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EEG Theta Rhythm Analysis using Nonlinear Granger Causality and Approximate Decomposition for Decoding of Motor Intention

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Abstract— **Granger Causality (GC) can detect directed influence of signals between multiple locations. Nonlinear GC has been used to analyze neural systems. However, the weakness of the nonlinear method is that frequency content is lost at the expense of a relatively accurate overall GC estimate. This paper investigates how nonlinear GC in different frequency bands can be obtained by the proper linearization process. When the error between the nonlinear fitting signal and the linear fitting signal falls below a specific threshold, the frequency components can be approximated. This frequency decomposition model does not rely on the formation of a nonlinear process and was evaluated on a brain computer interface (BCI) application using 128 EEG electrodes, for the decoding of the intended arm reaching movement in the left or right directions. The center of strength for each GC map in each frequency band, ranging from 3-12Hz, was also computed. The centers of strength associated with left and right motor intention were found to be highly separable in the theta rhythm (3-8Hz) only.**

I. Introduction

The Granger Causality (GC) analysis [1] has been developed to explore the directional properties in complex dynamics consisting of multi-variable observations. It has been applied to many biological and physical system phenomena [2]. A linear GC measure can define the causal relationship between a specific location and its nearby units by creating linear regressive predictive models and computing the decrease in the prediction error if the information from neighboring units is included. However, the linearity associated with this GC approach limits its applicability on many systems where the relationship between units could be nonlinear. One alternative method to incorporate the nonlinearity characteristics is through the bivariate GC analysis [3]. Our group has previously presented a general framework of extracting only the relevant information from the nonlinear causality map based on a statistic-based thresholding method.Its effectiveness was illustrated in a brain computer interface (BCI) application [4] for the decoding of the motor intention of human subject undergoing reaching movements [5]. We also defined a measure that quantifies the uniqueness of the GC vectors with respect to the decoded directions. In this study, we addressed a possible way to obtain the frequency information of the causal analysis, which is generally lost in the nonlinear GC framework. This allows the nonlinearity aspect of the GC detection method to be kept, while having the ability to obtain valuable frequency information related to these corresponding nonlinear processes between different recording locations. As a proof-of-concept study here, we applied this strategy to an identical BCI setup as [3] where the effective connectivity between different activated brain areas was investigated to decode the directions of the intended arm movement using different frequency bands. Previously, researchers distinguished the different reaching movement directions associated with different neuronal activities by calculating the power spectrum and coherence. Theta wave (3-8Hz) activity was observed in the posterior parietal cortex [5]. These observations should provide validation to our proposed method. Little has been reported on how different neural groups are connected with respect to frequency content of the EEG data, especially in the context of surface EEG measurements. By analyzing the center of strength of the GC map at each frequency band, our result agrees with the literature that active theta rhythms (3-8Hz) were able to provide the strongest feature for the separation of motor intention direction.

II. Methods

A. Experimental Protocol and Data Acquisition

The protocol has been approved by the Louisiana Tech University IRB Committee. Three healthy, right-hand participants with normal or corrected to normal eye sight were recruited. They were instructed to perform 450 trials of reaching tasks using their right arm, to the targets located 45 degrees to the left and to the right directions according to the visual cues provided by the E-Prime 2.0 system. Surface EEG signals were recorded using 128 channels HydroCel Geodesic Sensor Net electrodes (Electrical Geodesics, Inc., Eugene, OR). All signals were amplified and anti-aliased low-pass filtered at 100Hz before 256Hz sampling.

B. Nonlinear Granger Causality Analysis

GC can define the existence and direction of signal influence in high dimensional data taken from multiple locations. It can quantify the improvement of predicting one time series x_k by incorporating other time series y_k nearby using the function $f(\cdot)$. Here k represents the index in time. The causal influence of a time series is computed in terms of the linear auto-regressive model in (1) and multi-regressive models in (2).

$$x_{k+1} = f(x_k) + \varepsilon_k \tag{1}$$

$$x_{k+1} = f(x_k, y_k) + \eta_k \tag{2}$$

In the nonlinear approach, Gaussian radial basis functions (RBF) [6] can be used to create multi-variable nonlinear models of the time series.

$$f = \sum_{m=1}^{C} \alpha_m \phi_m(\mathbf{x}) + \sum_{n=1}^{C} \beta_n \phi_n(\mathbf{y}) \tag{3}$$

The influence of information from one location to another can be computed in terms of the variance of the errors associated with the nonlinear model.

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$$\mathrm{GC}_{X\to Y} = \ln\frac{\mathrm{var}(\varepsilon_k)}{\mathrm{var}(\eta_k)} \quad (4)$$

The time series **x** and **y** are delay-embedded into D-dimensional state spaces. C is the total number of RBFs used. The centers of RBF are determined through fuzzy c-mean clustering method [7] and the coefficients are trained through Kalman Filter [8]. The effectiveness of this RBF nonlinear model has been successfully shown [3], which forms the basis for the frequency information extraction method.

C. Frequency Decomposition

It is possible to examine the directional causal relations in the frequency domain using linear GC models in a bi-variate system. The causal frequency influence is defined by the logarithm of ratio of the integral frequency response and the intrinsic frequency response [9].In nonlinear case however, there is no direct method to obtain the frequency influence through Fourier transform because there is no transfer function from the analytic expression of the RBFs. Here, a linear system approximation of the nonlinear GC model based on simple curve fitting can be applied. In detail, let x_k be the original time series, $\tilde{x}_k$ be the predictive time series computed from the nonlinear model of function, $\hat{x}_k$ be the linear fitting time series computed from the following linear regressive system,

$$\tilde{x}_k = \sum_{p=1}^{P}\lambda_k x_{k-p} + \sum_{p=1}^{P}\upsilon_k y_{k-p} + \sigma_k \quad (5)$$

$$\hat{x}_k = \sum_{p=1}^{P}\lambda_k x_{k-p} + \sum_{p=1}^{P}\upsilon_k y_{k-p} \quad (6)$$

where P is the proper order of linear system. Ideally, $\hat{x}_k$ is expected to be perfectly matched with $\tilde{x}_k$. Realistically, an error would exist between the two time series. If the error is too big, the substitute GC value would not represent the nonlinear GC value, which defines the sufficiency criterion. If the error is too small, the frequency GC would keep fluctuating in different orders, which defines the efficiency criterion. Once the mean square approximation of σ_k reaches under 20% of the mean square nonlinear predictive error η_k from (2), the linear system is considered to be sufficient substitution of the nonlinear system. Frequency decomposition can then be performed.

D. Order Selection for Regression Model

A very important job in the linear approximation system is to determine the order for regression model. In auto-regression model, the most weighted coefficients distribute at the region closest to the predictive point. In our model, the output of the nonlinear function in (3) was regressively modeled. Although the two signals were very close, the distribution of the linear model coefficients may change drastically as the order increases. Thus, we cannot use the routine method to determine the order [10]. Instead, we proposed a correlation method for doing so. A correlation of frequency response between the P^{th} and $(P-1)^{th}$ order linear fit was tracked as a curve. If the bi-directional correlations remained high (having a value greater than 0.85 for over multiple consecutive orders), the nonlinear model was considered to be efficiently linearized. Then the peak values in their corresponding frequency response curves were obtained. The final order of linear regression model was selected to be the order associated with a maximum peak.

E. Observation and Quantification

To quantitatively demonstrate this analysis in motor intention, the coordinates of GC center of strength is defined as follows: Let (x_i, y_i) be the coordinates of i^{th} electrode in space, the coordinates of GC center of strength $(\bar{x}, \bar{y})$ is calculated in a similar fashion as the center of mass computation.

$$\bar{x} = \frac{\sum_i x_i GC_i}{\sum_i GC_i} \quad \bar{y} = \frac{\sum_i y_i GC_i}{\sum_i GC_i} \quad (7)$$

III. Results

A. Reliability Test

Six Gaussian functions in a five-dimension embedding space were used as an initial starting point to model the nonlinear regressive relationships between different sEEG recording sites [3]. The width of Gaussian was initially chosen as the average spacing between each pair of Gaussian centers. After estimating the nonlinear predictive curve, a linear regressive model was setup using the proposed correlation method to select P. Surrogate method was used to test the reliability of our method.

$$a_k = \cos(\omega k) + \text{noise} \quad (8)$$

$$b_k = \sum_{i=1}^{p} c_i \cos(\omega(k-i)) + \text{noise} \quad (9)$$

Where *a* is a cosine wave, with normalized frequency ω and *b* is the signal regressively constructed by cosine wave with the same frequency. Signal *a* has strong causal influence to *b* in ω .In our experiment ω was selected as 0.2. Fig.1 illustrates the effectiveness of our method.

B. Order selection for Regression Model

A high correlation between the frequency responses at successive linear model orders indicates that the nonlinear response can be somehow linearized. So far, two conditions for linearizing the nonlinear predictive model were discovered; when the fitting error fell below a specific threshold, and when a "plateau" existed in multiple sequential highly correlation model order. As illustrated in Fig. 2, the order of P = 23 to 31 shows that the bi-directional correlation exceeded 0.85. After finding the peak value of the frequency response curve corresponding to P = 23 to 31of the linearized model (Fig. 3), the frequency response selected was the one having a maximum peak value. It should be noted that such "plateau" does not always exist. Only 57.08% of the electrodes' pairs in our dataset were found the existence of "plateau". If there was no "plateau", a linearization of such nonlinear GC in this pair of signals was considered impossible and frequency information was not extracted.

C. Theta Rhythms in Motor Intention

Using the RBF nonlinear predictive model and the linear approximation method described before, the causal influence of the intention movement in the left and right directions was analyzed at different frequency bands, as shown in Fig. 4. The GC connectivity was found to be more concentrated on the ipsilateral side of the intended movement direction at the low theta frequency range of 3-4Hz and 5-6Hz. In the frequency band of 7-8Hz, we found strong GC connectivity on both ipsilateral and contra-lateral sides, but the ipsilateral side still maintained slight dominance. In the frequency band of 9-12 Hz, the GC connectivity map appeared to be evenly distributed across the whole posterior region. Furthermore, the center of strength analysis on the GC maps at low theta frequencies appeared to be most capable of separating and decoding the intended motor movement directions. The linear GC in frequency domain was found to be inseparable between the left and right directions, as shown in Fig. 5.

IV. Discussion

GC is an important tool for the detection of directional information in dynamic networks such as neural interactions, cell culture, genetic networks and protein interaction networks. However, the linear formation of GC is limited by its inability to acquire accurate information in a highly nonlinear environment. The problem with nonlinear GC is the lack of an apparent frequency information extraction method. The method proposed in this research illustrates the possibility of finding the frequency information lost in the nonlinear GC model setup. Through a carefully selected linearization process, frequency information associated with nonlinear GC can be estimated. The application of intended reaching movement decoding was used as an illustrative example for the proposed strategy. Previous reports have demonstrated the emergence of theta waves in the active regions of the brain during motor intention. The areas of the established GC maps based on nonlinear GC method are consistent with previous power and coherence analysis, providing us with further evidence for the validation of our approach. The frequency information from any formation of nonlinear model can be extracted by our model. The nonlinear process was treated as a black box. The questions were: Whether the nonlinear system can be uniquely substituted by a linear model? And if the fitted model is not unique, how can the frequency content be found? This paper does not address the theoretical solution to the latter question. Instead, we quantify the likelihood of fitting the estimated model to the nonlinear system by computing whether its frequency response is in possession of maximum range of similarity. The frequency response is calculated based on the linear coefficients and predictive errors. The final frequency response is calculated using the linearization coefficients based on the nonlinear predictive error. The predictive curve obtained from our method is different from that of the direct linear GC and the frequency information of motor intention is more consistent with those reported from the BCI literature. The effectiveness of the nonlinear model must be ensured before this method would be successful. Although not explicitly shown in this paper, we have implemented and evaluated different preprocessing methods to different signals before achieving the final results in Fig. 3. These preprocessing methods include current source density transform, signal truncation and normalization. A direct frequency extraction from the original nonlinear process is the best for sure in any model, however, if it is not possible or very difficult to do so, our substitution approach could be an alternative. Finally, we found directional information from GC frequency decomposition to be consistent with low theta rhythms as suggested by previous studies of motor intention decoding. The success of the frequency dependent GC mapping in the theta range indicated a prospect of distinguishing the motor intention of the human subject using surface EEG recordings. The corresponding linear substitution method for frequency decomposition can overcome some potential weaknesses for the lack of direct frequency information using nonlinear GC analysis.

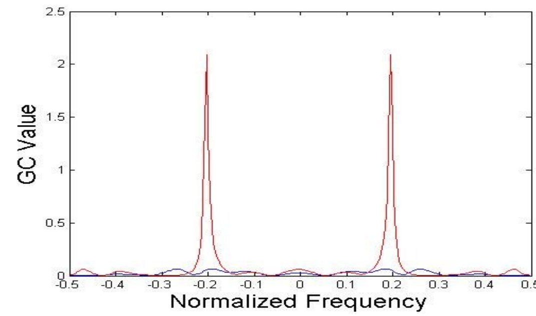

Figure 1. A test of reliability of the proposed substitute method was applied to surrogate signals. The red curve is the frequency GC from signal a to signal b and blue curve is the frequency GC from signal b to signal a. The substitute order selected was 15.

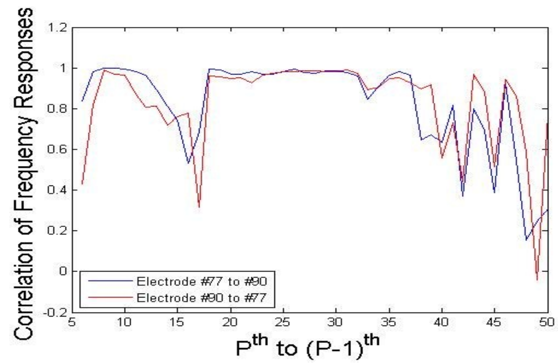

Figure 2. Correlation of the frequency response between the P^{th} and $(P-1)^{th}$ orderlinear model is shown for a representative electrode pair.

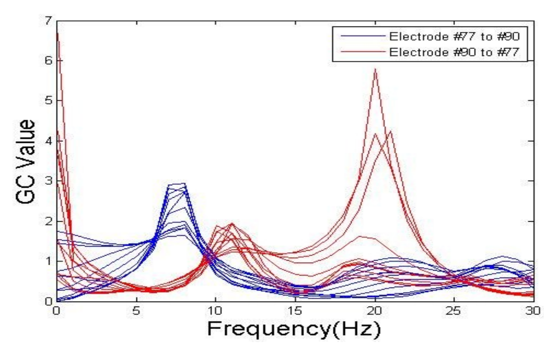

Figure 3. Bi-directional GC frequency response corresponding to p = 23 to 31 in Fig. 2 After finding the peak value of frequency response in each order, the real GC frequency response is selected as the one having the maximum peak value.

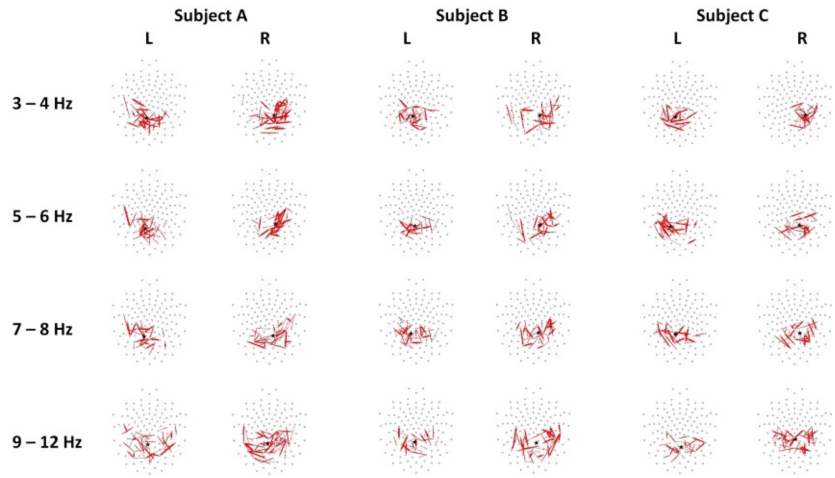

Figure 4. A summary of decoding the direction of motor intention using frequency information of substitute linear GC maps. Blue dots represent the electrode locations from a overhead view. Red arrows denote the directional GC vectors of each frequency band for each intended direction.he centers of strength are represented by black star-shape markers. The GC connectivity was found to be more concentrated on theipsilateral side of the intended movement direction at the low theta frequency range of 3-4Hz and 5-6Hz.

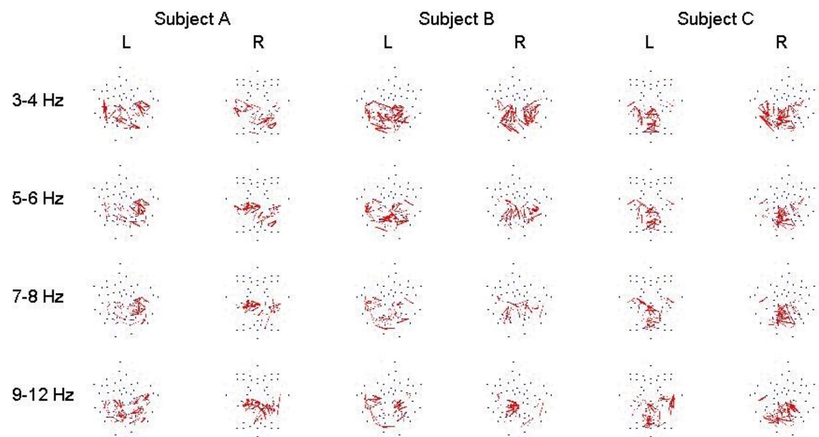

Figure 5. A summary of decoding the direction of motor intention using frequency information of linear GC maps.

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