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Noise-assisted Multivariate Empirical Mode Decomposition based Causal Decomposition for Detecting Upper Limb Movement in EEG-EMG Hybrid Brain Computer Interface

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Abstract— EEG-EMG based hybrid Brain Computer Interface (hBCI) utilizes the brain-muscle physiological system to interpret and identify motor behaviors, and transmit human intelligence to automated machines in AI applications such as neurorehabilitations and brain-like intelligence. The study introduces a hBCI method for motor behaviors, where multiple time series of the brain neuromuscular network are introduced to indicate brain-muscle causal interactions, and features are extracted based on Relative Causal Strengths (RCSs) derived by Noise-assisted Multivariate Empirical Mode Decomposition (NA-MEMD) based Causal Decomposition. The complex process in brain neuromuscular interactions is specifically investigated towards a monitoring task of upper limb movement, whose 63-channel EEGs and 2-channel EMGs are composed of data inputs. The energy and frequency factors counted from RCSs were extracted as Core Features (CFs). Results showed accuracies of 91.4% and 81.4% with CFs for identifying cascaded (No Movement and Movement Execution) and 3-class (No Movement, Right Movement, and Left Movement) using Naive Bayes classifier, respectively. Moreover, those reached 100% and 94.3% when employing CFs combined with eigenvalues processed by Common Spatial Pattern (CSP). This initial work implies a novel causality inference based hBCI solution for the detection of human upper limb movement.

I. Introduction

The brain-muscle physiological network focused on the function and regulation of a complex process between brain and neuromuscular systems, and served for hybrid Brain Computer Interface (hBCI) by disclosing brain-behavior architecture and operational principles of the network, similarly as previous techniques in brain network (e.g., Functional Connectivity, Causal Modeling, and Multivariate Modeling) have been discussed [1] [2].

Causality analysis is a commonly used tool for effective connectivity that infers the cause-effect relationship across distributed brain responses [3]. The most prevalent theory currently was Granger causality, which relied on time dependency of time series, and requested a priori of the temporal separability between cause and effect [4]. However, such separability would not critically be handled in complex systems such as physiological processes, and may fail to identify the causality. Thus Yang et.al. proposed Ensemble Empirical Mode Decomposition (EEMD) based Causal Decomposition, and introduced fundamentals of cause-effect is phase-dependent, rather than time-dependent [5].

Following this work, Zhang et.al further extended causal decomposition to brain physiological network in bivariate and multiscale time series, called Noise-assisted Multivariate Empirical Mode Decomposition (NA-MEMD) based Causal Decomposition. This method defined Intrinsic Causal Components (ICCs) sets from the naturally decomposed Intrinsic Mode Functions (IMFs). In ICCs sets, the primary ICCs are then determined, and then the causal inference is identified by Relative Causal Strengths (RCSs) in the procedure of causal decomposition [6], [7].

Many studies also have addressed machine learning for identifications of upper limb movements. Schwarz et.al utilized EEG time series in motor execution (reaching and grasping actions of human upper limbs), obtaining the accuracy of 74.2% for cascaded and 65.9% for multi-class recognitions [8]. Cho et.al investigated hand motions with 20-channel EEGs by extracting Common Spatial Pattern (CSP) as Core Features (CFs), and reached 56.83% using the regularized Linear Discriminant Analysis (LDA) classifier [9]. Ofner et.al used low-frequency time-domain EEG signals ($<$ 3 Hz) to extract Discriminative Spatial Pattern (DSP) as features and classify them by LDA, reaching the accuracy of 87% for cascade task and 55% for 5-class [10]. There were also studies mentioned about the detection of upper limb movement by using motor imaginary EEG and EMG data [11].

This study proposed a detection method for up-

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per limb movement using NA-MEMD based Causal Decomposition combined with CSP. 63-channel EEG and 2-channel EMG time series data were acquired from the subject experiment. NA-MEMD based Causal Decomposition was also used for the determination of EEG channel selection. RCSs and CSP derivatives were introduced to form the input feature for two or multi-class classifications (Figure 1).

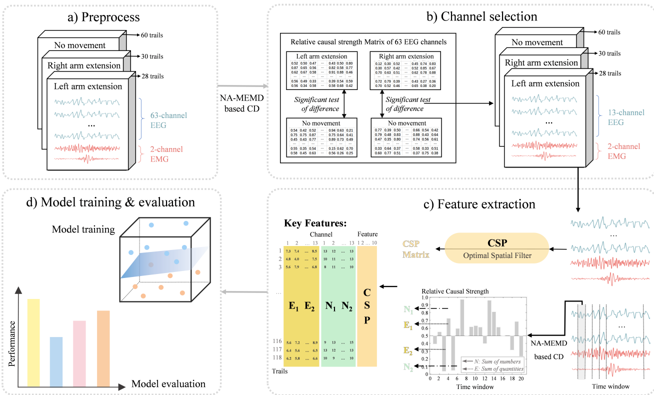

Fig. 1. The overall procedure of a detection method of NA-MEMD based Causal Decomposition combined with CSP for upper limb movements.

II. Experiments

The experimental procedures involving human subjects described in this paper were approved by the ethics committee of University of Electronic Science and Technology of China (UESTC). One right-handed and untrained healthy female subject aged 24 participated in the experiment. The experiment was set in a darkened environment, during which 2-channel EMG data from biceps brachii of left and right upper limbs and 63-channel EEG were collected by the ANT Neuro eego^{TM} Mylab device. Especially, a bipolar electrode configuration and a differential amplify measurement was used for EMG measures. Two 5 $\times$ 3.5 cm rectangular electrode pieces were pasted closely on center of the biceps brachii. The experiment session included three-second resting followed by 30 repetitions of limb extension and flexion while holding with 2.5 kg dumbbell. More related details can refer to preliminarily studies [6].

III. Methods

A. Preprocessing

The raw EEG and EMG data first were processed to eliminate power-line interference. The average reference method was applied in EEG time series data.Then, the bandpass Butterworth filters of 1-160 Hz and 20-350 Hz were used to EEG and EMG time series, respectively [6]. The one-second data (2000 data points) collected at the onset of upper limb movement was targeted as the trial data. Totally 30 trials for right arm extension and 28 trials for left were collected. The onset time of the limb movement was trial-by-trial calibrated by the threshold θ of the corresponding EMG time series. θ was defined as, $\theta = \mu + k\sigma$, where k was set to 10, and μ and σ were the mean and standard deviation of the corresponding EMG time series [12]. In addition, 60 trials in the rest period were also segmented as the same data length with 58 EEG-EMG paired trials. Any trials with EEG artefacts, including Electrooculogram (EOG), and slight head or body movements, were manually viewed and rejected from the study use. It was concluded that a total of 118 samples were included in the study.

B. Channel Selection

The details of the theoretical work of NA-MEMD based Causal Decomposition can be followed by [6]. In this study, 63-channel EEG and 2-channel EMG time series were together processed by NA-MEMD, and generated a set of IMFs. According to earlier findings in neuroscience, neuromuscular activities in the limb movement were confirmed to be driven by brain cortex, especially by primary motor cortex (M_1) [1]. Therefore, the 63-channel EEGs of the whole brain perhaps contained redundant information, which may degrade the identification performance. In this study, NA-MEMD based Causal Decomposition was first applied to channel selection, which was specified by (*i*) computing Relative Causal Strengths (RCSs) between 63-channel EEG and 2-channel EMG via NA-MEMD based Causal Decomposition for the trials in the rest period; (*ii*) obtaining RCSs between EEGs and one EMG (either left or right) from the biceps with movement; (*iii*) the significant test was applied between (*i*) and (*ii*) to find independent EEG channels that primarily caused limb behaviors. One-way analysis of variance (ANOVA) was then used to test the significant difference in the condition of whether movements occurred. The channels with significant differences ($p < 0.05$) were regarded as causality correlation in terms of EEG-EMG channels.

C. Feature Extraction

In order to obtain CFs in representation of EEG-EMG causal interactions in terms of upper limb movement, the time window was first applied to time series trials. Based on preliminary studies [6], the time window was set to 100 data points with no overlapping. The quantified effects of causality were measured by (1) the quantities of RCSs with respect to time, namely Energy factor (E); (2) the quantities of the number of the directed causal relationship, namely Frequency factor (N). E and N were applied as CFs for recognizing the two or multi-classifications of upper limb movement. In addition, CSP was also retained as the input CFs referring to its acceptable outcome reported from previous studies [13].

D. Model Training and Evaluation

Four classifiers were compared for classification performance, Naive Bayes (NB), Random Forest (RF), Support

Vector Machine (SVM) and K-nearest Neighbor (KNN). The batch-size and the number decimal places in NB classifier were set to 120 and 3, respectively. The number of trees, execution slots, iterations and seeds were set to 100, 1, 100 and 1 in RF, respectively. c (loss function) and γ (kernel function) in SVM were set to 1 and 0.001, respectively. The parameter k in KNN was set to 3. Two classification tasks were taken in the study, (*i*) Cascaded (movement execution (58 samples) v.s. no movement (60 samples)) and (*ii*) 3-class (left movement (28 samples) v.s. right movement (30 samples) v.s. no movement (60 samples)). Samples were randomly divided into training and test sets, 70% for training and 30% for testing. Ten-fold cross validation was used in training set to ensure the accuracy and generalization of the model. Accuracy (ACC), Precision Rate (PR), Recall Rate (RE), and Area Under Curve (AUC) were used to evaluate the model.

IV. Results

Raw data collected from our experiment were pre-processed and segmented by EEGLAB, including 118 samples for left/right arm movement modes and no movement mode in 63-channel EEG and 2-channel EMG time series. NA-MEMD based Causal Decomposition was applied to select EEG channels, by which RCSs were calculated in each channel. The one-way ANOVA analysis was then tested between movement and non-movement modes. As a result, 13 EEG channels were significantly caused the upper limb movement, whose labels were followed by F_3 (p=0.0206), FC_1 (p=0.0496), C_3 (p=0.p0077), C_4 (p=0.0043), T_8 (p=0.0047), AF_7 (p=0.0021), FCz (p=0.0336), PO_6 (p=0.0045) for the left mode, and T_7 (p=0.044), C_3(p=0.0028), M_2 (p=0.0001), F_5 (p=0.0215), FCz (p=0.0301), C_5(p=0.0354), PO_8 (p=0.0439) for the right mode.

Each trial (2000-point time series) was segmented according to time window, while obtaining 20 data segments (100 data points) with no data overlapping. Based on the data segment, RCS was obtained between EEGs (13-channel) and EMGs (either left or right biceps) time series, and the noise level parameter of NA-MEMD based Causal Decomposition algorithm was set to 0.01. Therefore, E and N values were accounted as the causality based CFs for further classifications. The training and test sets were randomly divided by Weka. Ten-fold cross validation was also applied to the training set to achieve the sophisticated model. Four classifiers were trained and their performance on ACC, PR, RE and AUC was evaluated (Table 1).

Multiple features were introduced to compose the feature matrix. Based on CSP feature extractions, time series data and their corresponding labels in the training set were utilized to obtain the optimal spatial filter. Then all data and labels in both training and test sets were projected based on the established optimal spatial filter, which generated 10×118 feature matrix. The proposed CFs were combined with CSP features to feed into the four classifiers. The four classifiers were trained and evaluated using CFs alone, CSP features alone and the combination of CFs and CSP features (Table 2). Results showed that the combined features can achieve the accuracy of 94.3% in the test set and 89% in the ten-fold cross validation of the training set in 3-class classification.

V. Discussions

EEG Channel selection is an important task not only in AI applications related to EEG-EMG based hBCI , but also in the nature of brain-muscle physiological responses to Motor Execution and Motor Imaginary. Effective Connectivity reflects the causality of observed dependencies deeply with specific direction [14]. Most of previous studies selected EEG channels related to ME by correlation analysis [15]. However, this study suggested an approach of NA-MEMD based Causal Decomposition to avoid the redundancy of EEG channels for the detection of upper limb movements. The results showed and confirmed that those selected EEG channels was almost located in the region of M_1 (C_3 and C_4), considered to be the core area where the brain drives muscle movements. In addition to the RCS values, most EEG channels on the left arm movement show a significant difference in the right hemisphere, and vice versa [1].

Different from previous research, this study also proposed the use of the RCS obtained from NA-MEMD based Causal Decomposition for feature extractions. We first compare the differences between the proposed feature extraction method and other methods, and then compare the differences between different classifiers to select the best classifier. The results shown in Table 1 and Table 2 indicated that the feature extract method based on causality analysis performs well in the complex dynamic EEG-EMG process, an accuracy of 91.4% in cascaded and 80.0% in 3-class classification. Moreover, it can be found that the combined feature matrix provided a better performance on the 3-class test with 94.3% by RF classifier, compared to 80% for CSP features alone.

However, outcomes of this study also were taken in certain limitations. Limited by experimental conditions, only one subject involved and few samples may lead to potential risks in model training, although our study did not use complex classifiers to avoid over-fitting and enhance the interpretability of the model. In addition, the parameters of classifiers have not been adjusted, which meant that the obtained evaluation index may be biased. Comparison of features extracted by different causal analysis methods and a visualizing toolbox implement (e.g., graphviz in Python) of proposed methods will be improved in future work.

VI. Conclusion

In this study, NA-MEMD based Causal Decomposition method was introduced in the detection of upper limb movement. The 63-channel EEG and 2-channel

TABLE I
Overall classification performance by using CFs in the training and the test sets

Classifiers	Cascade				3-class			
	ACC(%)	PR(%)	RE(%)	AUC	ACC(%)	PR(%)	RE(%)	AUC
Naive Bayes	87.3 / 91.4	87.5 / 91.6	87.3 / 91.4	0.934 / 0.935	81.4 / 80.0	81.5 / 80.0	81.4 / 80.0	0.902 / 0.890
SVM	84.7 / 85.7	84.8 / 85.9	84.7 / 85.7	0.847 / 0.858	74.6 / 68.6	74.1 / 69.1	74.6 / 68.6	0.831 / 0.815
KNN (K=3)	81.4 / 85.7	81.4 / 85.9	81.4 / 85.7	0.848 / 0.879	66.1 / 68.6	65.6 / 72.0	66.1 / 68.6	0.767 / 0.803
RF	82.2 / 85.7	82.3 / 85.8	82.2 / 85.7	0.902 / 0.925	77.1 / 71.4	75.6 / 70.6	77.1 / 71.4	0.890 / 0.875

The left side of / indicated outcomes on the training set via ten-fold cross validation, the right side of which was that based on the test set.

TABLE II
Overall classification accuracy by using CFs alone, CSP features alone and the combination of CFs and CSPs in the training and the test sets (%).

Classifiers	Training sets via ten-fold cross validation						Test sets					
	Cascade			3-class			Cascade			3-class		
	CF	CSP	[CF CSP]	CF	CSP	[CF CSP]	CF	CSP	[CF CSP]	CF	CSP	[CF CSP]
Naive Bayes	87.3	100	100	81.4	80.5	89	91.4	100	100	80	80	88.6
SVM	84.7	100	100	74.6	81.4	85.6	85.7	100	100	68.6	85.7	85.7
KNN (K=3)	81.4	100	100	66.1	83.1	86.4	85.7	100	100	68.6	77.1	85.7
RF	82.2	100	100	77.1	84.7	87.3	85.7	100	100	71.4	80	94.3

EMG were collected. The causality of each EEG channel with EMG was calculated and statistically analyzed by one-way ANOVA, which concluded that 13-channel EEG distributed near M_1 were related to certain movement. The time series data from selected channels were segmented, and causality features were generated. Those were used to train the model by the NB classifier and performed an accuracy in cascaded for 91.4% and 3-class for 80%. Furthermore, they were also compared to CSP features, which would further improve the accuracy in 3-class identification (from 80% to 94.3%). The NA-MEMD based Causal Decomposition approach would be a new guidance to recognize motor behaviors and develop an EEG-EMG based hBCI system for AI applications.

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