ORIGINAL ARTICLE

Estimating the Relationship between EMG Signals and EEG Signal Connections Using Convolutional Neural Networks

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Abstract

Purpose: Understanding the functional relationships between different parts of the human body can enhance the control of Brain-Computer Interface (BCI) systems. The brain, as the decision-making organ, controls all body parts to perform activities. In this study, the main objective is to estimate the activation of hand muscles and the effect of each muscle on another using Electroencephalogram (EEG) signals.

Materials and Methods: To discover the connection of hand muscles through brain signals, brain connections are extracted as influential components, and a convolutional network is utilized to assess the impact of EEG signals on the relationships among hand muscles. Five different connectivity methods were used to analyze the connections between EEG signal channels, such as correlation, coherence, the directed transfer function, Granger causality, and the phase delay index. The relationships between electromyogram (EMG) signal channels are also calculated using Granger causality. Signals are recorded in two phases: rest and activity, and ultimately, the EMG signal activity is estimated solely using EEG signals.

Results: Simulation results estimate the correlation between the estimated and actual patterns for test data to be around 0.949, indicating a high correlation between the estimated outputs and actual values.

Conclusion: Research indicates that exploring techniques for calculating relationships can be useful in evaluating the synergy and causal connections between EMG and EEG signals. In comparison to alternative graph-based techniques, this approach, utilizing regression analysis, demonstrated notably superior performance. This study could contribute to advancements in rehabilitation techniques and brain-computer interfaces.

Keywords: Vital Signal Connections; Brain Computer Interface; Regression; Convolutional Networks.

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1. Introduction

The interpretation of biological signals is a fundamental outcome of signal-processing techniques and has been extensively explored in the literature. These signals range from hand tremor recordings to more complex neurophysiological signals such as Electroencephalography (EEG), which has been developed for over a century, and functional Magnetic Resonance Imaging (fMRI), [1] introduced a few decades ago—both of which are used to investigate brain function. Biomedical signal processing is widely employed in research and clinical practice to detect abnormalities, diagnose diseases, and classify subjects into normal and abnormal groups. One of the most promising biomedical signal processing applications is Brain-Computer Interface (BCI) technology. It leverages brain activity to facilitate direct interaction between the brain and external devices, presenting new opportunities for individuals with motor impairments [2-5]. BCI technology allows individuals who cannot speak or move their limbs to communicate or operate assistive devices for walking and handling objects [6]. A BCI is a computer-driven system that records brain signals, processes them, and converts them into commands to operate a device for a specific task. As a result, BCIs circumvent the usual pathways of peripheral nerves and muscles. The EEG equipment captures brain signals but does not generate an output that interacts with the user's surroundings [6]. One of the challenging issues in BCI discussions is the limitations of EEG signals in converting rules corresponding to other signals. For instance, hand muscle signals are much more efficient for guiding and controlling an electric arm than EEG signals. However, EMG signals are less frequently used for reasons such as amputation and the need for needle electrodes. BCI systems that use EEG signals to estimate EMG signals are known as Hybrid BCIs. These systems utilize the electrical activities of the brain (EEG) and muscles (EMG) to control devices or send commands to external systems. The advantages of developing Hybrid BCIs include increased accuracy and speed of control, enhanced user capabilities, and reduced user fatigue. These systems can be applied in medical fields (such as motion rehabilitation for individuals with motor disabilities) and non-medical fields (such as controlling video games). Therefore, having an interface that can read the information transmitted to the muscles from EEG signals can be fruitful. Limited studies have been conducted in this area to extract this hidden information from EEG signals. In 2014, Panzicha and his group [7] analyzed the connection between brain and muscle signals using coherence connections in patients with Unverricht-Lundborg disease, which causes uncontrollable muscle spasms. Thirteen patients and twelve healthy individuals participated in this experiment. The normal and daily muscle behaviors of these individuals were studied. In 2017, Perez and his group [8] worked on the connection between brain and muscle signals in patients with spinocerebellar ataxia, a condition where individuals lose coordination among their muscles. This research involved 19 patients and 25 healthy individuals, during which participants lifted objects. The patients were in the initial phases of the illness. The findings indicated that the correlation between EEG and EMG signals in the patients was considerably less than that observed in healthy individuals, and this information could be utilized for the early detection of the disease. In 2018, Larraz and his group [9] used EEG and EMG signals to diagnose movement decisions in stroke patients. This study involved 20 patients. The group concluded that these two signals contained complementary information, and by combining them, more accurate movement decision diagnoses could be achieved. Recently, graph theory-based methods have been used to analyze and investigate diseases of nervous origin, such as Alzheimer’s. In a study by Jalili and his group in 2020 [10], Alzheimer’s was diagnosed using graph features. Initially, functional connections were obtained, and then graph features were derived using the connectivity matrix. Genetic algorithms and ant colony algorithms were used to reduce the graph features. In 2020, Kim and colleagues [11] estimated two-dimensional wrist movements based on seven-channel electromyography signals in both moving and stationary hand states. Synergy-based linear regression model combined with a musculoskeletal model was used to process EMG signals. When trained on each wrist movement test, the synergy-based linear regression model demonstrated statistically significant effectiveness, as indicated by the Pearson correlation coefficient for both dynamic and static wrist states. The electromyography signals were analyzed using a linear regression model based on synergy and a musculoskeletal model. Using each of the wrist movement tests as a training set, the synergy-based linear regression model demonstrated statistically significant performance with a Pearson correlation coefficient for both moving and stationary wrist states. In 2023, Borzelli and his colleagues [12] conducted a regression-based estimation for mapping EMG to force. Two datasets, both collected during submaximal isometric force applications in various directions with the upper limb, were utilized. One dataset included data collected over five sessions, while the other was gathered during force applications and the creation of different contraction levels. The accuracy and consistency of the EMG-to-force mappings were evaluated to determine the strengths and weaknesses of each algorithm [12]. In 2023, Donahoe and his colleagues [13] utilized synergy functions to recognize muscles that engage in synergistic interactions within a muscle group, thereby simplifying the complexity of wearable sensor arrays. Electromyography (EMG) and kinematic data from nine healthy individuals' leg muscles were collected while they walked. Synergy models for four distinct pairs of muscle input model sets were confirmed using EMG data. The impact of incorporating kinematic data (angular velocity) from the thigh and shank regions was also investigated [13]. In 2023, Das *et al.* used a neuromuscular approach to create a hierarchical synergy between EEG and EMG for predicting finger movement and estimating its kinematics. EEG, EMG, and kinematics of the Metacarpophalangeal (MCP) joint were obtained during five finger flexion movements in humans. EMG was estimated for five finger movements and kinematics from EEG using linear regression [14]. A Long Short-Term Memory (LSTM) network and a random forest regression were hierarchically connected to predict finger movements and estimate finger kinematics from the estimated EMG [14]. In 2025, Zhang proposed a multimodal fusion method based on functional connectivity between EEG and EMG signals to detect pre-movement intentions. By constructing EEG-EMG connectivity networks from signals recorded before movement onset, the method extracted discriminative spatial features. Zhang reported a classification accuracy of 94.33 % using mutual information–based EEG EMG connectivity, significantly outperforming EEG-only (73.89 %) and EMG-only (89.16 %) approaches, which demonstrated that leveraging EEG-EMG functional connectivity can enhance the performance of brain-machine interface systems [15]. Wang and colleagues in 2025 introduced a hybrid Brain-Machine Interface (BMI) that combines Steady-State Visually Evoked Potential (SSVEP)-based EEG and facial EMG signals to enhance multimodal control while mitigating user fatigue in assistive applications. By dynamically alternating between EEG and EMG inputs, the system adapted to task demands, optimizing control and reducing physical strain. In a virtual navigation task, the hybrid system achieved task completion times comparable to EMG-only approaches, with 90% of users reporting reduced or equal physical demand. These findings underscored the potential of multimodal BMI systems to improve usability and long-term adherence in assistive technologies [16]. A recent pilot study in 2025 investigated inter-muscular connectivity among lower limb muscles using Magnitude-Squared Coherence (MSC) across alpha (8–13 Hz), beta (13–30 Hz), and gamma (30–100 Hz) frequency bands during postural control tasks. The study found a significant increase ($p < 0.05$) in beta and gamma band coherence between the medial gastrocnemius and soleus muscles under challenging balance conditions, indicating enhanced neural coordination for maintaining stability. These findings highlight the functional relevance of EMG connectivity metrics in assessing neuromuscular control strategies during dynamic postural adjustments [17]. Another study in 2020 investigated intermuscular beta-band coherence during gait in young and older adults, reporting significant age-related decreases of 43–62% in coherence between key lower limb muscle pairs such as gastrocnemius medialis–soleus (GL–SL) and Rectus Femoris–Vastus Lateralis (RF–VL). Additionally, experimentally induced fatigue modulated connectivity patterns, with reductions in coherence between rectus femoris–biceps femoris (RF–BF) and increases between Tibialis Anterior–Peroneus Longus (TA–PL). These findings emphasize the utility of EMG-based coherence metrics for assessing neuromuscular coordination and its alterations due to aging and fatigue [18]. In the domain of hand gesture recognition, functional muscle networks derived from coherence analyses of multi-channel EMG signals have demonstrated high discriminative power. A 2024 study employing 12 EMG channels recorded during 17 hand gestures achieved an 85.1% classification accuracy using solely coherence-based network features, without resorting to deep learning models. This underscores the critical role of inter-muscular connectivity patterns in encoding complex motor intentions, providing a robust basis for prosthetic control and human-machine interfaces [19]. Another Research in 2024 on diabetic peripheral neuropathy patients highlighted alterations in muscle network connectivity, where transfer entropy measures between pairs of muscles (e.g., tibialis anterior–extensor digitorum) exhibited significant reductions ($p < 0.01$) compared to healthy controls. These connectivity disruptions correlated with clinical neuropathy severity, suggesting that EMG-based connectivity metrics can serve as sensitive biomarkers for early neuromuscular impairments and guide therapeutic interventions [20]. Albarracin *et al.* (2025) investigated intermuscular connectivity using EMG coherence analysis across six lower-limb muscles during postural control tasks with and without visual feedback. Their findings revealed task-dependent changes in beta-band coherence, with decreased global connectivity and increased bilateral coordination under challenging conditions. The results demonstrate that muscle networks dynamically reorganize in response to sensory constraints, reflecting adaptable neuromuscular strategies for balance maintenance [21]. In this study, regression between the connectivity matrices of EEG and EMG signals was used to establish this relationship. Deep convolutional networks were also employed for creating the regression. The article is organized in a way that the proposed method will be detailed in the second part. The third section will focus on discussing and presenting the results, while the final section will summarize the conclusions.

2. Materials and Methods

In this paper, the goal is to estimate the relationship between EEG signal connectivity and EMG signal connectivity. For this purpose, methods for calculating signal relationships were applied, and then the data was input into convolutional networks aimed at regression between this information. The proposed approach's detailed block diagram is shown in Figure 1.

2.1. Data Recording

The steps of the study are shown in Figure 1. A one-kilogram weight was hanging from the hand of the participant sitting behind the table. While concurrently recording EEG and EMG signals, [22] the elbow angle was kept at 90 degrees. The design of the chair armrests is such that, when individuals are seated and move their arms parallel to the armrests, the elbow angle naturally assumes a 90-degree position. Any potential displacement is minimal, on the order of a few millimeters, and is considered negligible for this study. With the usage of an advanced Biopac device, it is possible to simultaneously record two signals

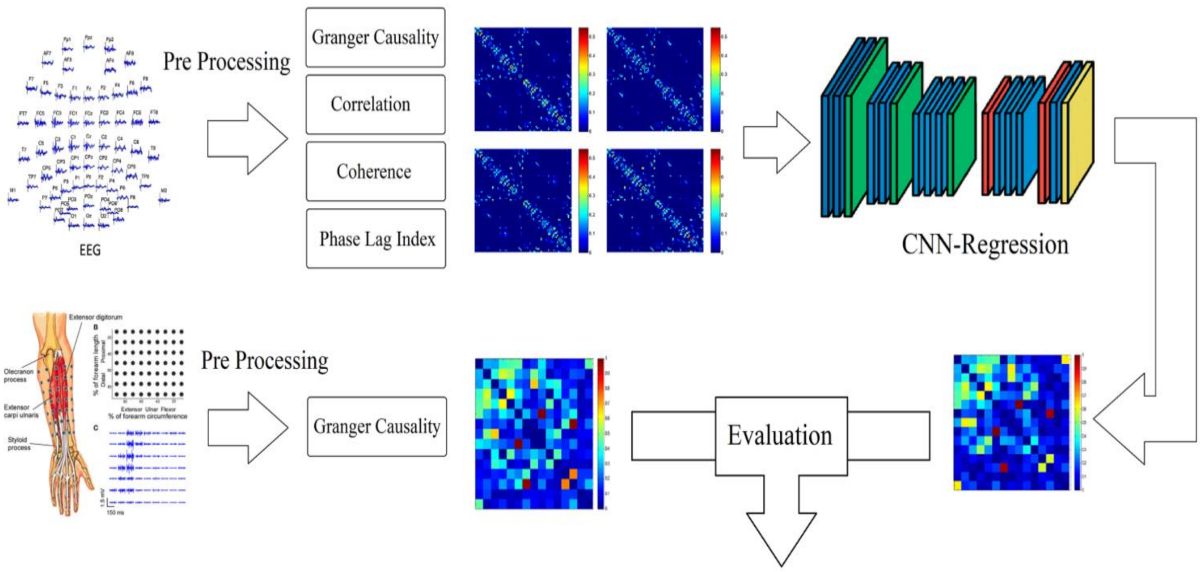

Figure 1. Detailed block diagram of the method used in this study

during this process; EEG and EMG signals were captured simultaneously. A data acquisition device with 19 channels was used for EEG recording using the International 10–20 system. In this study,1 KHz was chosen as a sampling frequency.

To maintain consistent joint positioning during the experiment, participants were seated on an ergonomically designed chair with armrests, which guided the arms to approximately a 90-degree elbow angle. The effects of joint angle and contraction force were thoroughly considered and, according to relevant studies and literature in this field, minor variations such as joint angle deviations less than 5 degrees are considered negligible [23]. Our experimental design was carefully structured to prevent participants from exceeding such angular deviations. Moreover, Participants were selected from non-athletes with approximately similar body size and weight to ensure comparable muscle mass and reduce inter-subject variability. We meticulously monitored the procedure and provided detailed instructions to ensure consistent force application. Movement speed was also synchronized with a trigger display. All these measures were implemented to guarantee uniformity and homogeneity in data acquisition. Therefore, in designing our data collection protocol, we deliberately minimized such variability to ensure it did not compromise the integrity of our results [24].

EMG was recorded from six muscles:[25] short head of the biceps brachii (BSH), long head of the triceps brachii (TRIO), Pectoralis Major (PMJ), deltoid (DEL), long head of the triceps brachii (TRIO), and lateral head of the triceps brachii (TRIA) [25]. Typically, 12 participants between the age range of 30-35 years participated in this study; we had two exclusion criteria that were removed due to high noise. Considering the difference in muscle mass between females and males, as the initial study in this field, we aimed for homogeneous results.

So, we exclusively chose participants from the male population, all of whom were right-handed. To be able to have sufficient data from each participant, 100 records (one record per minute) were obtained. About 1000 records were collected. EMG and EEG records were collected through 6 channels - 12 leads and 19 channels, respectively (Figure 2).

It is essential to highlight that all participants were made aware of the project and gave their consent by signing a formal agreement. Furthermore, the ethics committee approval ID is IR.IAU.SRB.REC.1400.111.

Figure 2. Data recording process

2.2. Preprocessing

For main processing, it is essential to preprocess the signals first. EEG and EMG signals are affected by unwanted effects from adjacent sources, which need to be eliminated using source separation analysis methods. For this purpose, Independent Component Analysis (ICA) is employed in this study. ICA is a widely used technique for blind source separation. It has been employed in various applications and is often used as a black box, with users not fully grasping its internal workings. ICA is viewed as an improvement over Principal Component Analysis (PCA) [26]. However, PCA focuses on optimizing the data's covariance matrix, which denotes second-order statistics, while ICA enhances higher-order statistics, such as kurtosis. Consequently, PCA detects uncorrelated components, whereas ICA finds components that are independent components. As a result, PCA can identify independent sources when the correlations of higher order in the mixed data are limited or negligible. Each signal is represented as a time-varying sequence [27].

2.3. Brain Connectivity

The main goal of brain connectivity is to fully map the connections between neural elements with their anatomical distribution [28]. These elements can be individual neurons, specific neural populations, or large-scale brain regions. The number of possible connections between these elements is vast [28]. For any network of N nodes, the number of possible connections is 2N [29]. There are three types of brain connectivity models: anatomical, functional, and effective [30]. The anatomical connection model represents the actual physical connections based on the structure and cellular organization of the brain [30]. Functional models represent a non-directional statistical relationship between brain regions [30], while effective models indicate a direct causal relationship between brain regions [30]. Different techniques are available for calculating brain connectivity, and this research utilizes four approaches: Granger causality, correlation, directed transfer function, and coherence, which will be discussed below.

2.3.1. Granger Causality

The Granger causality index [31], which signifies how channel x is affected by channel y, is defined as the ratio of the residual variance logarithm for a single channel to the residual variance of a dual-channel model [32] (Equation 1):

$$GCI_{y \to x} = ln\left(\frac{e}{e_1}\right) \tag{1}$$

This definition can be broadened to encompass a multi-channel system by analyzing the impact of a particular channel on the residual variance ratios. To measure the direct effect from channel (x_j) to (x_j) for the autoregressive process of channel (n) in the time domain, we take into account the following MVAR models (n) and (n-1). Initially, the model is applied to the complete n-channel system, yielding the residual variance (V_[7](t) = \text[8](E_[8](t))) for the signal (x_i).[33] Next, an MVAR model with (n-1) dimensions is applied to (n-1) channels, excluding channel (j), which produces the residual (V_{i,n-1}[3](t) = \text[8](E_{i,n-1}(t))). Granger causality is subsequently defined by Equation 2:

$$GCI_{j \to i}(t) = ln\left(\frac{V_{i,n}(t)}{V_{i,n-1}(t)}\right) \tag{2}$$

The Granger causality index cannot exceed 1, as the variance in the n-dimensional system is less than that of the residual variance in the n-1-dimensional system. GCI(t) evaluates causal relationships within the time domain. The spectral features of the brain signals are considerable, since during a unique task, a growth in propagation in a specific frequency band may coincide with a reduction in another frequency band [34].

2.3.2. Correlation

In a simple sense, the correlation of signals from two anatomically separated brain regions indicates that these areas are functionally related in the brain [35]. Statistical dependencies between two signals can arise in various ways [36], but in statistics, it typically refers to the degree of linear relationship between a pair of variables. Correlation is expressed as Equation 3 [37]:

$$\rho_{X,Y} = corr(x,y) = \frac{E[XY] - E[X]E[Y]}{\sqrt{E[X^2] - E[X]^2}.\sqrt{E[Y^2] - E[Y]^2}} \tag{3}$$

where E[.] denotes the expected value. Using the above relation, the connectivity of each signal channel with another will be calculated in the form of a matrix.

2.3.3. Direct Transfer Function

Kaminski and Blinowska [38] presented the direct transfer function as Equation 4 follows:

$$DTF^2_{j \to i}(f) = \frac{\left|H_{ij}(f)\right|^2}{\sum_{m=1}^{k} |H_{im}(f)|^2} \tag{4}$$

Hij(f) denotes a component of the transfer matrix in the MVAR model. The DTF signifies the causal influence of channel j on channel i at frequency f. Equation 7 outlines a normalized form of DTF that ranges from 0 to 1; this is achieved by calculating the ratio of the flow from channel (j) to channel (i) against the total inputs received by channel (i). The unnormalized DTF, which is directly associated with pairwise power [39], is defined as Equation 5:

$$NDTF^2_{j \to i}(f) = \left|H_{ij}(f)\right|^2 \tag{5}$$

In addition to reflecting direct flows, DTF shows cascading flows too; it means that if there is propagation from channel 3 to channel 2 and then to channel 1, it also indicates propagation from channel

3 directly to channel 1. The directed direct transfer function (dDTF) was introduced to differentiate direct flow from indirect flow [40]. dDTF is characterized as the result of a modified DTF adjusted by partial coherence. The alteration of the DTF entails normalizing the function to guarantee that the denominator is unaffected by frequency. The dDTFj→i from channel j to i is defined as Equation 6:

$$dDTF_{j\to i}^{2}(f) = F_{ij}{}^{2}(f)C_{ij}{}^{2}(f)$$
$$F_{ij}{}^{2}(f) = \frac{|H_{ij}(f)|^{2}}{\sum_f \sum_{m=1}^{k} |H_{im}(f)|^{2}} \tag{6}$$

Cij(f) presents the partial coherence. When both functions Fij(f) and Cij(f) are non-zero, dDTFj→i will also have a non-zero value, signifying a direct causal relationship between channels (j) and (i). DTF can be utilized to assess propagation in point processes [41], such as spike trains, or to evaluate causal relationships between spike trains and local field potentials [42].

2.3.4. Coherence

Coherence is a factor in signal processing that can be utilized to analyze the connection between two signals or datasets, and it is frequently employed to assess the power transfer between the input and output of a linear system [43]. The coherence between two signals x(t) and y(t) is a real-valued function described as Equation 7:

$$C_{xy}(f) = \frac{|G_{xy}(f)|^{2}}{G_{xx}(f)G_{yy}(f)} \tag{7}$$

In this function, (G_{xy}(f)) denotes the cross-spectral density of signals (x) and (y), whereas (G_{xx}(f)) and (G_[43](f)) indicate the auto-spectral densities of (x) and (y), respectively. The magnitude of the spectral density is denoted by |G|.[44] Considering the previously mentioned constraints. (ergodicity, linearity), the coherence measures the extent to which y(t) can be predicted from x(t) using the optimal linear least squares function [44]. Coherence values always range between 0 and 1. For an ideal linear system with a fixed parameter and a single input x(t) and a single output y(t), coherence will equal one [44].

2.4. Convolutional Neural Networks

Deep Convolutional Neural Networks (CNNs) have shown considerable success as versatile models for a wide range of issues, particularly in tackling regression problems in recent times. CNNs are primarily used for two-dimensional arrays such as image data. However, CNNs can also be applied to analyze regression data [45]. In this study, a neural network is designed with a structure similar to the well-known SegNet, which was created to solve image segmentation problems. The difference between this network and the SegNet architecture lies in the number of layers and the input-output size [46]. In SegNet, the input and output are equal. However, in this network, the input size corresponds to the number of EEG channels [46], while the output size corresponds to the number of EMG channels [46].

The input layer is chosen to be 5*19*19, where 5 i ndicates the count of connectivity computational tech niques,19 denotes the quantity of EEG channels, resu lting in 19*19 because of the interconnections among each channel and itself. The layers were created using built-in MATLAB functions, and the architecture was developed through an iterative trial-and-error process. This procedure was systematic rather than arbitrary: we started with a minimal network and incrementally increased the number of layers following standard neural network design practices. At each stage, the model was trained with fixed hyperparameters such as optimizer, activation functions, and learning rate to isolate the impact of architectural changes. To ensure robust evaluation and prevent overfitting, 80% of the dataset was used for training, within which a subset of 10% was allocated for validation during hyperparameter tuning and architecture selection via cross-validation. The remaining 20% of the data was held out as an independent test set, used only for the final performance evaluation after model selection, thus preventing data leakage and providing an unbiased assessment of the model's generalization . The intended output is the connectivity matrix of the EMG signal, represented as a 6 by 6 matrix corresponding to the number of EMG signal channels [22]. To calculate this matrix, the Granger causality method is used. The structure proposed to address this problem is illustrated in Table 1:

Table 1. The arrangement of the network created to tackle the regression problem that involves transforming the EEG signal connectivity matrix into the EMG signal connectivity matrix.

Layer number	Layer type	Layer properties
1	**Image Input**	**Input layer with size 5*19*19 with zero center normalization**
2	**Convolution**	**25 kernels with size 7x7 with step 1 and without layering**
3	**ReLU**	**Activity function**
4	**Convolution**	**50 kernels with size 5x5 with step 1 and without layering**
5	**ReLU**	**Activity function**
6	**Convolution**	**100 kernels with size 3x3 with step 1 and without layering**
7	**ReLU**	**Activity function**
8	**Fully Connected**	**Fully connected layer with 36 neurons**
9	**Regression Output**	**Output layer with mean squared error cost function**

After designing the networks, they are subjected to the training process. For this purpose, the characteristics of the network must also be designed. Therefore, the features of the constructed networks are shown in Table 2.

Choosing a suitable optimization algorithm for the deep learning model is very important and has a significant impact on the time taken to reach the desired outcome. The Adam optimization algorithm [47] is considered a generalized version of the Stochastic Gradient Descent (SGD) algorithm, which has been more widely used for deep learning applications in the fields of computer vision and natural language processing [47, 48]. The Adam algorithm can be considered as a combination of RMSprop and stochastic gradient descent with momentum [49]. These various trial-and-error tests have been conducted to tune these parameters, and the results will be reported below.

Table 2. Tuned features for training the network

Feature	Value
Optimizer function	**Adam**
Maximum repetitions	10
Primary education rate	0.01
Reduction coefficient of the education rate	95%
The period of reduction in the education rate	Each 2 Repetition
Validation error calculation step	4
Maximum chance of validation error	20

3. Results

The connectivity matrix between the EMG signal channels was calculated using the Granger causality method. Therefore, there is only one configuration for training the network. Four methods are used to validate the results generated against the expected actual values. The four methods consist of Mean Squared Error (MSE), Mean Absolute Error (MAE), the R-squared metric, and the correlation coefficient. Each of these metrics has its distinct evaluations. For instance, R-squared reflects the degree to which the regression model aligns with the data, whereas the correlation coefficient assesses the degree of similarity (correlation) between the output estimated by the regression model and the actual output [50]. While R-squared is a relative metric for assessing the appropriateness of model fitting to dependent variables, MSE is an absolute metric for this purpose [50]. The MAE metric is similar to MSE in terms of characteristics, with the difference that in MAE, the absolute error is calculated instead of the mean squared error [50] (the difference between the estimated output and the actual output).

In deep learning, the data is categorized into three groups for model training: training, validation, and testing. This is done because, with limited data, the model is trained so that other data can be used for evaluation. In this study, the ratios of 70%, 10%, and 20% are determined for training, validation, and testing data, respectively. Figure 2 shows the training trend chart for the connectivity matrix between the

EMG signal channels with the parameters set in Table 2.

By changing the optimizer from Adam to SGD and RMS-Prop, the RMSE and error functions will be as shown in Figures 3 and 4.

Adam's lower, but their initial error was better than Adam's. However, it can ultimately be claimed that the Adam function performed better than the other two functions due to its evaluation parameters. Table 3 presents the results of the simulated evaluation parameters for the regression between the EEG signal connectivity matrix and the EMG signal connectivity matrix.

4. Discussion

The current study sought to reveal the functional connections between hand muscles utilizing EEG signals, with the ultimate goal of enhancing the control mechanisms of BCI systems. Our findings suggest a significant correlation ($r \approx 0.949$) between the estimated EMG signal activity derived from EEG and the actual muscle activation patterns. This high correlation underscores the potential of EEG-based estimations in accurately reflecting muscle activity, paving the way for more intuitive BCI applications. Our approach leveraged convolutional networks and advanced signal processing techniques, including

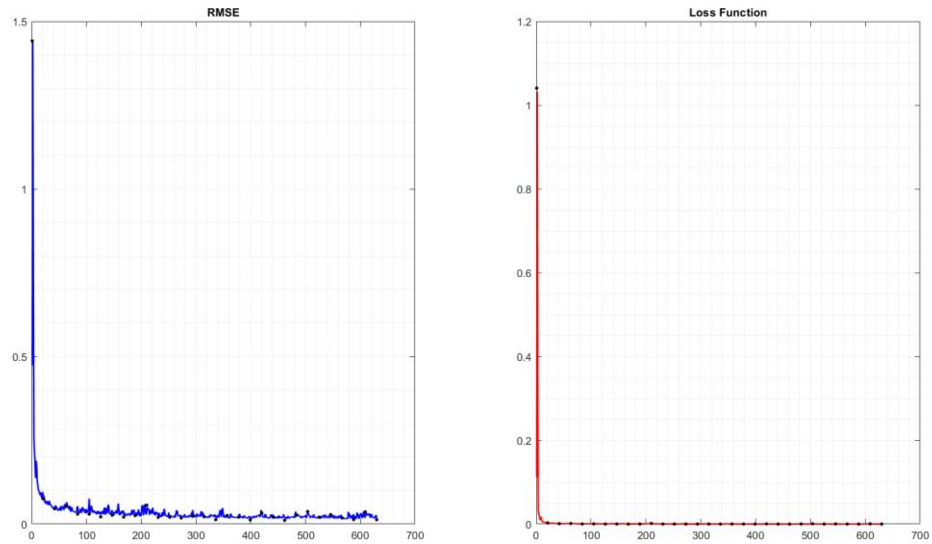

Figure 3. Training trend chart for regression among the EEG signal connectivity matrix and the EMG signal connectivity matrix using the Adam function

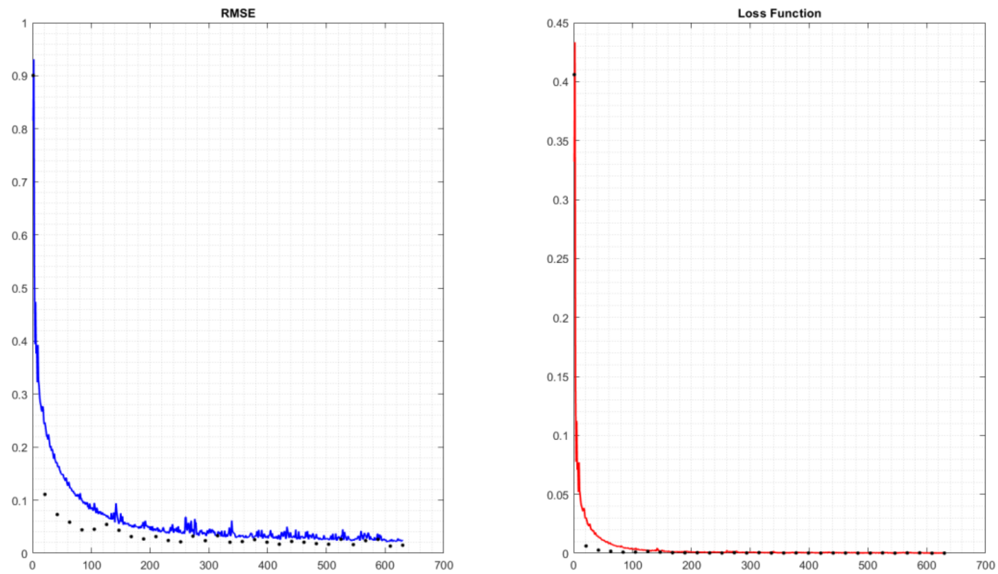

Figure 4. Training trend chart for regression among the EEG signal connectivity matrix and the EMG signal connectivity matrix using the SGD function

Table 3. Regression among the EEG signal connectivity matrix and the EMG signal connectivity matrix

R-Square	MSE	MAE	Correlation	Data	
0.9432	0.0153	0.0003	0.9738	Education	Adam function
0.9149	0.0196	0.0004	0.9379	Validation	
0.9270	0.0185	0.0004	0.9489	Test	
0.9352	0.0173	0.0004	0.9682	Total data	
0.8985	0.0254	0.0006	0.9392	Education	SGD function
0.9125	0.0255	0.0007	0.9287	Validation	
0.9182	0.0252	0.0006	0.9301	Test	
0.9284	0.0253	0.0006	0.9292	Total data	
0.9385	0.0201	0.0004	0.9673	Education	RMS-Prop function
0.9083	0.0222	0.0005	0.9569	Validation	
0.9271	0.0226	0.0005	0.9490	Test	
0.9224	0.0204	0.0004	0.9578	Total data	

Granger causality and coherence analyses, to elucidate the interactions between EEG signals and muscle outputs. As this study focused on temporal and causal interactions using Granger causality, conventional EMG-derived features such as RMS and spectral moments were not included in the analysis. This choice aligns with the study's objective to emphasize intermuscular information flow rather than signal amplitude or spectral content. Nevertheless, integrating such features in future research may complement causality-based measures and enhance the robustness and interpretability of synergy models. The use of these sophisticated methods allowed us to effectively model the complex interrelationships among hand muscles, revealing how activation in one muscle group can influence the activity of others. This finding aligns with existing literature that recognizes the interconnected nature of muscle activation in motor tasks. In comparison to conventional approaches, our regression-based methodology exhibited superior performance in estimating EMG signals from EEG data. This superiority is particularly noteworthy considering the challenges associated with extracting meaningful signals from the EEG due to noise and interference, which often complicate traditional methods. The implementation of directed transfer functions and phase delay indices contributed to a deeper understanding of the causal dynamics involved, highlighting the potential for these techniques in future research on neural control of movement. While our results are promising, the study is not without limitations. The reliance on simulation data necessitates further validation with real-time BCI applications. Future studies should investigate incorporating additional modalities, such as real-time feedback mechanisms, to strengthen the robustness of our model. Additionally, expanding the participant demographic in follow-up studies may yield insight into interindividual variability in muscle activation patterns, which is crucial for the generalization of our findings across diverse populations. Estimating inter-muscle connectivity from EEG offers a more realistic representation of neuromuscular control, as natural movements are driven by coordinated patterns of interaction among multiple muscles rather than isolated activations. This perspective enhances BCI-based rehabilitation, particularly in Functional Electrical Stimulation (FES) systems, by enabling stimulation strategies that reflect the brain's inherent muscle coordination patterns. As a result, it can improve the effectiveness of artificially induced movements, reduce compensatory activations, and support adaptive, patient-specific neurorehabilitation, especially in individuals with motor impairments such as spinal cord injury.

Ultimately, this study adds to the expanding body of knowledge on the interaction between neural signals and muscular activity, with implications for the development of advanced rehabilitation techniques and more efficient BCI systems. As we continue to refine our understanding of these connections, we can create more sophisticated tools for individuals with motor impairments, ultimately enhancing their quality of life.

5. Conclusion

Considering the activation command issued and how it is generated by the brain, research into the relationship between EEG and EMG signals still has ambiguities that, if resolved, could aid patients with muscular issues and stroke survivors. If the interaction between these two signals can be thoroughly examined, it would be possible to seek compensatory methods in case of problems within any components of this system.

The goal of this research was to explore the connection between hand muscles and how each muscle affects the others by utilizing EEG signals. Before selecting the subjects, a mental health test will be conducted under the supervision of a neurologist and psychologist to ensure the physical and mental well-being of individuals. Their physical condition will also be assessed, and participants will be selected from healthy and normal individuals (not engaged in professional sports). The stimulation and motor command will be presented to the individual via a monitor, and the brain and muscle signals will be recorded. In this study, arm position was visually controlled using a chair design that naturally aligned the elbow at a 90-degree angle. Although precise biomechanical tools were not used, this method aligns with established practices in recent literature. Combined with repeated trials and participant selection criteria aimed at reducing inter-subject variability, this approach helped mitigate inconsistencies in movement execution. For future studies, we recommend incorporating more explicit biomechanical measurements, such as goniometric tracking or force sensors, to further improve control over motor parameters and enhance data reliability. A directional image of hand movement will be displayed on the monitor. The individual should not think about anything else during the experiment, which is why a rest period is required before starting the stimulation, facilitated by the monitor for the participant. Therefore, this research investigates the relationship between brain and muscle signals for rehabilitation and recovery purposes. Future research could benefit from incorporating additional EMG-derived features, such as spectral moments and RMS, to enhance the predictive capabilities and robustness of muscle synergy analyses. Expanding the feature set may provide deeper insights into neuromuscular dynamics and improve the applicability of the developed models. Based on the information gathered so far from research and literature, there has been no examination of the EEG signal graph concerning motor and muscular subjects and their relationship with the EMG signal. Since muscle behaviors require activity from various points and commands from the brain, it is expected that a collection of brain points will be active in this process. Thus, using graph theory can provide better insights into this interaction compared to conventional methods like examining brain connectivity. It should be noted that not much research has been done on this topic. So, we collected our data exclusively from males to ensure that variations in muscle mass and physical strength do not adversely impact the outcomes. In future and later studies, we could also record signals from the statistical population of women to generalize the findings. Another limitation of the present study lies in the unavailability of a comprehensive feature importance analysis, primarily due to constraints in data dimensionality and sample size. Given that the EEG recordings were limited to 19 channels, performing a reliable assessment of the individual predictive contributions of connectivity features was not methodologically feasible without introducing risks of overfitting and statistical instability. In future research, utilizing EEG systems with a higher number of channels may enable a more granular investigation of individual connectivity features, allowing for a clearer understanding of their respective contributions to model performance.

Acknowledgments

The data acquisition protocol was approved by the Institutional Review Board (IRB) and the Ethical Committee of Islamic Azad University. Notably, all participants were fully informed about the project and provided their consent by signing a formal agreement. Moreover, the ethics committee approval ID is IR.IAU.SRB.REC.1400.111.

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