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Causality from Cz to C3/C4 or between C3 and C4 Revealed by Granger Causality and New Causality during Motor Imagery

Sanqing Hu, Hui Wang, Jianhai Zhang, Wanzeng Kong
College of Computer Science
Hangzhou Dianzi University
Hangzhou, Zhejiang Province, China 310018
Email: sqhu@hdu.edu.cn

and Yu Cao
Department of Computer Science
The University of Massachusetts Lowell
MA 01854, USA
Email: ycao@cs.uml.edu

***Abstract*—Interaction between different brain regions has received wide attention recently. Granger causality (GC) is one of the most popular methods to explore causality relationship between different brain regions. In 2011, Hu et. al [1] pointed out shortcomings and/or limitations of GC by using a large of number of illustrative examples and showed that GC is only a causality definition in the sense of Granger and does not reflect real causality at all, and meanwhile proposed a new causality (NC) which is shown to be more reasonable and understandable than GC by those examples. Motor imagery (MI) is an important mental process in cognitive neuroscience and cognitive psychology and has received growing attention for a long time. However, there is few work about causality flow so far during MI based on scalp EEG. In this paper, we use scalp EEG to study causality flow during MI. The scalp EEGs are from 9 subjects in BCI competition IV held in 2008 [2] and provided by Graz University of Technology. We are interested in three regions: Cz (the centre of cerebral cortex), C3 (the left of cerebral cortex) and C4 (the right of cerebral cortex) which are considered to be optimal locations for recognizing MI states in literature. We apply GC and NC to scalp EEG and find that i) there is strong directional connectivity from Cz to C3/C4 during left hand and right hand MI based on GC and NC. ii) During left hand MI, there is directional connectivity from C4 to C3 based on GC and NC. iii) During right hand MI, there is strong directional connectivity from C3 to C4 which is much clearly revealed by NC method than by GC method. iv) Our results suggest that NC method in time and frequency domains is demonstrated to be much better to reveal causal influence between different brain regions than GC method. Thus, we deeply believe that NC method will shed new light on causality analysis in economics and neuroscience.**

I. Introduction

GC is one of the most popular methods to detect the directional influence of system components because of its simplicity and easy implementation, and plays a key role in understanding systems behavior in many different areas, such as economics [3] and [4], climate studies [5] and [6], genetics [7], and neuroscience [8] and [9]. In neuroscience, GC has been mainly applied to disclose effective connectivity of brain regions, which is defined as the influence one neuronal system exerts over another [10]. The basic idea of GC was originally conceived by Wiener in 1956 [11], and later formalized by Granger in 1969 [12] in the form of linear regression model. The idea can be briefly described as follows: If the historical information of time series Y significantly improves the prediction accuracy of the future of time series X in a multivariate autoregressive (MVAR) model, then GC from time series Y to X can be identified. In classic GC, time-invariant MVAR models are used to fit the experimental data of the observed time series [13]. Although GC has tremendous applications in many areas, this success has also been accompanied by criticism from different prospectives [14] and [15]. The criticism of GC has most been centered around the philosophical debate on the relationship between GC and true causality. As its name implies, GC is not necessarily true causality [16]. For example, if both X and Y are driven by a common third process with different lags, one might still fail to reject the alternative hypothesis of GC and may produce misleading results. In 2011, Hu et. al [1] pointed out shortcomings and/or limitations of GC by using a large of number of illustrative examples and showed that GC is only a causality definition in the sense of Granger and why GC does not reflect real causality at all, and meanwhile proposed NC defined as a causality from any time series Y to any time series X in the linear regression model of multivariate time series, which describes the proportion that Y occupies among all contributions to X and is shown to be more reasonable and understandable than GC to reveal real causality by those examples. NC is a natural extension of GC and overcomes GC's shortcomings and/or limitations.

Brain-computer interface (BCI) is an emerging technology dealing with computer-aided control using exclusive brain activity, and has found application across bioengineering fields and in neuroprosthetics [17]. The most commonly used experimental paradigm in this context is motor imagery (MI) [18], that is, the imagination of a motor action without any actual movement of limbs, which has clear practical significance and provides a new communication channel between the human brain and the computer [19]. MI is the mental simulation of a motor act that includes preparation for movement, passive observations of action and mental operations of motor representations implicitly or explicitly. The neuronal representations of MI have been studied intensively for years using brain imaging techniques, such as functional magnetic resonance imaging (fMRI), electroencephalogram (EEG) and positron emission tomography (PET) [8], [20]-[22]. MI as preparation for immediate movement likely involves activation of the motor executive brain regions. Recent findings based on fMRI

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suggest the existence of the causal connectivity of motor related core regions in fronto-parietal circuit [8] during MI. In EEG-based BCI research, C3, C4 and Cz are demonstrated to be optimal for recognizing MI states [23]. In this study we will discuss whether or not there exists causal connectivity among C3, C4 and Cz based on scalp EEG during MI.

In this paper, firstly we will describe GC and NC in time and frequency domains in time-invariant bivariate autoregressive model, and show the differences between GC and NC in mathematical way. Then we apply GC and NC to analyze the data sets 2b from BCI competition IV held in 2008 [2] and provided by Graz University of Technology. The data includes 3 bipolar EEG channels (C3, C4 and Cz) and is from 9 subjects. We apply GC and NC to EEGs and find that i) there is strong directional connectivity from Cz to C3/C4 in both time domain and frequency domain (mu rhythm ($8 \sim 12$Hz)) during left and right hand MI based on GC and NC where mu rhythm is an important property of EEG signals during MI [23]. ii) During left hand MI, there is strong directional connectivity from C4 to C3 based on GC and NC in both time domain and frequency domain. iii) During right hand MI, there is strong directional connectivity from C3 to C4 in both time domain and frequency domain. iv) For causality from C4 to C3 during left hand MI and causality from C3 to C4 during right hand MI, the portion of GC values having peeks in mu rhythm is 32%, however the portion of NC values having peaks in mu rhythm is 55%. This once again strongly demonstrates that NC method is much better than GC to reveal real directional causality flow in real EEG data. Therefore, NC method may open a new window to study causality relationships and may have wide applications in economics and neuroscience.

II. GC AND NC

Consider two stochastic time series which are assumed to be jointly stationary. Individually, under fairly general conditions, each time series admits an autoregressive representation

$$\begin{cases} X_{1,t} = \sum_{j=1}^{m} a_{11,j} X_{1,t-j} + \epsilon_{1,t} \\ X_{2,t} = \sum_{j=1}^{m} a_{22,j} X_{1,t-j} + \epsilon_{2,t} \end{cases} \tag{1}$$

and their joint representations are described as

$$\begin{cases} X_{1,t} = \sum_{j=1}^{m} a_{11,j} X_{1,t-j} + \sum_{j=1}^{m} a_{12,j} X_{2,t-j} + \eta_{1,t} \\ X_{2,t} = \sum_{j=1}^{m} a_{21,j} X_{1,t-j} + \sum_{j=1}^{m} a_{22,j} X_{2,t-j} + \eta_{2,t} \end{cases} \tag{2}$$

where $t = 0, 1, \cdots, N$, the noise terms are uncorrelated over time, ϵ_i and η_i have zero means and variances of $\sigma^2_{\epsilon_i}$, and $\sigma^2_{\eta_i}$, $i = 1, 2$. The covariance between η_1 and η_2 is defined by $\sigma_{\eta_1\eta_2} = cov(\eta_1, \eta_2)$ [1].

GC in Time Domain

Now consider the first equalities in (1) and (2), if $\sigma^2_{\eta_1}$ is less than $\sigma^2_{\epsilon_1}$ in some suitable sense X_2 is said to have a causal influence on X_1. In this case, the first equality in (2) is more accurate than in (1) to estimate X_1. Otherwise, if $\sigma^2_{\eta_1} = \sigma^2_{\epsilon_1}$, X_2 is said to have no causal influence on X_1. In this case, two equalities are same. Such kind of causal influence, called GC [24], [25], is defined by

$$F_{X_2 \to X_1} = \ln \frac{\sigma^2_{\epsilon_1}}{\sigma^2_{\eta_1}} \tag{3}$$

Obviously, $F_{X_2 \to X_1} = 0$ when there is no causal influence from X_2 to X_1 and $F_{X_2 \to X_1} > 0$ when there is. Similarly, the causal influence from X_1 to X_2 is defined by

$$F_{X_1 \to X_2} = \ln \frac{\sigma^2_{\epsilon_2}}{\sigma^2_{\eta_2}} \tag{4}$$

NC in Time Domain

Based on the first equality in (2), we can see contributions to $X_{1,t}$, which include $\sum_{j=1}^{m} a_{11,j} X_{1,t-j}, \sum_{j=1}^{m} a_{12,j} X_{2,t-j}$ and the noise term $\eta_{k,t}$ where the influence from $\sum_{j=1}^{m} a_{11,j} X_{1,t-j}$ is causality from X_1's own past values. Each contribution plays an important role in determining $X_{1,t}$. If $\sum_{j=1}^{m} a_{12,j} X_{2,t-j}$ occupies a larger portion among all those contributions, then X_2 has stronger causality on X_1, or vice versa. Thus, a good definition for causality from X_2 to X_1 in time domain should be able to describe what proportion X_2 occupies among all these contributions. So based on this general guideline NC from X_2 to X_1 is defined as [1]

$$n_{X_2 \to X_1} = \frac{\sum_{t=m}^{N} \left(\sum_{j=1}^{m} a_{12,j} X_{2,t-j} \right)^2}{\sum_{h=1}^{2} \sum_{t=m}^{N} \left(\sum_{j=1}^{m} a_{1h,j} X_{h,t-j} \right)^2 + \sum_{t=m}^{N} \eta^2_{1,t}} \tag{5}$$

Similarly, NC in time domain from X_1 to X_2 is defined by

$$n_{X_1 \to X_2} = \frac{\sum_{t=m}^{N} \left(\sum_{j=1}^{m} a_{21,j} X_{1,t-j} \right)^2}{\sum_{h=1}^{2} \sum_{t=m}^{N} \left(\sum_{j=1}^{m} a_{2h,j} X_{h,t-j} \right)^2 + \sum_{t=m}^{N} \eta^2_{2,t}} \tag{6}$$

Taking Fourier transformation on both sides of (2) leads to

$$\begin{cases} X_1(f) = a_{11}(f) X_1(f) + a_{12}(f) X_2(f) + \eta_1(f) \\ X_2(f) = a_{21}(f) X_1(f) + a_{22}(f) X_2(f) + \eta_2(f) \end{cases} \tag{7}$$

where $a_{lj}(f) = \sum_{k=1}^{m} a_{lj,k} e^{-i2\pi fk}$, $i = \sqrt{-1}$, $l, j = 1, 2$.

GC in Frequency Domain

Granger causal influence from X_2 to X_1in frequency domain is defined by $I_{X_2 \to X_1}(f) =$

$$-\log\left(1 - \frac{(\sigma_{\eta_2}{}^2 - \frac{\sigma_{\eta_1\eta_2}{}^2}{\sigma_{\eta_1}{}^2}) |\, H_{12}(f)\,|^2}{S_{X_1X_1}}\right) \in [0, +\infty) \tag{8}$$

where the transfer function $H(f) = A^{-1}(f)$ whose components are

$$H_{11}(f) = \tfrac{1}{det(A)} \overline{a}_{22}(f),\ H_{12}(f) = \tfrac{1}{det(A)} \overline{a}_{12}(f),$$

$$H_{21}(f) = \tfrac{1}{det(A)} \overline{a}_{21}(f),\ H_{22}(f) = \tfrac{1}{det(A)} \overline{a}_{11}(f),$$

$A = [\overline{a}_{ij}]_{2\times 2}$, $\overline{a}_{kk}(f) = 1 - \sum_{j=1}^{m} a_{kk,j} e^{-i2\pi fk}$, $k = 1, 2$.
$\overline{a}_{hl}(f) = -\sum_{j=1}^{m} a_{hl,j} e^{-i2\pi fk}$, $h, l = 1, 2$, $h \neq l$.
Similarly, we define Granger causal influence from X_1 to X_2 by

$$I_{X_1 \to X_2}(f) = -\log\left(1 - \frac{(\sigma_{\eta_1}{}^2 - \frac{\sigma_{\eta_1\eta_2}{}^2}{\sigma_{\eta_2}{}^2})\mid H_{21}(f)\mid^2}{S_{X_2X_2}}\right) \in [0, +\infty) \quad (9)$$

where $S_{X_iX_i}(f)$ is the spectrum of $X_i, i = 1, 2$.

NC in Frequency Domain

From (7), one can see that contributions to $X_1(f)$ include $a_{11}(f)X_1(f)$, $a_{12}(f)X_2(f)$ and noise term $\eta_1(f)$. So NC from X_2 to X_1 in frequency domain is defined as $N_{X_2 \to X_1}(f) =$

$$\frac{\mid a_{12}(f)\mid^2 S_{X_2X_2}(f)}{\mid a_{11}(f)\mid^2 S_{X_1X_1}(f) + \mid a_{12}(f)\mid^2 S_{X_2X_2}(f) + \sigma^2_{\eta_1}} \quad (10)$$

Similarly, NC from X_1 to X_2 in frequency domain is defined as $N_{X_1 \to X_2}(f) =$

$$\frac{\mid a_{21}(f)\mid^2 S_{X_1X_1}(f)}{\mid a_{21}(f)\mid^2 S_{X_1X_1}(f) + \mid a_{22}(f)\mid^2 S_{X_2X_2}(f) + \sigma^2_{\eta_2}} \quad (11)$$

Remark: In [1] we pointed out that i) for the simple illustrative example in (10), (11) of [1] GC from X_2 to X_1 is mathematically equivalently defined on (17) and by (18) or (13) of [1], however (17) is only partial contribution of X_1 (see (11) of [1]). Any real causality definition should consider all contributions of X_1. Thus, GC in (12) or (13) of [1] does not define real causality from X_2 to X_1 at all. ii) NC is much better than GC to reveal real causality by a larger number of illustrative examples in [1] which include an experimental EEG data set. iii) In this study, we will further demonstrate that NC is better than GC to reveal real causality influence based on EEG during MI states.

III. Experimental Method

In this section, we first describe our EEG data for analysis. The data sets 2b from BCI competition IV held in 2008 were used and provided by Graz University of Technology [2]. These data sets consist of EEG data from 9 subjects. The subjects were right-handedness, had normal or corrected-to-normal vision and were paid for participating in the experiments [2]. All volunteers were sitting in an armchair, watching a flat screen monitor placed approximately 1 m away at eye level. For each subject 5 sessions were provided, whereby the first three sessions were training data, and the last two sessions were evaluation data. We only analyzed the training data because the classification result of the evaluation data was unknown. Thus, there are totally $9 \times 3 = 27$ sessions for our analysis. The cue-based screening paradigm consists of two classes, namely left hand MI (Class 1) and right hand MI (Class 2). Each session contains some trails of Class 1 and some trails of Class 2. For each session we extract all the trails data of MI. Then put the left hand MI trail data together and average the trials data as one time series data of Class 1. For the right hand MI trial data, we do the same preprocessing to get one time series data of Class 2. Each class data consists of 3 channels (C3, Cz and C4) data. In this study, we analyze the data as follows: firstly, we detect the effective connectivity in time domain by calculating GC and NC between Cz and C3/C4 and between C3 and C4. Secondly, we calculate GC and NC in frequency domain between Cz and C3/C4 and between C3 and C4, and choose three subjects as representatives to show our results. For GC and NC results in time and frequency domains we make comparison to conclude that NC is much better than GC to reveal real causality based on EEG data during MI states.

IV. Simulation Results

Effective Connectivity Analysis in Time Domain

For the MI data including Class 1 and Class 2, we extract channels (C3, C4 and Cz) data as three time series. For each class, we first apply GC to calculate $F_{C3\to Cz}$, $F_{Cz\to C3}$, $F_{C4\to Cz}$, $F_{Cz\to C4}$, and meanwhile we apply NC to calculate $n_{C3\to Cz}$, $n_{Cz\to C3}$, $n_{C4\to Cz}$, $n_{Cz\to C4}$. The results are shown in Fig.1 (Class 1) and Fig.2 (Class 2) where each session has one causality value for each method and as a result there are totally 27 point for each curve because of 27 sessions being involved, and summarized in Table I and Table II. From Table I and Table II one can see that there is strong directional connectivity from Cz to C3/C4 in time domain during left and right hand MI based on GC and NC.

By observing the red lines in Fig.1 and Fig.2, one can see that curves by NC method are less oscillative than that by GC method, this means those results by NC method are more stable and less changed during left hand MI and right hand MI. This is reasonable from the point of view of physiological phenomenon. On the contrary, curves by GC method have higher oscillation, as a result, this is unreasonable from the point of view of physiological phenomenon. So, NC method identifies the causal influence from Cz to C3/C4. Therefore, in time domain, we demonstrate that NC method is much better than GC method to reveal causal influence among different brain regions during MI states.

TABLE I. The Proportions in Class 1

Causality Methods	$Cz \to C3 > C3 \to Cz$	$Cz \to C4 > C4 \to Cz$
GC	0.89	0.93
NC	0.93	0.89

TABLE II. The Proportions in Class 2

Causality Methods	$Cz \to C3 > C3 \to Cz$	$Cz \to C4 > C4 \to Cz$
GC	0.78	0.78
NC	0.85	0.96

Next, we apply GC to calculate $F_{C3\to C4}$, $F_{C4\to C3}$, and apply NC to calculate $n_{C3\to C4}$, $n_{C4\to C3}$. The results are shown in Fig.3 and summarized in Table III.

TABLE III. The Proportions in Class 1 and Class 2

Causality	class 1	class 2
$F_{C3\to C4} > F_{C4\to C3}$	0.37	0.60
$F_{C4\to C3} > F_{C3\to C4}$	0.64	0.41
$n_{C3\to C4} > n_{C4\to C3}$	0.37	0.81
$n_{C4\to C3} > n_{C3\to C4}$	0.64	0.19

From Fig.3 and Table III, one can see that i) during left hand MI, there is strong directional connectivity from C4 to

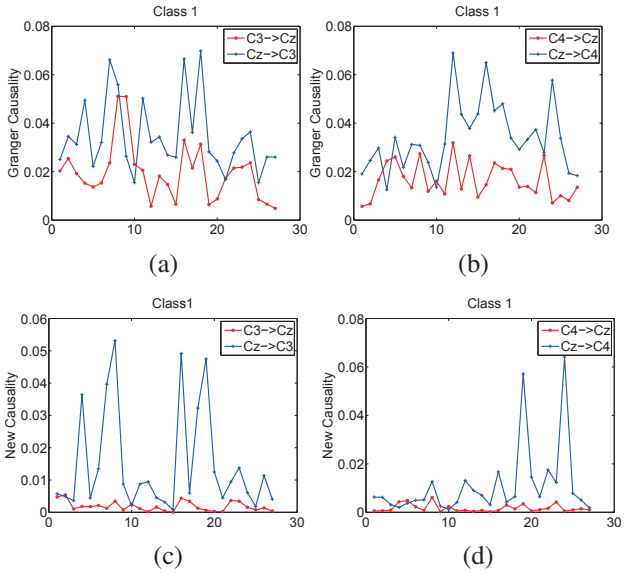

Fig. 1. (a), (b) GC between Cz and C3/C4 in time domain during left hand MI. (c), (d) NC between Cz and C3/C4 in time domain during left hand MI.

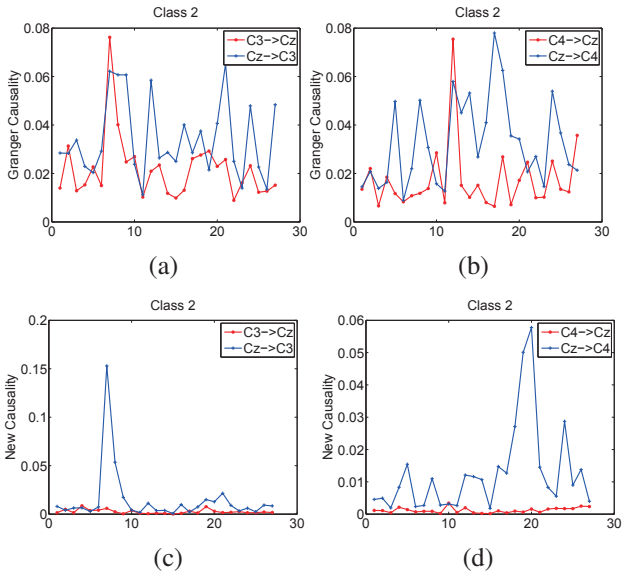

Fig. 2. (a), (b) GC between Cz and C3/C4 in time domain during right hand MI. (c), (d) NC between Cz and C3/C4 in time domain during right hand MI.

C3 based on GC and NC, more exactly, the portion of causality values from C4 to C3 being larger than that from C3 to C4 is 64%. ii) During right hand MI, there is strong directional connectivity from C3 to C4, more exactly, the portion of causality values from C3 to C4 being larger than that from C4 to C3 is 60% by GC method, and 81% by NC method. We also note that during right hand MI, the portion (60%) of GC values from C3 to C4 being larger than that from C4 to C3 is much less than the portion (81%) of NC values from C3 to C4 being larger than that from C4 to C3. So, NC method identifies the causal influence from C3 to C4 during right hand MI more clearly than GC method. Therefore, in time domain, we once again demonstrate that NC method is much better than GC method to reveal causal influence among different brain regions during MI states.

Effective Connectivity Analysis in Frequency Domain

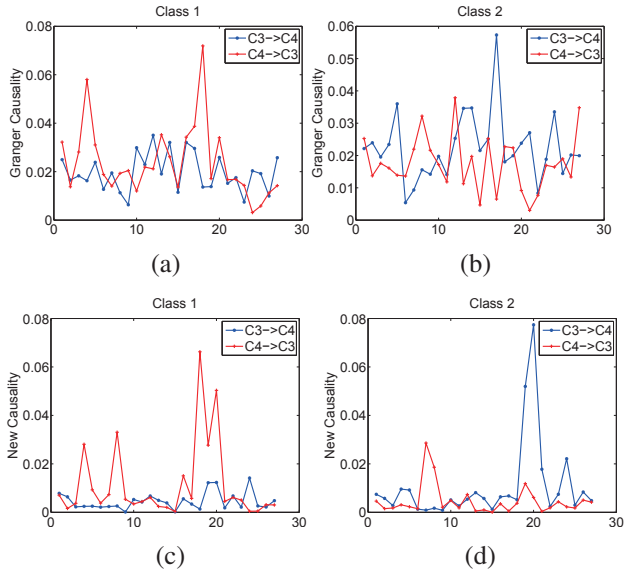

Fig. 3. (a), (b) GC between C3 and C4 in time domain. (c), (d) NC between C3 and C4 in time domain.

In frequency domain, we will apply GC method (8) and NC method (10) to calculate spectral causality. We calculate the causality between Cz and C3/C4, and between C3 and C4. We choose three subjects as representatives to show how to analyze the MI data. For each subject, we also show the power spectrums of Cz, C3, C4 of Class 1 and Class 2.

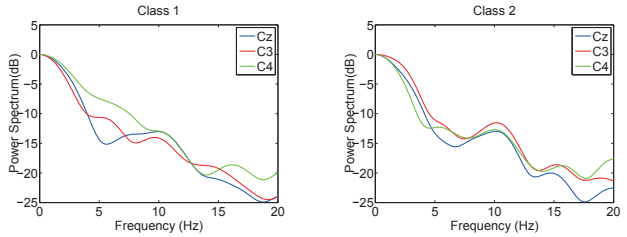

Fig. 4. Subject 1: (a) The power spectrums of Cz, C3, and C4 during left hand MI. (b) The power spectrums of Cz, C3, and C4 during right hand MI. From (a) and (b), one can clearly see mu rhythm $(8 \sim 12$ Hz) for all three channels.

Subject 1: The power spectrums of Cz , C3 and C4 are shown in Fig.4 where there are clearly peaks in mu rhythm $(8 \sim 12$Hz) of the power spectrums during left hand and right hand MI. The feature is a basic characteristic of EEG signals during MI [23].

GC and NC between Cz and C3/C4 in frequency domain during left hand MI and during right hand MI are shown in Fig.5 and Fig.6, respectively. From Fig.5 and Fig.6 one can see that i) in mu rhythm there always exist

$$I_{Cz\to C3} > I_{C3\to Cz},\ I_{Cz\to C4} > I_{C4\to Cz},$$

$$N_{Cz\to C3} > N_{C3\to Cz},\ N_{Cz\to C4} > N_{C4\to Cz}.$$

These results are consistent with the findings got in time domain, that is, there is strong causal influence from Cz to C3/C4 during left hand and right hand MI. ii) The peaks always appear in mu rhythm $(8 \sim 12$ Hz) for all NC results (blue curves) which are consistent with peaks of the power spectrums in Fig.4, but they do not appear in GC results except for (a)

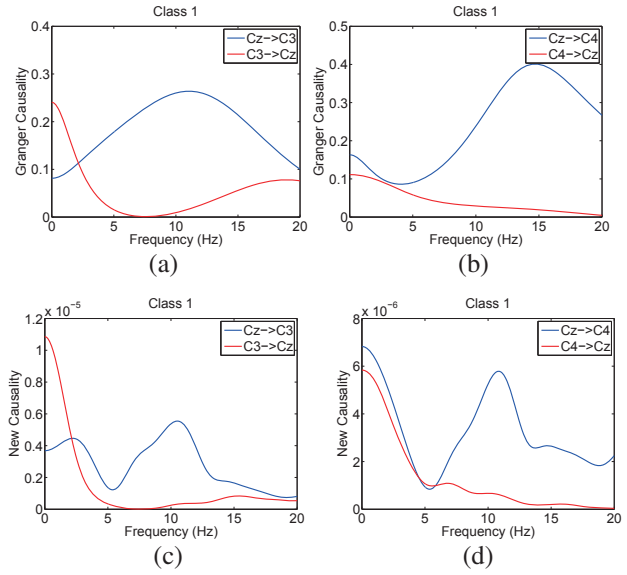

Fig. 5. Subject 1: (a), (b) GC between Cz and C3/C4 in frequency domain during left hand MI. (c), (d) NC between Cz and C3/C4 in frequency domain during left hand MI. One can see peaks in mu ($8 \sim 12$ Hz) appear for NC results (blue curves), but do not appear in (b) of GC results.

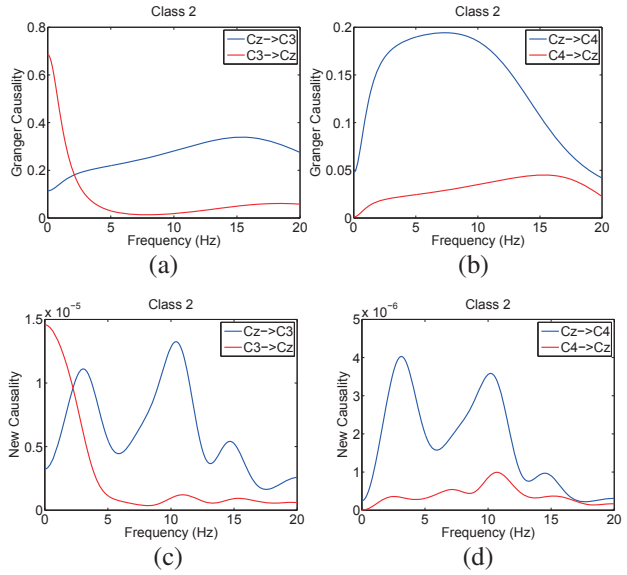

Fig. 6. Subject 1: (a), (b) GC between Cz and C3/C4 in frequency domain during right hand MI. (c), (d) NC between Cz and C3/C4 in frequency domain during right hand MI. One can see peaks in mu ($8 \sim 12$ Hz) appear for NC results (blue curves), but do not appear for GC results.

of Fig.5. This means NC method can better reveal real causal influence from Cz to C3/C4 than GC method in frequency domain.

GC and NC in frequency domain between C3 and C4 are shown in Fig.7 from which one can see that i) the causality of C4 on C3 in mu rhythm is larger than that of C3 on C4 during left hand MI, but the results are reversal during right hand MI. This consequence is consistent with the conclusion got in time domain. ii) During right hand MI, the peaks in mu rhythm ($8 \sim 12$ Hz) appear for NC results in (d), which are consistent with peaks of the power spectrums in Fig.4, but they do not appear for GC results in (b). This also demonstrates that NC method is better than GC method to reveal real causal

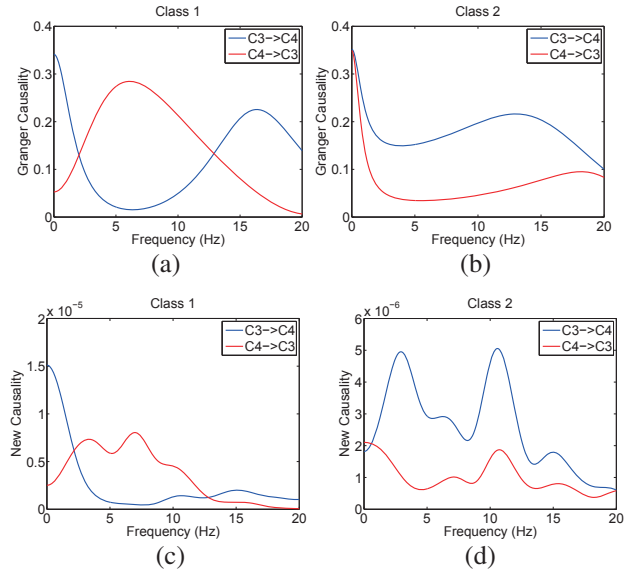

Fig. 7. Subject 1: (a), (b) GC between C3 and c4 in frequency domain. (c), (d) NC between C3 and C4 in frequency domain.

influence between C3 and C4 during this right hand MI in frequency domain.

Subject 2: The power spectrums of Cz, C3 and C4 are shown in Fig.8 where there are clearly peaks in about 10 Hz of during left hand and right hand MI for all three channels. It indicates the subject performed well during MI.

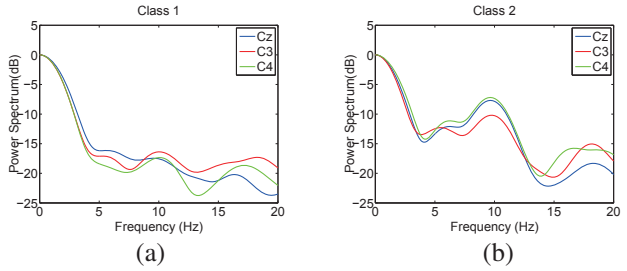

Fig. 8. Subject 2: (a) The power spectrums of Cz, C3, and C4 during left hand MI. (b) The power spectrums of Cz, C3, and C4 during right hand MI. From (a) and (b), one can clearly see the peaks in about 10Hz for all three channels.

GC and NC between Cz and C3/C4 in frequency domain during left hand MI and during right hand MI are shown in Fig.9 and Fig.10, respectively. GC and NC in frequency domain between C3 and C4 are shown in Fig.11. We can make similar discussions as in Subject 1 omitted here for brevity.

By the above analysis from two representative subjects, we can make the following conclusions: i) there exists obvious causal influence from Cz to C3/C4 in mu rhythm which is stronger than that from C3/C4 to Cz during left hand and right hand MI, that is, Cz region has causal influences on C3 and C4 regions during MI. ii) There exists clear causal influence from C4 to C3 in mu rhythm which is larger than that from C3 to C4 during left hand MI, but the result is reversal during right hand MI. Thus, different MI can lead to different directional causal influence. iii) NC method can better reveal real causal influence among Cz, C3 and C4 three regions in mu rhythm than GC method during MI.

In our experiment analysis, there are 9 subjects (27 training

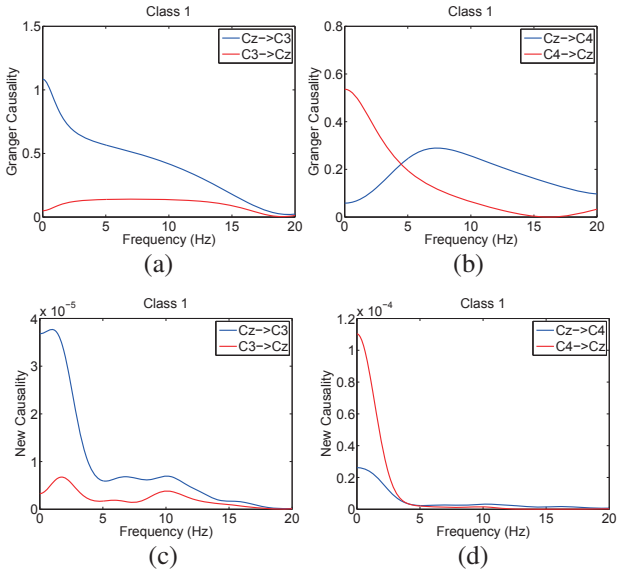

Fig. 9. Subject 2: (a), (b) GC between Cz and C3/C4 in frequency domain during left hand MI. (c), (d) NC between Cz and C3/C4 in frequency domain during left hand MI. One can see peaks in about 10Hz appear for NC results, but do not appear for GC results.

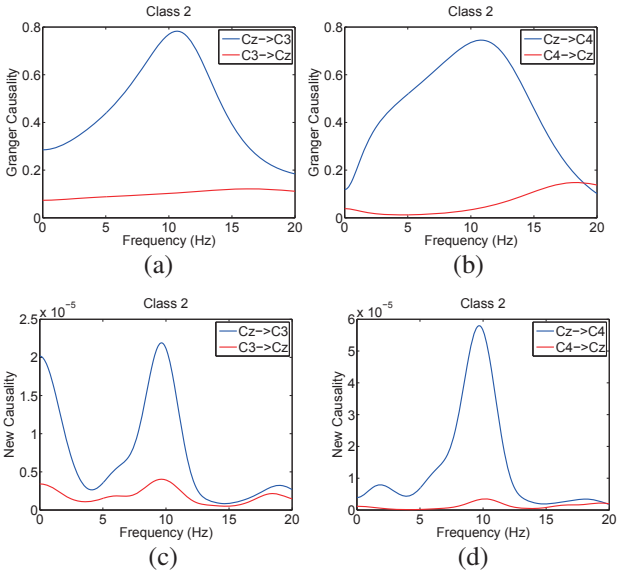

Fig. 10. Subject 2: (a), (b) GC between Cz and C3/C4 in frequency domain during right hand MI. (c), (d) NC between Cz and C3/C4 in frequency domain during right hand MI. One can see peaks in about 10Hz appear for NC results, but do not appear for GC results.

sessions data sets). Similar to the process as in above two subjects, we dealt with all the data sets and summarize the results in Table IV. It is noted that mu rhythm ($8 \sim 12$Hz) is a well-known neurophysiological phenomenon in EEG during MI [23], so, we marked the data as "good" if the power spectrums of three channels have obvious mu rhythm. Otherwise, we marked the data as "bad". In this way, we have totally 5 bad data sets and 22 good data sets (see the column of power spectrum in Table IV). In our analysis in frequency domain, we only handled these 22 good data sets for which we have three kinds of results in mu rhythm as follows: Case 1) calculate GC and NC between Cz and C3/C4 during left hand and right hand MI. If causality value from Cz to C3/C4 is larger than

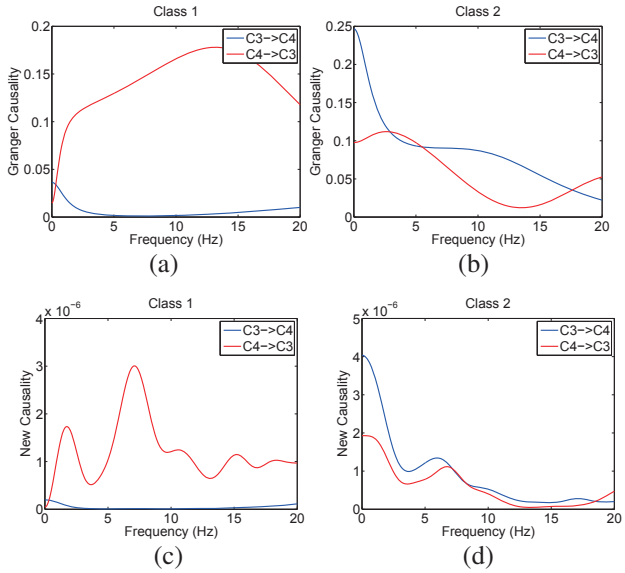

Fig. 11. Subject 2: (a), (b) GC between C3 and c4 in frequency domain. (c), (d) NC between C3 and C4 in frequency domain.

that from C3/C4 to Cz, then the result of this data is viewed as "good", otherwise, it is viewed as "bad". Case 2) Calculate GC and NC between C3 and C4 during left hand MI. If causality value from C4 to C3 is larger than that from C3 to C4, then the result of this data is viewed as "good", otherwise, it is viewed as "bad". Case 3) Calculate GC and NC between C3 and C4 during right hand MI. If causality value from C3 to C4 is larger than that from C4 to C3, then the result of this data is viewed as "good", otherwise, it is viewed as "bad". Results in Case 1, Case 2 and Case 3 are reported in Table IV. According to these results, we have 17 good data sets in Case 1, 15 good data sets in Case 2 and 13 good data sets in Case 3. So, the portion of spectral causality value from Cz to C3/C4 being larger than that from C3/C4 to Cz based on GC and NC during left hand and right hand MI is $17/22 = 77\%$, the portion of spectral causality value from C4 to C3 being larger than that from C3 to C4 based on GC and NC during left hand MI is $15/22 = 68\%$, and the portion of spectral causality value from C3 to C4 being larger than that from C4 to C3 based on GC and NC during right hand MI is $13/22 = 59\%$

To demonstrate advantage of NC over GC in frequency domain, we further mark whether there are peeks in mu rhythm for the results in Case 1, Case 2 and Case 3 of Table IV. The corresponding results are summarized in Table V and Table VI. From Table V one can see that there always exist peaks in mu rhythm for all 17 good data set in Case 1 of Table IV by NC method. So, for the results in Case 1 of Table V, during left hand and right hand MI the portion of spectral NC value from Cz to C3/C4 being larger than that from C3/C4 to Cz and meanwhile having peaks in mu rhythm is $17 * 4/(22 * 4) = 77\%$. However, the corresponding portion based on GC is only $(10 + 11 + 9 + 11)/(22 * 4) = 53\%$ from Table V. From Table IV one can see that the portion of spectral causality values between C3 and C4 have peaks in mu rhythm by NC method is $(12 + 12)/44 = 54\%$). However the corresponding portion by GC method is $(6 + 8)/44 = 32\%$). Thus, NC method is much clearer to reveal the causal influence among Cz, C3 and C4 than GC method in frequency domain.

TABLE IV. SPECTRAL GC AND NC RESULTS SUMMARY FOR ALL 27 TRAINING SESSIONS DATA

Subject	Power Spectrum	Case 1	Case 2	Case 3
subject101	good	good	good	good
subject102	good	good	good	bad
subject103	good	bad	bad	bad
subject201	good	good	good	good
subject202	good	good	good	good
subject203	good	good	bad	bad
subject301	bad	–	–	–
subject302	bad	–	–	–
subject303	good	good	good	good
subject401	good	bad	good	good
subject402	good	bad	good	good
subject403	good	good	bad	bad
subject501	good	good	good	good
subject502	good	good	good	good
subject503	good	good	good	good
subject601	good	good	good	bad
subject602	good	good	good	good
subject603	good	good	good	bad
subject701	good	good	good	bad
subject702	good	good	bad	good
subject703	bad	–	–	–
subject801	good	good	bad	good
subject802	bad	–	–	–
subject803	bad	–	–	–
subject901	good	good	bad	bad
subject902	good	bad	good	good
subject903	good	bad	bad	bad

TABLE V. THE CAUSALITY BETWEEN CZ AND C3/C4 IN CLASS 1 AND CLASS 2

Causality Method	Class 1 $Cz \leftrightarrow C3$	Class 1 $Cz \leftrightarrow C4$	Class 2 $Cz \leftrightarrow C3$	Class 2 $Cz \leftrightarrow C4$
GC	10	11	9	11
NC	17	17	17	17

V. CONCLUSIONS

Nowadays many researchers apply different causality measures to investigate how different brain regions may causally influence on each other. In this paper, we use scalp EEG to study causality flow during MI. We particularly are interested in three regions: Cz, C3 and C4 which are shown to be optimal locations for recognizing MI states [23]. The scalp EEGs are from 9 subjects in BCI competition IV held in 2008 and provided by Graz University of Technology. We calculate GC and NC in both time and frequency domains.

In time domain, our results suggest that i) there is strong directional connectivity from Cz to C3/C4 during left and right hand MI based on GC and NC (see Fig.12(a)). ii) During left hand MI, there is strong directional connectivity from C4 to C3 (see Fig.12(b)) based on GC and NC. During right hand MI, there is strong directional connectivity from C3 to C4 (see Fig.12(c)). The results in frequency domain are consistent with that in time domain, especially in mu rhythm.

There are several evidences to strongly demonstrate that NC method is much better than GC method to reveal real causality flow among different brain regions during MI states: i) By observing the red lines in Fig.1 and Fig.2, one can see that curves by NC method are less oscillative than that by GC method, this means those results by NC method are more stable and less changed during left hand MI and right hand MI. This is reasonable from the point of view of physiological phenomenon. On the contrary, curves by GC method have higher oscillation, as a result, this is unreasonable from the point of view of physiological phenomenon. ii) During right hand MI, the portion (60%) of GC values from C3 to C4 being larger than that from C4 to C3 is much less than the portion (81%) of NC values from C3 to C4 being larger than that from C4 to C3. So, NC method identifies the causal influence from C3 to C4 during right hand MI more clearly than GC method. iii) For the two subjects analyzed, the peaks in mu rhythm mostly appear for spectral NC results which are consistent with peaks of the power spectrums of Cz, C3 and C4. However, they do not appear in spectral GC results.iv) The portion of spectral causality values between C3 and C4 have peaks in mu rhythm by NC method is 54%. However the corresponding portion by GC method is only 32%). Thus, NC method is much clearer to reveal the causal influence between C3 and C4 than GC method in frequency domain.

TABLE VI. THE CAUSALITY BETWEEN C3 AND C4 IN CLASS 1 AND CLASS 2

Causality Method	Class 1 (15 data sets)	Class 2 (13 data sets)	sum
GC	6	8	14
NC	12	12	24

In this paper, we only use bivariate autoregressive model to discuss causal influence among three optimal locations during MI. Since NC definition may be defined for multiple channels, our future work will focus on applying NC method to reveal effective connectivity structure of whole brain during MI states and/or other cognitive experimental tasks.

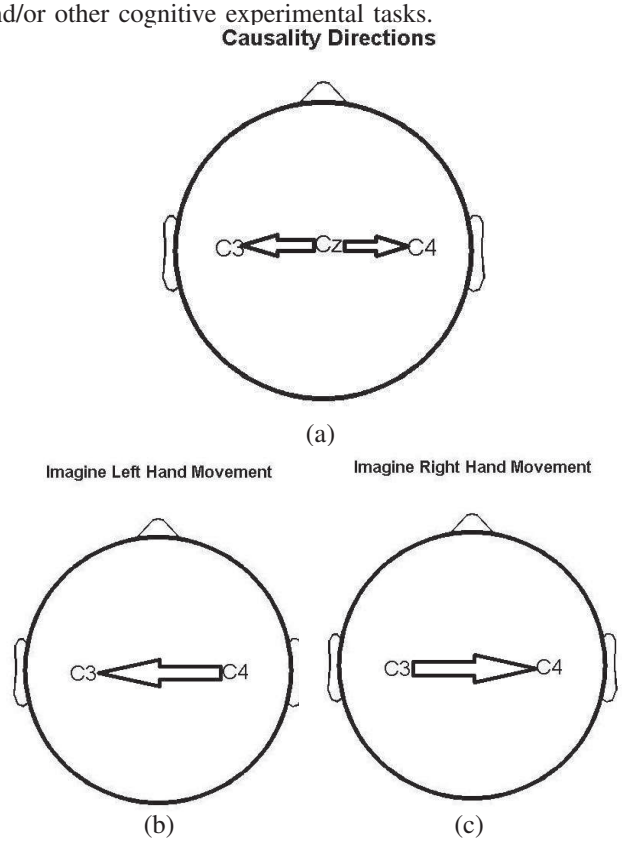

Fig. 12. (a) Cz has influence on C3 and C4 during MI. (b) C4 has influence on C3 during left hand MI. (c) C3 has influence on C4 during right hand MI.

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