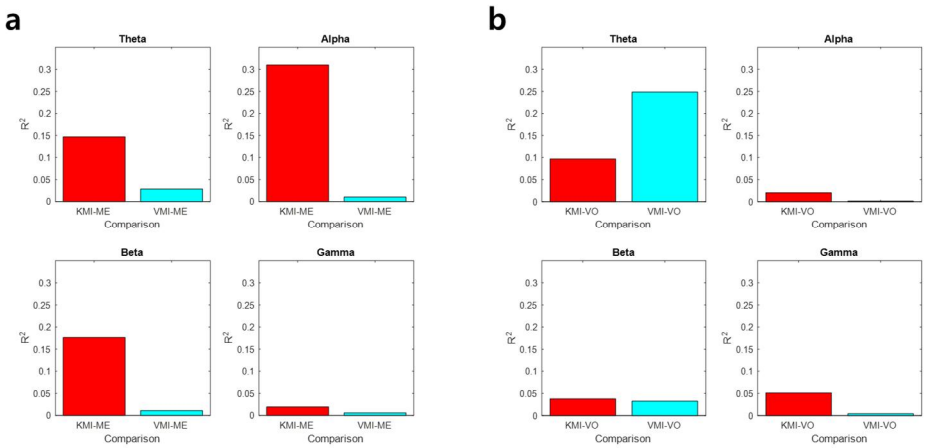

Figure 4. Comparison of correlation coefficient. Comparison between KMI and VMI by correlation coefficient which calculated using all possible combination edges (a) with ME and (b) with VO state. Y axis in each figure means square value of correlation coefficient. Red and blue bars designate the correlation with KMI and VMI, respectively.

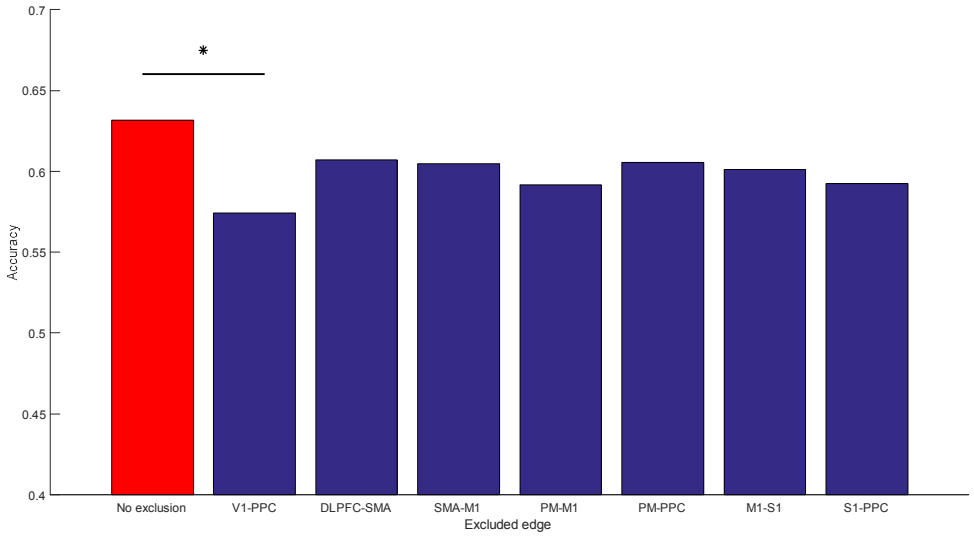

Figure 5. Comparison of accuracy. The graph of accuracy with considering all edges (red bar) and excluded edge (blue bars). Red bar means the accuracy of classifier for the separation of KMI and VMI using all edges in network. Blue bars indicate the accuracy of classifier generated by excluding the edge labeled on x axis. Star (i.e., *) denote significant difference (uncorrected Wilcoxon signed rank test, $p < 0.05$).

국문초록

뇌 연결성 패턴을 이용한 움직임 상상 유형의 구분 연구

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움직임 상상은 주어진 운동을 머릿속으로 재구성하는 정신 과정으로, 실제로 움직일 때와 비슷한 뇌 영역이 활성화 된다고 알려져 있다. 움직임 상상은 그 유형과 전략에 따라 서로 다른 뇌의 반응을 야기할 수 있다고 조사되어 왔다. 특히, 감각적 움직임 상상과 시각적 움직임 상상은 주로 활성화 되는 뇌 영역 마저도 차이가 있다는 것이 밝혀졌다. 그러나 이제까지의 움직임 상상 기반 뇌-컴퓨터 인터페이스(BCI) 연구는 움직임 상상을 구분하여 실험을 설계하지 않았다. 우리는 움직임 상상 유형 구분의 부재가 BCI 사용자의 약 30%에서 나타나는 BCI 문맹의 요인일 것이라고 생각하였고, 움직임 상상의 종류를 구분하여 피험자를 지도해야 할 필요성을 느꼈다. 우리의 선행 연구에서 움직임을 계획하는 동안 기능적 연결성(functional connectivity)이 증가하였음을 확인하였기 때문에, 기능적 연결성의 패턴으로 피험자의 각 상태를 구분할 수 있을 것이라고 예측하였다. 본

실험에서는 BCI를 사용할 때 대표적으로 나타날 수 있는 상태인 움직임 수행(ME), 감각적 움직임 상상(KMI), 시각적 움직임 상상(VMI), 단순 시청(VO)을 네 가지의 분류할 상태로 규정하였고, 이들이 가질 수 있는 뇌 영역 간의 연결성을 고려하여 네트워크(network)를 설정하였다. 네트워크를 구성하는 간선(edge)들은 ANOVA와 순열 검정(permutation test)을 통해 구분에 적합한 특징(feature)으로 증명되었다. 선택된 간선들로 만들어진 나이브-베이즈 분류기 (naïve Bayes classifier)는 네 가지의 상태를 분류할 수 있었으며, 그 정확도는 네트워크에 포함되지 않은 간선들로 만든 분류기의 정확도보다 유의미하게 컸다. 또한 KMI와 VMI의 서로 다른 특징을 조사하기 위해 행동 조건(ME, VO)과 각 상상 조건(KMI, VMI)의 상관관계(correlation coefficient)를 구했다. 기능적 연결성으로 구한 우리의 결과에서도 KMI와 ME가 모든 간선에서 비슷한 패턴을 보이고, VMI는 ME와 비슷한 패턴을 보이지 않아 선행 연구들에 부합하는 결과를 얻었다. 특히 KMI와 VMI를 구분하기 위해 만들어진 분류기의 정확도가 V1(primary visual cortex) – PPC(posterior parietal cortex) 간선을 특징에서 제외했을 때 주요한 변화를 보였다. 이를 통해 우리가 제안한 기능적 연결성 네트워크를 통해서 KMI와 VMI를 포함한 네 가지 상태를 구분해 낼 수 있다는 것을 확인하였다. 우리가 제안하는 상태 분류기는 피험자의 상태를 객관적으로 파악할 수 있어, 앞으로의 BCI 연구에서 움직임 상상의 종류를 구분하여 실험을 설계할 수 있을 것이라 기대한다. 이러한 방법을 통해 상상의 방법을 통제하고 피험자에게 적절한 피드백을 준다면 향후의 연구에서 기존에 보고되었던 문제점들을 해결할 수 있을 것이다.

주요어: 감각적 움직임 상상, 시각적 움직임 상상, 기능적 뇌 연결성, 뇌 네트워크, 뇌-컴퓨터 인터페이스, 뇌전도

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