Connectivity Pattern Modeling of Motor Imagery EEG

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Abstract—In this paper, the functional connectivity network of motor imagery based on EEG is investigated to understand brain function during motor imagery. In particular, partial directed coherence and directed transfer function measurements are applied to multi-channel EEG data to find out event related connectivity pattern with the direction and strength. The t-test is applied to these connectivity measurements to compare the network between motor imagery and the rest state. The possible relationship between this connectivity pattern and subjects performances are discussed. Based on the Granger causality analysis, a feature extraction method is proposed to compensate for non-stationarity in data. By attenuating the time-lagged correlation, this feature extraction method based on the multi-variate auto-regression model is proposed to reduce the effects of noises caused by time propagation. The validity of the proposed method is verified through experimental studies with a two-class dataset, and significant improvement in term of classification accuracy is achieved.

I. INTRODUCTION

Motor impairment caused by stroke is one of the major causes of permanent disabilities [1]. Active movement training (AMT) is one of common approaches to restore patient motor function, but this kind of traditional therapy is quite labor intensive. Motor imagery, a dynamic state facilitated by the motor system, relates to intending and preparing movements, and it is also generally assumed to cause the same motor representation internally as the corresponding motor execution by motor imagery [2]. Therefore, motor imagery represents an intriguing alternative therapy approach in the sense that it activates the motor system, especially the primary motor cortex, independent of residual function. Moreover, many findings suggest that there exist parallels between motor imagery and executed movement, i.e., close temporal coupling between motor imagery and executed movement. Motor imagery can even lead to performance improvement for athletes, and previous studies suggest the effectiveness of motor imagery training for functional recovery of stroke patients [1].

Motor imagery can be accessed from EEG, as studies have shown that distinct brain signals such as event-related desynchronization (ERD) or event-related synchronization (ERS) are detectable from EEG for both real and imagined motor movements in healthy subjects [3], [4]. Motor imagery based brain-computer interface (BCI) has become a highly intensive research area because this technology, requiring no voluntary muscle control, could be a new valuable interaction option especially for those with motor disabilities. For example, BCI-based robotic rehabilitation is introduced as an alternative to labor-intensive and expensive traditional physical therapy for stroke patients to regain functional impairment [5], [6], [7]. In recognition of its great importance, there has been remarkable advances of this topic in recent decades. BCI, especially noninvasive BCI, has been enhanced in terms of usability, information transferring, and robustness by virtue of modern machine learning and signal processing technology [8], [9].

Given multiple simultaneously recorded EEG signals, the analysis of neural connectivity is gaining more attention in the neuroscience field because it describes the general functioning of the brain and communication between its different regions [10]. Many computational methods have been proposed to explain how the regions work together. One of the commonly used measurements is coherence analysis, which is aimed to evaluate brain activity from both amplitude estimation and interregional synchronization [11]. However, coherence analysis does not provide connectivity pattern with the direction and strength of the information flow between different brain regions.

To meet the demands, the Granger causality estimation method is introduced to neural system identification to explore the dynamic causal relationship between two time series [12], [13], [14]. Based on vector autoregressive models, Granger causality estimation can reveal the directional nature of the information flow. In addition, as two multivariate extensions of Granger causality estimation, partial directed coherence (PDC) and directed transfer function (DTF), are proposed to determine directional influence between any given pair of channels in a multivariate dataset in the frequency domain [15], [16], [17].

The interest in the application of this functional neural connectivity analysis also lies in the possible use of this brain connectivity analysis in BCI, especially motor imagery-based BCI. To be specific, such EEG connectivity measure could pro-
vide insight for inferring new feature space based on functional coordination between brain regions in BCI [18]. Moreover, connectivity assessment could be used to compensate for data non-stationarity [19], and extract components of connectivity to enhance the model robustness.

In this work, a study of functional connectivity analysis is conducted to describe the complex network behavior of motor imagery. DTF and PDC measurements are used to determine connectivity pattern with direction and strength of the multi-channel EEG data. To find out which connections are significantly different under different conditions, for each pair of electrodes, DTF and PDC estimations of the motor imagery and rest sets are obtained and compared using t-test, so that the event related connectivity pattern can be identified. Based on the Granger causality analysis, a feature extraction method is proposed to compensate for the non-stationarity in the data. Linear spatial filters based on common spatial pattern analysis (CSP) suppress signal channels that are noisy or of less discriminative power and enhance the ones that are best related to the task. However, such a non-stationary effect of one channel cannot be totally removed as there exists a time-lagged correlation between channels. Therefore, by attenuating this correlation, a feature extraction method based on the multi-variate auto-regression (MVAR) model is proposed to reduce the effect of noise caused by time propagation.

Based on the above discussion, we highlight the contributions of this paper:

(i) a MVAR model is used to estimate DTF and PDC and to investigate the coupling between EEG sources during motor imagery;

(ii) the event-related connectivity pattern is identified based on t-test and the implication of the connectivity pattern on performances of subjects is analyzed; and

(iii) a feature extraction method is developed based on this MVAR model to remove the time-lagged correlation between channels and compensate for the non-stationarity.

This paper is organized as follows. In Section II, Granger causality estimation is introduced briefly, followed by the description about how t-test is used to find out significant change of connectivity patterns during motor imagery. In Section III, CSP is introduced and the details of the proposed feature extraction method based on the MVAR model are presented. In Section IV, results of Granger causality analysis are shown and the validity of the proposed method is verified by experiment studies on two-class motor imagery classification. Discussion and concluding remarks are given in Section V and VI respectively.

II. CONDITIONAL GRANGER CAUSALITY ANALYSIS OF MOTOR IMAGERY EEG

A. Calculation of Conditional Granger Causality

Granger causality is a method for evaluating causal dependence between two signals [12]. To be specific, this causal dependence is determined by the reduction of prediction error of one signal (putative cause) in addition to past observations of another signal (putative effect) in past observations of this signal. To differentiate whether the interaction between two time series is direct or mediated by recorded time series, conditional Granger causality (CGC) is introduced [13], [14]. As two multivariate extensions of CGC, PDC and DTF are introduced in the following to identify the neural system mechanism during motor imagery.

Let \( X(t) \) be the multi-channel EEG signal at time \( t \), then it can be described by the following MVAR model

\[
X(t) = \sum_{\tau=1}^{p} A(\tau) X(t - \tau) + N(t)
\]

where \( N(t) \) is the prediction error, or it can also be regarded as the innovation process because it is totally spontaneous and cannot be predicted by past observations.

(1) is rearranged in the following form to make the input-output relationship more compact

\[
N(t) = \sum_{\tau=0}^{p} \hat{A}(\tau) X(t - \tau)
\]

where

\[
\hat{A}(\tau) = \begin{cases} -I, & \tau = 0; \\ A(\tau), & \tau > 0. \end{cases}
\]

Transforming (2) into the frequency domain yields

\[
N(f) = A(f) X(f) \quad \quad (4)
\]

\[
A(f) = \sum_{\tau=0}^{p} \hat{A}(\tau) e^{-j2\pi f \tau}
\]

where \( f \) is the frequency. Therefore, the transfer function of the system \( H(f) \) can be obtained as

\[
G(f) = A(f)^{-1}
\]

such that \( X(f) = G(f) N(f) \).

Based on \( G(f) \) and \( A(f) \), the CGC estimations, PDC and DTF, can be obtained as

\[
\pi_{ij}^{PDC}(f) = \frac{\frac{g_{ij}(f)}{\sqrt{\sum_{k=1}^{C} |a_{kj}(f)|^2}}}{\sqrt{\sum_{k=1}^{C} |g_{ik}(f)|^2}}
\]

\[
\pi_{ij}^{DTF}(f) = \frac{\frac{g_{ij}(f)}{\sqrt{\sum_{k=1}^{C} |g_{ik}(f)|^2}}}{\sqrt{\sum_{k=1}^{C} |a_{kj}(f)|^2}}
\]

Both \( \pi_{ij}^{PDC}(f) \) and \( \pi_{ij}^{DTF}(f) \) are estimations of causal dependence between \( X_i \) and \( X_j \) at frequency \( f \) in difference ways. \( \pi_{ij}^{PDC}(f) \) in (7) is a complex measure which can be interpreted as the CGC from \( X_j \) to \( X_i \) normalized by the total amount of causal outflow from \( X_j \), so that

\[
\sum_{i=1}^{C} \pi_{ij}^{PDC}(f) = 1
\]

A higher \( \pi_{ij}^{PDC} \) means among all the signals that signal \( j \) is influencing, signal \( i \) is affected more. In addition, if signal \( i \) has a higher \( \sum_{j=1}^{C} \pi_{ij}^{PDC} \), there is more information flow
into signal $i$ from all other signals. In other words, signal $i$ represents a major “destination” of the information flow.

On the other hand, DTF in (8) can be interpreted as the total information flow from $X_j$ to $Y_i$ conditioned on the total amount of information flow to $X_i$, so we have

$$\sum_{j=1}^{C} \pi_{ij}^{DTF}(f) = 1$$

Similarly, a higher $\pi_{ij}^{DTF}$ means that among all the signals influencing signal $i$, signal $j$ affects signal $i$ more. In addition, if signal $j$ has a higher $\sum_{i=1}^{C} \pi_{ij}^{DTF}$, it affects all the other signals more. In other words, signal $j$ represents a major “source” of the information flow. In this work, we are more interested in signals with a higher $\sum_{i=1}^{C} \pi_{ij}^{DTF}$.

B. Comparison of Granger Causality Between Different Cognitive Tasks

EEG connectivity measures could provide insight for inferring connection networks and even new features of subjects in BCI [18]. Therefore, we use $\pi_{ij}^{PDC}(f)$ and $\pi_{ij}^{DTF}(f)$ to analyze the connectivity in EEG recordings which will reveal the synchronized interaction between different regions of the brain.

Based on (7) and (8), we obtain $\pi_{ij}^{PDC}(f)$ and $\pi_{ij}^{DTF}(f)$ between EEG signals from any two channels at a given frequency $f$. Then, $\pi_{ij}^{PDC}(f)$ and $\pi_{ij}^{DTF}(f)$ are integrated on $f$ at the range of the alpha band to infer the average CGC within alpha band of each pair of electrodes. Equivalently, we have

$$\bar{\pi}_{ij}^{PDC} = \int \pi_{ij}^{PDC}(f) df$$

$$\bar{\pi}_{ij}^{DTF} = \int \pi_{ij}^{DTF}(f) df$$

Then, t-test is applied to $\bar{\pi}_{ij}^{PDC}$ and $\bar{\pi}_{ij}^{DTF}$ between all motor imagery trials and rest trials. In particular, one-sided t-test is used so that only significantly enhanced connections during motor imagery compared to that during rest are spotted. The t-test results are denoted by $h_{ij}^{PDC}$ and $h_{ij}^{DTF}$ which have binary values. $h_{ij}^{PDC} = 1$ or $h_{ij}^{DTF} = 1$ means $\bar{\pi}_{ij}^{PDC}$ or $\bar{\pi}_{ij}^{DTF}$ is significantly higher during motor imagery than that during rest respectively. To obtain the estimation that reflects the overall change of effect on or from signal $i$, we need to sum $h_{ij}^{PDC}$ or $h_{ij}^{DTF}$ of all channels. In other words, the total number of significantly enhanced inflow into signal $i$ or increased outflow from signal $j$ is calculated as

$$H_{i}^{PDC} = \sum_{j=1}^{C} h_{ij}^{PDC}$$

$$H_{i}^{DTF} = \sum_{i=1}^{C} h_{ij}^{DTF}$$

As discussed before, PDC reveals the major “destination” of the information flow while DTF reveals the major “source” of the information flow. In this way, the signal with higher $H_{i}^{PDC}$ means a significantly increased flow into this signal during motor imagery, while higher $H_{i}^{DTF}$ means a significantly increased flow from this signal.

III. Feature Extraction Based on the MVAR Model

Based on the Granger causality analysis, we propose a feature extraction method which compensates for data non-stationary. During motor imagery, non-stationary activations exist and they cannot be separated by linear spatial filters of CSP due to time-lagged interactions. Therefore, a more effective source separation method is needed to investigate the possible casual relationship between useful information and components unrelated to events of interest. In this section, we will develop a feature extraction method based on the MVAR model which reduces the effect of noises by attenuating the time-lagged correlation.

A. Common Spatial Patterns Analysis

In this section, we briefly introduce CSP analysis to make this paper self-contained. In a nutshell, the CSP filters maximize the variance of the spatially filtered signal under one condition while minimizing it for the other condition.

Let $R \in R^{C \times C}$ be the estimates of the covariance matrices of the band-pass filtered EEG signal under the following two conditions

$$R_{c} = \frac{1}{Q_{c}} \sum_{Q_{c}} X_{i}(X_{i}^{T}), \ c \in \{1, 0\}$$

where $c$ indicates the class number, $X_{i}$ are the data matrices of a short segment of the band-pass filtered for trial $i$ of class $c$, and $Q_{c}$ is the number of trials belonging to each class.

CSP analysis is performed by the simultaneous diagonalization of the following two covariance matrices

$$W^{T} R_{c} W = \Lambda^{c}$$

which can be simply achieved by solving the generalized eigenvalue problem. The significance of this transformation lies in $\Lambda^{1} + \Lambda^{0} = I$. $\Lambda^{i}$ is the variance of the signal after the projection

$$Y^{i} = WX^{i}$$

$$Y^{i}(Y^{i})^{T} = \Lambda^{i}$$

Therefore, $\Lambda^{i}$ should be close to $\Lambda^{1}$ or $\Lambda^{0}$. Usually, the first $r$ and the last $r$ rows that contain the most discriminative information of $W$ are used, and the feature vector is generated by taking the logarithm of the variance as in the following:

$$F^{i} = \log \frac{\text{var}[y^{i}_{j}]}{\sum_{j} \text{var}[y^{i}_{j}]}, \ j = 1, \ldots, r, N - r + 1, \ldots, N$$

where $y^{i}_{j}$ is the $j$th row of $Y^{i}$. 

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B. Feature Extraction

In [20], it is explained that relationships between EEG sources are probably due to time-lagged axonal propagation of macroscopic neural behavior among distant regions of the brain. Such a propagation effect can be described by the MVAR model (1) as mentioned above.

As introduced in III-A, CSP is aimed at capturing the event-related information and filtering the non-discriminant information in EEG via its covariance matrices. Ideally, $y_j$, $j = 1, \ldots, r, N - r + 1$ should be the signals with maximized discriminant power, while the others contain noisy or event-unrelated information.

Substituting (17) into (1), we have

$$Y(t) = \sum_{\tau=1}^{p} WA(\tau)W^{-1}Y(t-\tau) + WN(t)$$

$$= \sum_{\tau=1}^{r} A_Y(\tau)Y(t-\tau) + N_Y(t)$$

From (19), we can find out that in the projected space, there exists time-lagged correlation between $y_j$, which means the first and last $r$ signals of $Y$ are influenced by signals $y_j$, $j = r, \ldots, N-r+1$ and subsequently contaminated by noises and useless information. Thus, (19) shows that linear spatial filters like CSP cannot remove noise or activities that do not contain discriminative information caused by time-lagged correlation. To solve this problem, the MVAR model can be used to eliminate such time-lagged correlation between signals.

Let $a_{i,j}(\tau)$ denote the elements in $A(\tau)$ in (1). They reflect the influence from past observations of channel $j$ on the current value of channel $i$, which is the time-lagged correlation we aim to remove. Thus, we construct another matrix $A'$ with the following elements

$$a'_{i,j}(\tau) = \begin{cases} 
0, & \text{when } i = j; \\
 a_{i,j}(\tau), & \text{otherwise.}
\end{cases} \quad (20)$$

Then, we can subtract the time-lagged correlation parts from the raw EEG data as

$$X'(t) = X(t) - \sum_{\tau=1}^{p} A'(\tau)X(t-\tau) \quad (21)$$

In this way, in multi-channel data $X'(t)$, the influence from past observations of one channel on other channels is attenuated greatly, because only the part predicted by the past observations of the same channel is kept. Then, CSP is applied to $X'(t)$ to extract features as (15) to (18) indicate.

IV. EXPERIMENT

A. Data Description

8 subjects participated in the study with ethics approval and informed consent. All of them performed motor imagery and passive movement on the right hand. EEG from totally 27 channels were obtained using Nuamps EEG acquisition hardware with unipolar Ag/AgCl electrodes channels. The sampling rate was 250 Hz with a resolution of 22 bits for voltage ranges of ±130 mV. A bandpass filter of 0.05 to 40 Hz is set in the acquisition hardware.

In the experiment, the training and test sessions are recorded on different days from the subjects performing motor imagery. During the EEG recording process, the subjects were asked to avoid physical movement and eye blinking. Additionally, they were instructed to perform kinesthetic motor imagery of the chosen hand in the two runs. During the rest state, they did mental counting as instructed to make the EEG signals more constant. Each run lasted for approximately 16 minutes comprising 40 trials of motor imagery and 40 trials of rest state. Each training session consisted of 2 runs and the test session consisted of 2-3 runs of experiments.

B. Data Processing

For each trial of data, time segments of 0.5 to 2.5s after the cue were used following most of the works that use this dataset, such as [21], [7]. The raw signal is filtered by band-pass filter of 8-35Hz for the same reason. The filtered signal is used to perform Granger causality analysis as in Section II and extract features as in Section III.

In short, the procedures of Granger causality analysis are as follows:

i) the MVAR model is built up based on raw EEG data as described by (1);

ii) PDC and DTF are calculated as in (7) and (8) and then integrated on $f$ in the range of alpha band;

iii) t-test is applied to compare the averaged PDC and DTF of each pair of connections between motor imagery trials and rest trials; and

iv) for each channel $i$, $H^{PDC}$ and $H^{DTF}$ are calculated according to (13).

The procedures of MVAR-based CSP are as follows:

i) the MVAR model is built up based on raw EEG data as described by (1);

ii) time-lagged correlation parts are subtracted from the raw EEG data as in (21); and

iii) CSP is applied to $X'$ in (21) and features are classified by support vector machine (SVM) classifier.

C. Results of CGC Analysis

As described in II-B, we find out the significantly enhanced connections during motor imagery compared to that in the rest condition. Different from simple correlation or coherence in [11], PDC and DTF estimate the causal dependence which indicates the connection with direction.

Figure 1 illustrates the CGC analysis results. The size of the red circles in the left scalp represents $H^{DTF}$ and the size of the blue circles in the right scalp represents $H^{PDC}$, where $i$ is the electrode index. The subject number and cross-validation accuracy are shown below the corresponding sub-figure and these sub-figures are listed in a descending order in the term of
cross-validation accuracy. As discussed in II-B, the larger the red circle, the greater the increase in flow from the electrode during motor imagery compared to that during rest. The same applies to the blue circle with respect to flow into the electrode.

On the DTF side, we see from Figure 1 that there are prominent enhanced sources in the left motor cortex for subjects 9 and 3. In particular, $H_{C3}^{DTF} = 27$ for subject 9, and $H_{C3}^{DTF} = 27$ and $H_{T}^{DTF} = 27$ for subject 3. Given that the total number of channels is $27$, $H_{C3}^{DTF} = 27$ means that activations in the left motor cortex have remarkably increased influence on all the brain regions. Subject 3 has obviously higher information flow from central motor cortex influence on all the brain regions. Subject 3 has obviously activations in the left motor cortex have remarkably increased and $H_{C3}^{DTF} = 27$. Subject 8 has increased source activation in the left motor cortex, although the significant sources are not concentrated around C3. We also observed that prominent source at $FC_4$ which corresponds to the sensorimotor area. Similarly, subject 2 has increased source activation in the left motor cortex which is stronger at the posterior motor cortex. Those subjects are the relatively high aptitude users with cross-validation accuracy of around 70%. For the rest of the subjects, we note that less significant influential sources are located in the left motor cortex. On the PDC side, except for subject 3, there is no prominent destination of information flow. Generally, the high aptitude users have more and bigger blue circles which indicate a general higher activation at all regions.

![Connectivity pattern based on t-test results](image)

**Fig. 1.** Connectivity pattern based on t-test results

### D. Results of MVAR Feature Extraction

Table I summarizes the performance of the proposed MVAR feature extraction method in terms of the classification accuracy of the test data. Note that because subject 8 has only participated in the calibration session, there is no test result for subject 8.

It is revealed from the comparison that the proposed MVAR feature extraction method improves the performance of the classifier, with the average classification accuracy of 64.97% higher than that of CSP (63.22%). Moreover, paired t-test is applied to the accuracy result, which is used to further evaluate the effectiveness of the proposed method. In particular, the improvement of accuracy is validated (indicated using “*” in Table I) at the 5% confidence level with $p = 0.044$. From the above results, we are able confirm that performance improvement of the classifier is achieved with the proposed method.

### V. DISCUSSION

As described in Section IV-C, there exists correlation between the performance of the subjects and the increased directional transfer flow from the left cortex. This is in accord with the fact that all the participants in this experiment perform right hand motor imagery. However, different from mere evaluation of increased activation in the corresponding motor cortex, such as direct measurement of ERD or ERS, this conditional causality analysis provides more insight into the network activation mechanism during motor imagery.

As shown in Figure 1, those subjects with better performance have more influential sources. Since most of the brain regions have stronger dependence on these one or two sources, the activation would be more synchronized with less effect from noise, which could partly explain the better performance of these subjects. However, for subject 7, although there exist sources with stronger information flow to other parts or the brain, they are not located at the motor cortex area. Moreover, subject 4 has a relatively clear pattern with increased information flow from $CP_3$ and $CP_2$, which should yield a better classification accuracy. A possible explanation for such inconsistency is that although generally there are sources with discriminant power which influence all brain regions, their effects could be hidden by noisy activations for a single trial. In other words, these source activations are not stationary or strong enough.

This analysis of connectivity gives us a hint on development of feature extraction methods. Particularly, the cross-validation accuracy is obtained based on CSP which is used to design the projection matrix using the covariance matrix. Since not only enhanced correlation but also any possible power change could be reflected in the projection matrix, CSP is prone to be affected by non-stationarity of EEG. Therefore, it is possible that such directional flow in these subjects are not strong enough and could be hidden by the non-stable power change, and consequently CSP fails to capture this event related causal dependence.
Based on the above ideas, we proposed a MVAR feature extraction method in this paper. By subtracting the time-lagged correlation parts from the raw EEG data, the casual dependence between signals is attenuated due to two reasons. First, as indicated in (19), such time-lagged correlation exists in the projected signals which means that signals corresponding to the first and last filters could also be influenced by unrelated signals. Second, an electrode that actually contains no discriminant information could possibly be given a higher weight due to information flow into this electrode from the true source. However, without the original discriminant power, these signals are sensitive to noises, as their dependence on true sources could be covered by noise when those sources are not sufficiently activated. The results from Table I validate our speculation to a certain extent as there is a constant improvement with time-lagged correlation parts of the signals removed.

Nevertheless, this is only a preliminary way to use the causal connectivity to enhance feature extraction. Based on the results in Sections IV-C and IV-D, it is concluded that the future studies on feature extraction are supposed to focus on the direction of the information flow rather than the mere power change.

VI. CONCLUSION

This work has addressed the issue of EEG connectivity analysis based on two extensions of CGC measurement, which are PDC and DTF. PDC and DTF can reveal the network connection with not only the synchronized interaction but also the causal dependence between different regions of brain. From the comparison of DTF and PDC, we find out that there exists a correlation between the performance of the subjects and the increased directional transfer flow from the motor cortex corresponding to the movement. Based on this analysis, a MVAR feature extraction method has been developed to attenuate the time-lagged correlation between signals. The experiment results have shown that the proposed MVAR feature extraction method yielded a better classification accuracy. The significance of this improvement has been validated using t-test.

As the direction of information flow could provide the insight on which signals are stationary event-related activations, the future work will focus on developing better source separation methods for feature extraction with the direction of information flow taken into consideration.

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