2021 43rd Annual International Conference of the
IEEE Engineering in Medicine & Biology Society (EMBC)
Oct 31 - Nov 4, 2021. Virtual Conference

EEG-EMG Correlation Analysis with Linear and Nonlinear Coupling Methods Across Four Motor Tasks*

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Abstract — **Correlation between brain and muscle signal is referred to as functional coupling. The amount of correlation between two signals greatly depends on the motor task performance. In this study, we designed the experimental paradigm with four types of motor tasks such as real hand grasping movement (RM), movement intention (Inten), motor imagery (MI) and only looking at virtual hand in three dimensional head mounted display (OL). We aimed to investigate EEG-EMG correlation with linear and nonlinear coupling methods. The results proved that high correlation could be occurred in RM and Inten tasks rather than MI and OL tasks in both linear and nonlinear methods. High coherence occurred in beta and gamma bands of RM and Inten tasks whereas no coherence was detected in MI and OL tasks. In terms of nonlinear correlation, the high mutual information was detected in RM and Inten tasks. There was slight mutual information in MI and OL tasks. The results showed that the coherence in the contralateral brain cortex was higher than in the ipsilateral motor cortex during motor tasks. Furthermore, the amount of EEG-EMG functional coupling changed according to the motor task executed.**

I. Introducion

The correlation between brain and muscle signal can occur during voluntary movement. These two signals synchronize well as a functional coupling during motor task performance. Stroke is one of leading causes of death [1]. Brain and muscle coordination is important for stroke patients in neurorehabilitation. The exact role of correlation in contralateral and ipsilateral motor cortex with muscle signals, however, is not yet fully understood for movement tasks. Thus, this study investigated the EEG-EMG functional correlation with coherence and mutual information methods across four tasks [2].

Cortico-muscular coherence is a potential biomarker for recovery from stroke [3]. It is a measure of synchronization between brain and muscle activity [4]. It is a linear technique for measuring the strength of correlations between signals [5].

Mutual information is a measure of nonlinear dependency between two signals [6]. It can be used to investigate the information transmission between two signals. It is a flexible framework and can be used regardless of the distributions of the data linear, nonlinear, and circular [7]. Some studies used MEG-EMG, ECoG-EMG and EMG-EMG, EEG-EEG to find out correlation between two signals [6],[8]. Although there were many studies concerned with correlation between signals, the results remained unclear with problems to be solved. Rectification of EMG signals can distort the frequency content of the signals. Rectification is a nonlinear operator and it is not appropriate for linear coherence method [9]. The next concern with correlation is that coherence can occur in the beta band during static movement and in the gamma band during dynamic performance [3],[10]. Some published papers concluded coherence which occurred during movement execution and motor imagery might contain overlapping neural networks in perirolandic cortical areas [3],[11]. Coherence can be detected during motor imagery condition [11]. However, there were controversial topics related to coherence in motor imagery conditions. Thus, this research was intended to solve the above unclear issues concerned with two signals correlation across four tasks as as novelty study.

We checked brain and muscle signals correlation with linear and nonlinear coupling methods in four different types of motor task condition such as hand grasping real movement (RM), movement intention (Inten), motor imagery (MI) and movement observation and only looking at virtual hand in three dimensional head mounted display (OL). The main objective is to investigate the correlation of two signals in terms of coherence and mutual information amount across four different motor tasks in both contralateral motor cortex, C3-EMG and ipsilateral motor cortex, C4-EMG. The new contribution of this study is that we considered motor imagery and movement observation as the task conditions and we investigated signals correlation on both motor cortices.

II. Materials

A. Participants

The right-handed thirteen participants participated in this experiment. All participants were Kyushu University students with the age of 21 to 28 years (23.92 ± 1.75 years, mean ± SD). Among them, two persons were females and eleven were males. The participants did not have any physical disorder and brain damage in the past. The study was conducted in accordance with the ethical principles of Kyushu University and Declaration of Helsinki with written informed consent form.

B. Experimental Setting

We used g.USBamp of g.tec medical engineering company to record the EEG and EMG signals. Ten EEG channels and three surface EMG channels were used. EEG electrodes were Fp1, Fp2, Cz, FC3, C3, CP3, FC4, C4, CP4, and Pz. Bipolar

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surface EMG electrodes were put on brachioradialis muscle, flexor carpi ulnaris muscle and flexor carpi radialis muscle respectively. We recorded both EEG and EMG signals with 1200 Hz sampling rate. All electrodes impedance values were under 1 kΩ. To suppress the power line noise interferences, the notch filter 60 Hz was used. The A1 electrode was set as a reference and AFz was set as a ground. In this experiment, we used Oculus company's oculus rift head mounted display HMD to make a virtual reality environment. We made the virtual reality environment by using Unity (2019.2.9f1) software and designed a place that looks like a real experimental room in a three-dimensional head mounted display (3D-HMD). We created hand models with MakeHuman software and Blender software for task instructions. After making a file of recording movement, we used this file as an input to the Unity which played this file by using trigger. We used two PCs in this experiment. One PC was used for signal recording and the other one was used for making a virtual reality environment.

C. Experimental Design and Procedures

We designed the 3D condition as a task condition in a virtual reality environment. We displayed the created hand model in virtual reality by using head mounted display, HMD for motor task instructions and motor learning of hand grasping tasks. We asked the participants to put both hands on the table in the same position of hand in a virtual reality environment. We placed the towel under the participant's hand in order not to include force. To reduce physiological artifacts, we asked the participant not to make eye blinking, clenching the jaw and unnecessary movements during recording. Firstly, we demonstrated the motor tasks presented in the work before data acquisition to acclimatize participants with the setup. Then, the instructions for the tasks were shown on the monitor screen via head mounted display, HMD in virtual reality environment. Fig. 1 shows the experimental design. We used four different motor tasks. RM is a task in which a participant moves his or her dominant hand in real-hand grasping movement. Inten is a kind of isometric contraction that involves the static contraction of a muscle without any visible movement in the angle of the joint. MI is a task in which participants did a mental process by rehearsing or simulating a given motor action. OL is a task in which participants just looked at virtual hand's movement without any brain imaging. To ensure the absence of bias, we designed the motor task with four patterns: Inten→OL→RM→MI, OL→RM→MI→Inten, RM→ MI → Inten → OL, and MI → Inten→ OL→ RM. The participants performed one pattern randomly selected from these four patterns. Fig. 2 shows the task flow of the experiment. There was a 2 min rest period as a baseline. Then, there were 8 s of rest, 2 s of being ready and 5 s of the task in 1 trial. We had designed a total of 40 trials in each motor task. A fixation cross was shown on the virtual palm during rest, which disappeared during the 2 s ready stage. The virtual hand grasping appeared on the monitor in HMD during 5 s task. The grasping movement was performed 2 times in 1 trial. The time to break between each motor task was 5 min, then RM, Inten, MI and OL tasks were performed respectively.

D. Data Analysis

Among ten channels of EEG data, we chose contralateral brain motor cortex, C3 and ipsilateral brain motor cortex, C4

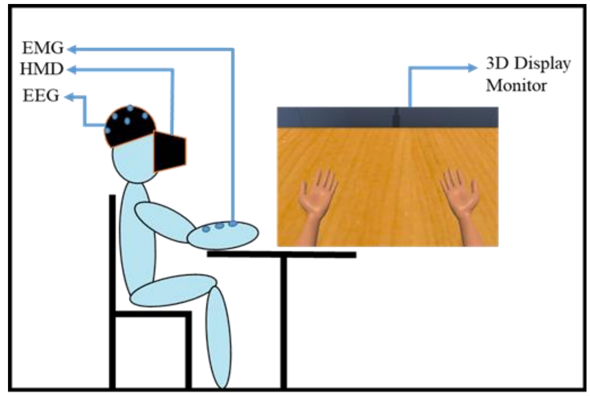


Figure 1. Experimental design for motor task performance.

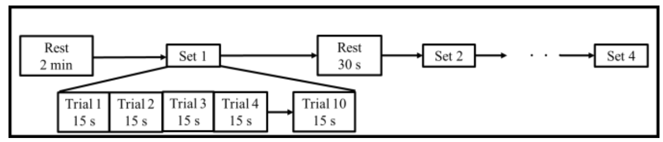


Figure 2. Experimental task flow.

for the calculation of correlation with EMG as they were concerned with body movement in the brain. Among the three surface EMG channels, we selected only flexor carpi ulnaris muscle since this muscle was directly involved in hand grasping movement. In data preprocessing, we resampled both signals to 256 Hz for reducing computation speed and time. We chose the bandpass filter range to 1 to 100 Hz for both signals. For reducing artifacts for EEG signals, we used Independent Component Analysis (ICA) as it is an effective tool for rejecting several types of non-brain artifacts. The EEG data that contained artifacts was determined by visual inspection with the use of EEGLAB. The data that exceeded the limit ±100 µV were excluded for further analysis. We extracted 5 s EEG data. For EMG signals, the 5 s non rectified EMG signals were filtered with selected bandpass filter and then exported to further analysis [2],[9]. For statistical analysis, we used Shapiro-Wilk normality test to verify the normality of the data with ($p>0.05$). Then, we conducted the ANOVA test Band × Coherence value as between subjects and within subjects value for the comparison of coherence in β and γ band ranges for four motor tasks. We had used LSD and Bonferroni correction post-hoc tests for multiple comparisons of tasks. For mutual information, the data showed non normal distribution with ($p<0.05$). Thus, we used Kruskal-Wallis test to compare more than two groups with nonparametric method. For all statistical comparisons, significance level was set to $p<0.05$. IBM SPSS 20 (SPSS Inc., Chigaco, IL, USA) was used.

III. Methods

A. EEG-EMG Coherence Method

After preprocessing the data, we took only 0-5 s EEG and nonrectified EMG data. We calculated the frequency space relationships between two data sets of EEG and EMG. The data were first divided into segments with 19-ms non overlapping Hanning window and then taking Fourier transform, FFT. After that, we computed auto power spectral S_{xx}, S_{yy} and cross power spectral S_{xy} for both signals. After calculating the auto power and cross power spectral analysis, we calculated the coherence in each trial. We calculated coherence values between EEG and EMG at frequency, f for every trial and then averaged the data to access the changes in coherence for all subjects across all tasks by using (1).

$$Coh_{xy}(f) = |S_{xy}(f)|^2 / S_{xx}(f) \times S_{yy}(f) \quad (1)$$

The coherence value's significance level was determined based on the confidence limit by using (2).

$$\text{Confident limit} = 1 - (1-\alpha)^{1/(L-1)} \quad (2)$$

where L represents the number of data segments used in the coherence calculation and α is a confidence interval and it is typically 95% as in [2].

B. EEG-EMG Mutual Information Method

To examine the nonlinear correlation, we computed the nonlinear mutual information. The data from two electrodes was computed with a sliding 100 ms segment and a step size of 50 ms over all trials in the data range of –2 s to 5 s time series, then we calculated the changes of mutual information between two signals. For the calculation the mutual information, we firstly calculated the entropy of each signal and then calculated the joint entropy of signals [2]. We calculated the amount of mutual information across all motor tasks by using (3).

$$MI(X,Y) = H(X) + H(Y) - H(X,Y) = \sum_{j=1}^{m}\sum_{i=1}^{n} p(x_i, y_j)\log_2[p(x_i,y_j)/p(x_i)\,p(y_j)] \quad (3)$$

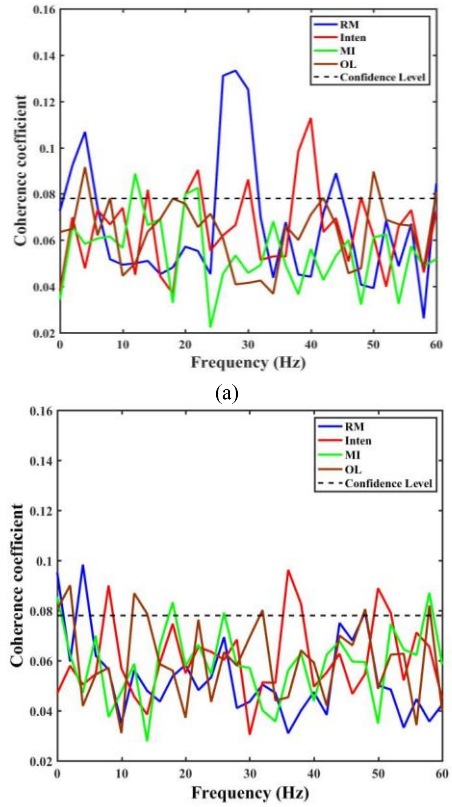
IV. Results

A. Investigation of EEG-EMG Coherence in Contralateral and Ipsilateral Brain Motor Cortices Area Versus EMG

We investigated the EEG-EMG coherence for checking the synchrony of brain and muscle signals. We hypothesized that the amount of coherence is different across task conditions of RM, Inten, MI and OL tasks. We had checked the coherence not only in the contralateral region but also in the ipsilateral motor cortex. The higher amount of coherence occurred in RM and Inten tasks rather than MI and OL tasks in C3-EMG as in Fig. 3(a). The coherence values were high in the range of beta band (13-30 Hz) and gamma band (31-50 Hz) in those tasks with no coherences in MI and OL tasks. On the other hand, the very low coherence values were in RM and Inten tasks but with no coherences in MI and OL tasks as in Fig. 3(b). The results showed that the higher coherences occurred in C3-EMG rather than C4-EMG. The findings proved that the coherence could be different across motor task conditions. The results also pointed out that there might not be a coherence between two signals if the brain and muscle signals did not couple during motor tasks.

B. Comparison of Coherence in Beta Band and Gamma Band Based on Motor Tasks Across All Subjects

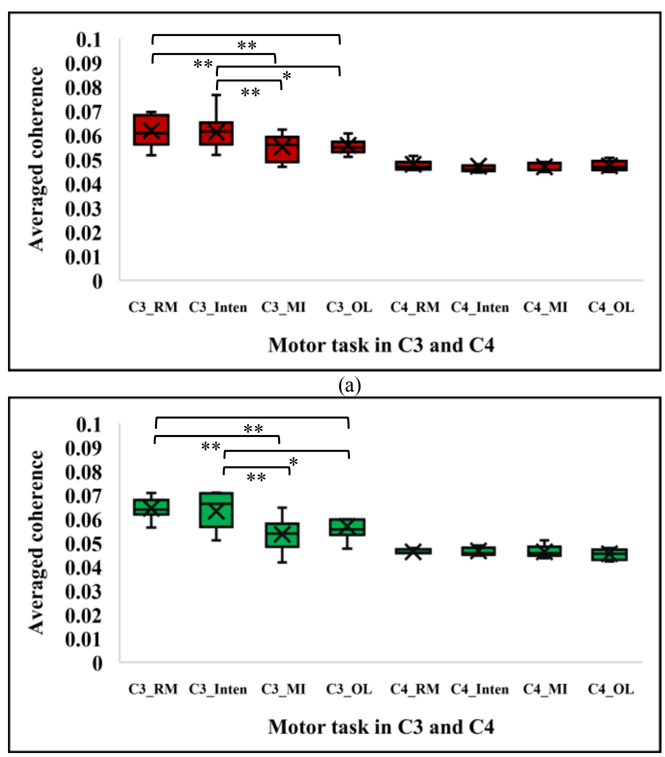
The high coherences occurred in both β and γ bands during motor tasks performance across all subjects. Thus, we selected only the β band (13-30 Hz) and γ band (31-50 Hz) ranges for both C3-EMG and C4-EMG in all subjects. According to statistical ANOVA results, the β band coherence showed significant difference with [$F(3,48) = 5.145$, $p = 0.004$] in C3-EMG across four motor tasks. There was no



(a)

(b)

Figure 3. Comparison of coherence results in one subject data across all motor task conditions. (a) C3-EMG (b) C4-EMG.



(a)

(b)

Figure 4. Comparison of averaged coherence based on motor tasks. (a) C3-EMG and C4-EMG in β band (b) C3-EMG and C4-EMG in γ band. The mean value is described by cross sign. The top and bottom of each box represent the 25th and 75th percentiles respectively. The horizontal black line represents the median. *p<0.05 **p<0.01.

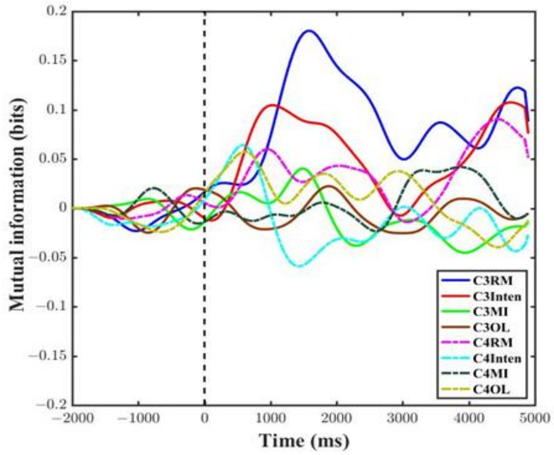


Figure 5. Comparison of mutual information in C3-EMG and C4-EMG of one subject data across all motor task conditions.

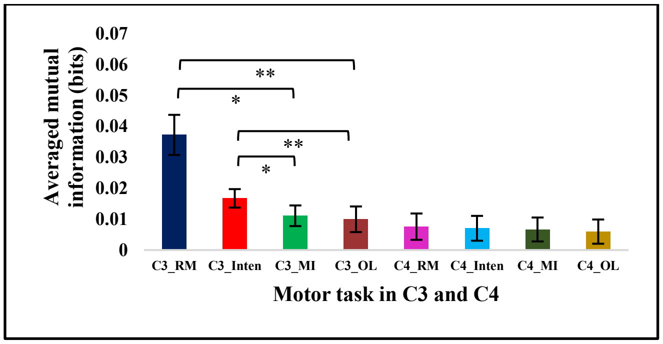


Figure 6. Averaged mutual information comparison for C3-EMG and C4-EMG in each motor task. The asymptotic significance (two-sided tests) are displayed with standard error bar. *p<0.05 **p<0.01.

significant difference with [F(3,48) = 0.149, p=0.930] in C4-EMG across all subjects in β band as in Fig. 4(a). In γ band, there was significant difference of coherence with [F(3,48)=9.812, p=0.001] in C3-EMG while there was no significant difference with [F(3,48)=0.108, p=0.955] in C4-EMG in Fig. 4(b).

C. Investigation of EEG-EMG Mutual Information in Contralateral and Ipsilateral Brain Motor Cortices Area versus EMG

For nonlinear correlation analysis, we had used mutual information method to compare functional coupling across tasks. We had investigated the amount of correlation between brain and muscle signals in both contralateral and ipsilateral cortices. The results proved that the high mutual information occurred in RM and Inten tasks rather than MI and OL tasks in C3-EMG. The two signals correlated well when motor unit firing and cortical neurons have good coupling. Amount of correlation in C4-EMG were low across four tasks as shown in Fig. 5. The results confirmed that high correlation could be occurred in C3-EMG during grasping tasks.

D. Comparison of EEG-EMG Mutual Information Across All Subjects

Next, we compared averaged mutual information for C3-EMG and C4-EMG across all motor tasks. We took the absolute mean values from 0-5 s data. Firstly, we checked the normality test with Shapiro Wilk test with p<0.05. The data were not normally distributed thus we used independent sample Kruskal-Wallis test for multiple group comparisons. There was a significant difference between four motor tasks (Chi square = 16.65, p = 0.001, df = 3) with mean rank scores were 37.50 for RM task, 34.72 for Inten task, 18.89 for MI task and 15.34 for OL task respectively in C3-EMG. For C4-EMG, there was no significant difference in tasks (Chi square = 7.859, p = 0.067, df = 3) with mean rank scores were 21.58 for RM, 20.92 for Inten, 21.96 for MI and 19.54 for OL tasks as in Fig. 6. Thus, the finding proved that the amount of correlation between EEG and EMG was smaller in the ipsilateral motor cortex versus EMG than the contralateral motor cortex versus EMG in all motor tasks.

V. Discussion And Conclusion

This study investigated the correlation of EEG and EMG signals with linear and nonlinear coupling methods. The coherence was higher in RM and Inten tasks than MI and OL tasks in both β and γ bands. Some subjects showed high coherence in both β and γ bands simultaneously while some subject showed only in β or γ bands. There was no coherence during motor imagery and movement observation. This could prove as a strong evidence for the controversial issues of previous studies. In mutual information, the higher correlations were detected in RM and Inten tasks of C3-EMG. There was very low mutual information in C4-EMG. In conclusion, the higher amount of correlation with EMG occurred in the contralateral motor cortex than the ipsilateral motor cortex and the amount varied with the motor tasks.

References

[1] V.L. Feigin, B. Norrving, G.A. Mensah, "Global burden of stroke," Circ Res. 120, pp. 439–448, 2016.

[2] B.Kim, L.Kim, Y.H.Kim, S.K.Yoo, "Cross-association analysis of EEG and EMG signals according to movement intention state," Elsevier, ScienceDir., vol. 44, pp. 1–9, Feb. 2017.

[3] Y. Hashimoto, J. Ushiba, A. Kimura, M. Liu, Y. Tomita, "Correlation between EEG-EMG coherence during isometric contraction and its imaginary execution," Act. Neuro. Exp., vol. 70, pp. 76–85, Feb. 2010.

[4] B. A. Conway, D.M. Halliday, S.F. Farmer, U. Shahani, P.Mass, A.I.Weir et al., "Synchronization between motor cortex and spinal motoneuronal pool during the performance of a maintained motor task in man," J. Physi., vol. 489, no. 3, pp. 917–924, 1995.

[5] J. R. Rosenberg, A. M. Amjad, P. Breeze, D. R. Brillinger, D. M. Halliday, "The Fourier approach to the identification of functional coupling between neuronal spike trains,". P. Bio., vol. 53, pp.1–31,1989.

[6] J. Jeong, J.C. Gore, "Mutual information analysis of the EEG in patients with Alzheimer's disease," Elsevier, vol. 112, pp. 827–835, doi: 10.1016/s1388-2457(01)00513-2, Feb. 2001.

[7] M. X. Cohen, "Analyzing neural time series data: Theory and practice," MIT Press, Chapter–29, pp. 389–407, 2014.

[8] O. Shinji, I.Akio, T.Waro, et al., "Electrocorticogram-Electromyogram coherence during isometric contraction of hand muscle in human," Elsevier, C.Neuro., vol. 111, pp. 2014–2024, Aug. 2000.

[9] V.M.McClelland, Z.Cvetkovic et al., "Recification of the EMG is an unnecessary and inappropriate step in the calculation of cortico-muscular coherence," vol. 205, pp. 190–201, 2012.

[10] J. T. Gwin, D.P. Ferris, "Beta and gamma-range human lower limb corticomuscular coherence," F.H.Neu., vol. 6, pp. 1–6, Sept. 2012.

[11] R.Xu, F. He, S. Qiu, L. Chen, et al., "Corticomuscular coherence based on wavelet transform during imagination, execution and stimulation tasks," J. Med. Imag. Health Inform., vol. 5, pp. 335–341, 2015.