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Statistical Threshold for Nonlinear Granger Causality in Motor Intention Analysis

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Abstract—**Directed influence between multiple channel signal measurements is important for the understanding of large dynamic systems. This research investigates a method to analyze large, complex multi-variable systems using directional flow measure to extract relevant information related to the functional connectivity between different units in the system. The directional flow measure was completed through nonlinear Granger Causality (GC) which is based on the nonlinear predictive models using radial basis functions (RBF). In order to extract relevant information from the causality map, we propose a threshold method that can be set up through a spatial statistical process where only the top 20% of causality pathways is shown. We applied this approach to a brain computer interface (BCI) application to decode the different intended arm reaching movement (left, right and forward) using 128 surface electroencephalography (EEG) electrodes. We also evaluated the importance of selecting the appropriate radius in the region of interest and found that the directions of causal influence of active brain regions were unique with respect to the intended direction.**

I. Introduction

The analysis of complex dynamics consisting of multi-variable observations is relevant to the investigation of many biological and physical system phenomena as well as the study of sociological behaviors [1]. Many important properties of a dynamic network are related to how the network units are connected. While coherence and synchronization theory can be used to detect mutual interactions between multiple units within a system through the analysis of the recorded signals from their respective locations [2], Granger Causality (GC) is able to provide additional information on the directional influence between different sites. 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. Other researchers have provided the nonlinear measures through bivariate Granger Causality analysis. In this paper, we present a general framework to evaluate the method to select the appropriate complexity and dimensionality of the nonlinear model, as well as the criteria for choosing threshold associated with the analysis.

To the best of our knowledge, the effectiveness of this nonlinear GC measure based on RBF functions has not illustrated in any biomedical applications. As a proof-of-concept study, we apply our strategy to a brain computer interface (BCI) application to assist in decoding the motor intention of human subject undergoing reaching movements [3]. Previously, researchers can distinguish the different reaching movement directions associated with different neuronal activities by calculating the power spectrum and coherence. Little was done to study how the different neural groups are connected, especially in the context of surface EEG measurements. Here, we investigate effective connectivity between activated brain areas to decode the directions of the intended arm movement on a grid of 128 surface EEG electrodes. Our result indicated consistent sequence of activated brain regions for each reaching direction (left, right or forward).

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II. Methods

A. Experimental Protocol and Data Acquisition

Four healthy, right-hand participants with normal or corrected to normal eye sight were recruited. The protocol has been approved by the Louisiana Tech University IRB Committee. They were instructed to perform 450 trials of reaching tasks (left, right and forward direction) according to the visual cues provided using the E-Prime 2.0 system (Fig. 1). The "Effectors cue" instructed whether the user should physically perform the reaching task or to imagine the movement only. The "Action cue" informed the user of the appropriate directions. EEG signals were recorded using 128 channels HydroGel Geodesic Sensor Net (Fig. 2) with the Net-Station 5.3 software. All signals were amplified and anti-aliasing low-pass filtered at 100Hz. The data was then digitized at a sample rate of 256Hz. Touch pads were placed at the base location and the targets to track whether the subject has performed the tasks correctly. The signals between the "Action cue" and the "Go cue" (700ms in duration) were used in this study.

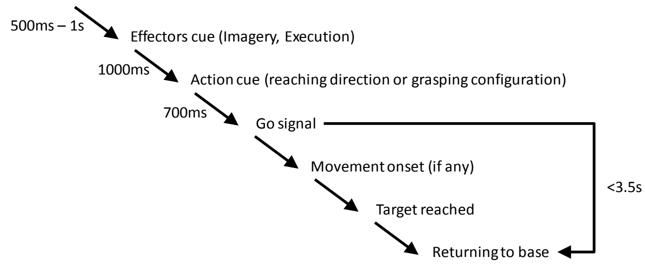

Fig. 1. The time course of one trial is illustrated.

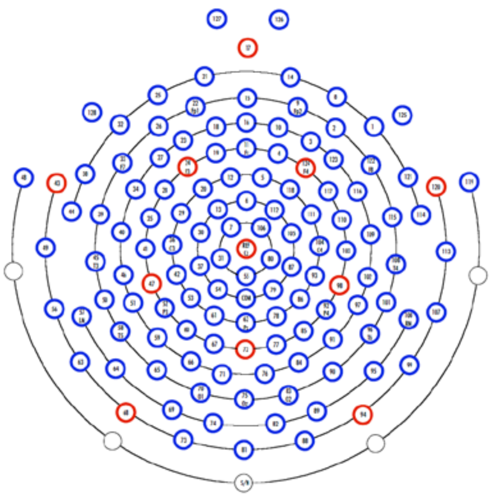

Fig. 2. The channel map as observed from the top of the subject's head with the front of the head pointing upward.

B. Nonlinear Granger Causality Analysis

Granger Causality (GC) can define the existence and direction of influence from high dimensional data from multiple locations. It can quantify the improvement of predicting one time series (x_k) by incorporating other neighboring time series (y_k) using any arbitrary function f(·). In linear GC analysis, the causal influence of a time series is computed in terms of the linear auto-regressive (2) and multi-regressive models (3). In the nonlinear approach, radial basis functions (RBF) [6] can be used to create multi-variable nonlinear models (3) and (4) of the time series.

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

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

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

$$\phi_m(\mathbf{x}) = \exp\left(-\sum_{i=1}^{D} \frac{(x_i - \mu_i)^2}{\sigma^2} \right) \tag{4}$$

The influence of information from one location to another can be computed in terms of the variance of the errors associ ated with the nonlinear model (5).

$$\mathrm{GC}_{X \to Y} = \ln \frac{\mathrm{var}(\varepsilon_k)}{\mathrm{var}(\eta_k)} \tag{5}$$

The time series x and y are delayed embedded into D-dimensional state spaces. C is the total number of RBFs used. Gaussian functions are used as the RBFs where the variable μ denotes the mean and σ is the standard deviation. The centers of RBF are determined through fuzzy c-mean clustering method [4] and the coefficients are trained through Kalman Filter [5]. The number of RBFs in the nonlinear model directly impacts the outcome of the GC analysis. Less number of clusters would produce large difference between the predicted and the actual output. More clusters would cause over fitting. Since it would be extremely time consuming and computationally expensive to compute the suitable number of Gaussian RBFs for each EEG channel pairs at different embedding dimensions, we preformed visual inspection of the state space and determine the number of Gaussian clusters for subsequent analysis.

C. Embedding Dimensions

The appropriate embedding dimension was determined through a statistical process. Unlike linear GC analysis where having more embedding dimensions would always decrease the error while the coefficients for samples further along in time would be getting smaller, the range of suitable embedding dimension for the nonlinear GC model must be obtained experimentally. For our application, a delay embedded EEG signal with dimension K would correspond to a history of K/256 seconds. Through a preliminary analysis using linear auto-regression (AR) model, the coefficients for $K>10$ quickly dropped to $<1\%$ of the maximum. This gave us a preliminary range of 2-20 dimensions for the investigation.

To determine the actual embedding dimension, ten pairs of EEG signals from different locations were random selected from one subject. In each pairs, the directional influence in the form of GC between electrode x and y was calculated in different embedding dimension (D= 2-20). The dimensions corresponding to GC values with relatively few fluctuations with subsequent dimensions across all 10 pairs of electrodes are chosen for the subsequent analysis of the remaining three subjects.

D. Threshold and Information Filtering

Once the appropriate embedding dimension and number of clusters have been selected, the causal information between every electrode pair can be obtained. An effective information filtering mechanism is proposed to display only the significant GC values, which includes a suitable radius for the regions of interest (ROI) and a GC threshold. The radius of ROI is selected based on the propagation velocity of the neural signal and the embedding dimension (or memory) of the nonlinear model. The GC is computed only for the electrodes pairs that are within the ROI of each other. Furthermore, GC values for electrodes outside of the cortical regions are not computed since they are more likely to be caused by muscular activity and EMG but not surface EEG.

We define a quality factor (Q) as the cumulative sum of GC within a ROI. The summation of Q under different percentages of the maximum GC value in each independent EEG space was obtained. The concept of Q is similar to the concept of probability of density in statistic, where Q in each threshold is equivalent to probability density and the Q vs. relative thresholds curve is analogous to the density distribution. The threshold was set at the point where only the top 20% of GC is shown (relative threshold of 0.8).

E. Observation of Uniqueness

We define uniqueness parameter (U) that quantifies the uniqueness of the GC vectors with respect to the direction of decoding in electrode grid map shown in Fig. 2. The parameter U is calculated as the dot product of each GC value vector with the unit vector in the projected direction. In our experiment, two template unit vectors were set as (-0.707, -0.707) for the left and (0.707, -0.707) for the right intended reaching directions. The magnitudes of the U parameter for each reaching direction were then compared between linear and nonlinear GC analysis.

III. RESULTS

A. Embedding Dimensions

As an initial estimation, we use five Gaussian RBFs to model the nonlinear auto-regressive and multi-regressive relationships between different channel pairs after visual inspection of the two-dimensional state space. After measuring the bivariate GC values for each embedding dimension, the GC for D=5-8 showed the least amount of variations. This observation is consistent across all 10 pairs of EEG channels randomly selected. This also corresponds to the system memory of 20ms to 31ms. When this is taken in consideration of the duration for each trial (700ms), up to 35 causal time windows can be observed.

B. Statistic-based Threshold

The ROI of a particular electrode is defined as a circle with radius of approximately 70mm. This value is determined by assuming that the max propagation of neural activities within the cortex is 2 m/s and multiplying it by the model history of 8 previous steps: (8+1)/256Hz = 0.035s. Fig. 3 gives an illustrative example of the quality factor (Q) for one subject. In Table 1, the thresholds for each of subject undergoing different reaching directions are shown.

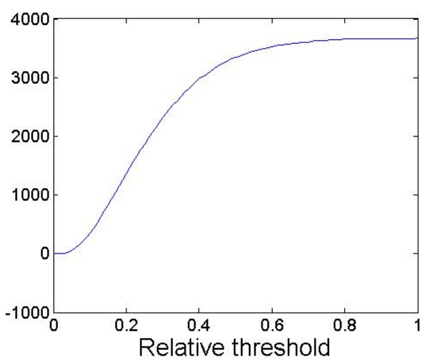

Fig. 3. The cumulative quality factor (Q) as a function of the relative threshold is shown for one subject. Threshold calculated from this curve is 0.41, corresponding to the top 20% of the Q factor.

TABLE I
RELATIVE THRESHOLD FOR EACH SUBJECT AND DIRECTION

Subject	Left	Forward	Right
A	0.41	0.31	0.31
B	0.46	0.35	0.36
C	0.39	0.32	0.37
D	0.52	0.50	0.53

C. Mapping of Reaching Movement Directions

The casual influence for each subject based on the linear and nonlinear models are shown in Fig. 4 and 5, respectively. The activities were typically directed to the posterior parietal cortices (PPC).

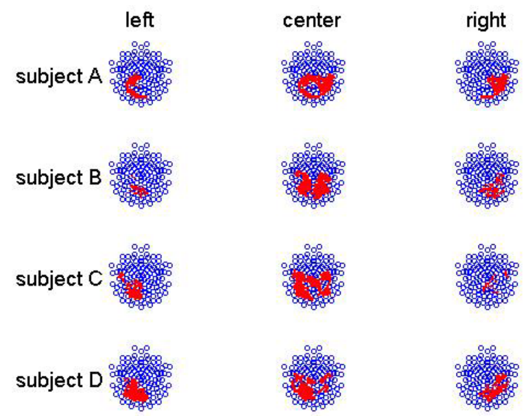

Fig. 4. The linear GC map (red lines) superimposed on the EEG electrodes (blue circles).

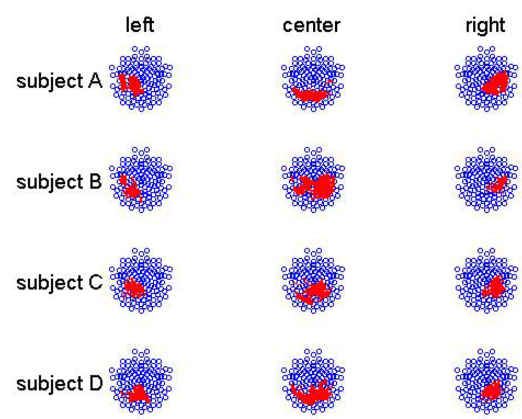

Fig. 5. The nonlinear GC map (red lines) superimposed on the EEG electrodes (blue circles).

D. Observation of Uniqueness

Table II gives the distinction of uniqueness in linear GC analysis and nonlinear GC analysis. The U values associated with linear GC analysis are generally smaller than those associated with the nonlinear GC analysis. This is consistent with the observation that linear GC vectors in Fig. 4 are more disorderly than the nonlinear GC vectors in Fig. 5.

TABLE II
THE UNIQUENESS PARAMETER (U) BASED ON LINEAR AND NONLINEAR GC ANALYSIS

	Left Direction		Right Direction	
Subject	Linear	Nonlinear	Linear	Nonlinear
A	1.03	3.45	-7.44	3.54
B	-0.26	1.20	-0.55	1.45
C	0.72	5.65	0.23	7.13
D	4.03	3.45	0.78	11.62

IV. DISCUSSION

The analysis of complex dynamic network using mathematical models is very important for the understanding of physical, biology and social phenomenon. We proposed the use of RBF-based nonlinear GC analysis on a BCI application by identifying the directional interactions and extracting the effective information using a threshold method based on statistics.

We decoded the intended reaching movement as an illustration for nonlinear GC on dynamic network. Reaching movement directions have been studied by many researchers [3]. In the active areas established based on nonlinear GC method are consistent with previous power and coherence analysis, providing us with further evidence for the validation of our approach. In addition, compared with the more traditional linear GC, the nonlinear GC method demonstrated unique and distinctive PPC areas, consistent with the physiology studies in the literature. RBF-based GC is better able to describe the nonlinearity of a dynamic system. It may also be used to improve the accuracy of predicting the intended reaching movement directions in future BCI applications. The linear GC used in this paper was based on bivariate GC model, generally, when there is a system comprised with three or more time series, a pairwise approach may lead to ambiguous results in terms of a direct causal influence and a mediated causal influence. A conditional GC can help solve this problem. However, the multivariate AR model in the conditional GC analysis would post a technical challenge for us due to the vast amount of data from 128 channels. Future study would be to investigate other GC methods [9].

The directed influence of dynamic networks (such as that of the surface EEG investigated here) is very complex, often filled with trivial interactions and connections caused by artifacts or other unrelated events. The effectiveness of Q parameter proposed here can help highlight the strongest causal interactions. More specifically, the magnitude of GC value might be affected by many factors and is subject-dependent. Conscious or unconscious brain processes might interfere with the intended reaching movements, which can affect the GC distribution in a local or global scale. Filtering the GC value from a single point perspective is not sufficient. Thus, it is very necessary to take into account the relative strength of the GC in the whole spatial domain. Our proposed relative threshold technique can remedy these issues as illustrated in its ability to differentiate intended motor movements.

Individual subject variability in the GC analysis might be embodied in the individual model set up. Our final result demonstrated consistent active regions depended on the direction of the intended movement. To improve this model, subject-dependent parameters such as the number of Gaussians and embedding dimensions may be selected. However, this is a very time consuming and computationally intensive process. The current criteria for selecting the model parameters may be improved in the future. Penalty functions (such as Akaike information criterion or similar measures) may be introduced to evaluate the appropriate number of RBF clusters needed. Although the current result is encouraging, we will develop a more objective approach to find the embedding dimension for each individual in the future.

Finally, the nonlinear GC analysis and the threshold method could be applied to the investigation of other dynamic networks such as cell culture, genetic networks and protein interaction networks. Our group is currently using this method to evaluate the relationship between causality in information flow and anatomical connectivity in cell cultures.

V. CONCLUSION

The success of GC mapping of information flow on surface EEG using nonlinear models and relative threshold method indicates a prospect of distinguishing the motor intention of the human subject using surface EEG recordings. The result of RBF-based nonlinear GC analysis showed a more orderly and distinctive directed influences over the traditional linear GC approach. The difficulty in implementing these nonlinear models is that the parameters must be selected properly. Furthermore, the relative threshold method was able to help differentiate intended motor movements by reporting only the strongest causality relationships between different electrode pairs within the regions of interest.

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