SYNERGY-BASED EEG DECODING FOR NATURAL HAND GRASPS: EXPLORING THE POTENTIAL FOR STROKE REHABILITATION

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Abstract

Synergies have been demonstrated to play a significant role in brain-machine interfaces (BMIs) controlling hand exoskeletons or robotic systems for motor assistance and rehabilitation. However, one major challenge of utilizing BMIs for individuals with stroke is the changes in cortical rhythms encoded in the motor-related areas. The suppression of sensorimotor rhythms in individuals with stroke may affect the decoding accuracy of BMIs. Therefore, investigating how changes in cortical rhythms influence synergy modulation is of paramount importance. This study aimed to explore the performance of the neural decoding of hand kinematics based on a linear model established between kinematic synergies and corresponding cortical rhythms. Our analysis successfully decoded two typical hand grasps representative of daily activities from cortical rhythms obtained from electroencephalography (EEG). Results offer promise for applications in noninvasive, synergy-based neuromotor control and rehabilitation, particularly for individuals with upper limb motor disabilities due to stroke.

Keywords: brain-machine interfaces, EEG, hand kinematics, kinematic synergies, neural decoding, motor control

1. Introduction

A significant portion of the population faces difficulties in performing simple activities of daily living (ADL) due to the loss of upper limb function caused by stroke or spinal cord injury. This impairment not only affects their independence of functional mobility and ability to perform daily tasks but also compromises their overall quality of life. In response to this critical issue, brain-machine interfaces (BMIs) have gained popularity in recent years as a potential solution for restoring motor function in individuals with disabilities. BMIs offer an alternative approach to bridging the communication gap between the brain and external devices, enabling stroke patients to regain motor control and independence. These interfaces have demonstrated significant progress in facilitating precise control of external devices, playing a crucial role in motor rehabilitation for both individuals with spinal cord injury [1] and stroke [2,3].

The development and application of BMIs hold substantial promise for improving the lives of individuals with upper limb paralysis. Over the past years, researchers have witnessed significant advancements in BMI technology, particularly in the context of motor control and rehabilitation. Numerous studies have provided compelling evidence supporting the efficacy of BMIs in facilitating communication and control for paralyzed individuals. Furthermore, BMIs have shown potential beyond motor control, demonstrating success in sensory restoration. This includes facilitating the perception of touch and proprioception through neural interfaces [4]. These groundbreaking findings have opened up new possibilities for restoring lost motor function and enhancing the overall well-being of affected individuals, especially stroke individuals.

Noninvasive BMIs have shown great promise in the application of stroke rehabilitation, which directly captures brain activity with great temporal resolution for dynamic exploration and further neural representation decoding. Functional near-infrared spectroscopy (fNIRS)- and electroencephalogram (EEG)-based BMI have been explored in upper limb/hand movement decoding, with positive results in achieving accurate control of robotic arms and prosthetic devices [5–9]. Moreover, EEG-based BMIs have been used to trigger functional electrical stimulation (FES) in stroke patients, facilitating muscle activation and motor relearning [4]. The BMI-FES approach combines the decoding of motor intentions through EEG with the application of FES to the affected muscles, creating a closed-loop system that encourages active participation and motor recovery. Several studies have demonstrated the feasibility and effectiveness of EEG-based BMIs in stroke rehabilitation. For instance, researchers have developed BMI systems that decode motor imagery tasks, allowing stroke patients to control virtual or robotic limbs with their thoughts [10]. This form of motor imagery-driven BMI has been shown to enhance cortical reorganization and promote functional recovery in stroke patients [11]. Furthermore, real-time EEG-based BMIs can provide immediate feedback during rehabilitation exercises, enabling patients to refine their movements and maximize rehabilitation outcomes [12].

These findings underscore the potential of EEG-based BMIs, providing valuable insights into neural representations and enhancing the overall performance of the BMI system. However, the successful implementation of BMIs comes with its own set of challenges. One of the primary obstacles is modeling the complex relationship between high-dimensional brain activity and intricate hand movements. The human hand possesses a large number of degrees of freedom (DoFs), which allows for tremendous movement flexibility but complicates the application of motor control strategies. Researchers have been exploring innovative approaches to address this issue, and one of the promising avenues of research is the utilization of synergies in motor control [13]. Studies have shown that the central nervous system (CNS) employs synergies to simplify and reduce the complexity of high-dimensional motor control by combining diverse actions into functional modules [14]. By representing hand kinematics (joint angular velocities) as a weighted combination of kinematic synergies with both spatial and temporal characteristics of hand movements, researchers have demonstrated the potential of synergy-based hand movement models in advancing dexterous motor control in the context of BMIs [15].

Previous studies have demonstrated the relationship between neural activity and hand movements by directly correlating neural features with hand kinematics or kinematic synergies, paving the way for synergy-based brain-machine interfaces (BMIs) for motor control [5,6,16]. These BMIs hold the potential to facilitate efficient BMIs in machine-assisted motor learning and movement rehabilitation [2,3,14]. Researchers have developed noninvasive electroencephalogram (EEG)-based BMIs capable of decoding hand kinematics for individual joints using low-frequency delta (0-3 Hz) waves, leading to successful real-time control of robotic arms [17]. Furthermore, investigations have pinpointed the mu and beta frequency bands of EEG as particularly effective for identifying movement intentions with high accuracy [18].

However, individuals who have suffered strokes often exhibit abnormal changes in mu/alpha (8–13 Hz) and beta (13–30 Hz) EEG waves [3,19]. Additionally, a reduction in premovement cortical activity below 5 Hz has been observed following acute motor stroke [20]. Furthermore, a previous study shows that compared to healthy individuals, motor cortex activations are greater in individuals with moderate motor deficit, but diminished or absent in severely affected patients when attempting to move their affected hands [19]. This evidence highlights the increased complexity of establishing a robust and effective BMI system based on the unaffected side of the brain in stroke patients. These changes in sensorimotor rhythms could potentially impact the accuracy of decoding EEG-based BMIs. Research findings provide evidence that individuals who have suffered strokes exhibit a less robust ability to decode hand movements using movement-related cortical potential (delta waves) compared to the healthy group [21]. Consequently, further research is crucial to understand how these changes in rhythms influence the modulation of synergies.

Despite significant progress, generalizing models for predicting and reconstructing basic building blocks of hand movements from recorded brain activity remains a significant hurdle in achieving dexterous motor control in BMIs. This study specifically explores the impact of cortical rhythms observed in EEG on the performance of neural decoding of hand kinematics, utilizing a linear model that links kinematic synergies with corresponding cortical rhythms. The promising applications of synergy-based BMIs hold the potential to provide assistance to individuals with upper limb motor deficits, supporting them with more efficient motor control and rehabilitation. A comprehensive understanding of the interplay between neural activity and cortical rhythms will be crucial for advancing these BMI technologies and optimizing their performance in real-world applications.

2. Methodologies

2.1 Experimental protocol

The experiment in this study recruited ten healthy, right-handed individuals with an average age of 23.0 ± 3.1 years old (4 males, 6 females). The experiment was conducted under institutional approval from the Internal Review Board (IRB). Participants were asked to perform two distinct types of hand grasp movements: whole hand grasp and precision grasp, which included a wide range of grasp tasks in activities of daily living (ADL). The objects selected for these two typical grasps are a water bottle for whole hand grasp and a bracelet for precision gras. During the experiment, participants sat in front of the designated experiment table with their dominant palm flat and downward, and auditory indicators were involved for the start and stop of each movement. Subjects were supposed to reach and grasp the target once they heard the 'start' beep and hold the object until a 'stop' beep was given. To avoid brain activity suppression due to repetitive movements from the same task, four other objects were also included in the experiment. Each object was presented in random order, and participants repeated each grasp 30 times. The hand movements and corresponding EEG signals were recorded simultaneously. During recording, participants were instructed to minimize blinking and swallowing, and trials with observed interferences were excluded from the analysis.

Hand movements were captured using CyberGlove (CyberGlove Systems LLC, San Jose, CA, USA) at a sampling rate of 125 Hz. The study measured ten joint angular changes from the hand joints including the metacarpophalangeal (MCP) joints of the thumb and four fingers, the interphalangeal (IP) joint for the thumb, and the proximal interphalangeal (PIP) joints of the four fingers. For EEG signal collection, a high-density EEG cap with 32 electrodes was placed at specific locations, covering frontal (F), central (C), and parietal (P) areas, as well as eight intermediate locations distributed on both sides of the central sulcus. Four of the intermediate locations were located on the left hemisphere around C1, C3, and C5, and the other four were placed near C2, C4 and C6 on the right hemisphere. The ground electrode was positioned at the nasion, and the reference electrode was placed on the right or left ear lobe. Data were continuously captured at a sampling rate of 256 Hz using BCI2000 [22].

2.2 Derivation of synergies

The dataset was separated into training and testing sets, where two-thirds of repetitions from each grasp type were used for synergy extraction, while the remaining repetitions were used as the testing dataset to determine decoding accuracy. Kinematic synergies were derived from movements recorded in the training set based on the synergy-based hand movement model [14]. Hand kinematics (joint angular velocities) from ten joints were calculated from the differential of recorded joint angles. Principal component analysis (PCA) was applied to decompose the hand kinematics, and the top six principal components were identified as kinematic synergies. These synergies were hypothesized to be common spatiotemporal patterns shared across various grasps and were later used for synergy-based reconstruction of movements in the testing set.

2.3 Neural features extraction

The raw EEG data were preprocessed to enhance the signal-to-noise ratio by applying common average referencing (CAR), which subtracts the common activity from each electrode. To remove baseline drift, the mean value of resting EEG signals was subtracted from each trial, and the linear trend of the EEG was eliminated. EEG signals were then broadly filtered in the frequency range of 0.1-58 Hz using a 5th-order Butterworth filter. To capture the complete reach-grasp-hold hand movement process, the preprocessed EEG data were segmented, specifically focusing on the first two seconds of the post-stimulus period.

Considering that EEG is a nonstationary signal with its frequency content changing over time, feature extraction in only the time or frequency domain can be challenging. To extract optimal features from EEG, a spectrogram was first calculated to estimate the spectrotemporal evolution of its frequency content. This process involved dividing the EEG data into segments of 20% of the total period, followed by a short-time Fourier transform with 90% overlapping to compute the spectrum on each widow segment.

The spectrogram was calculated on six frequency bands: delta (0-4Hz), theta (4-8Hz), alpha (8-13Hz), beta (13-30Hz), low gamma (30-58Hz), and the covering frequencies from 0.1Hz to 58Hz. After the spectrogram was estimated from specific ranges of frequency bands, the average power across the frequency range was calculated along the time series in the frequency amplitude plane, and the resulting spectral envelopes were considered as neural features. This process is illustrated in Figure. 1. The spectral envelope represents dynamic changes from different EEG rhythms and this procedure was implemented on each EEG electrode to extract the spectral envelope of each electrode. As 32 EEG electrodes simultaneously recorded neural activity, PCA was applied to extract top-ranked components as neural features, capturing common characteristics across multiple spectral envelopes.

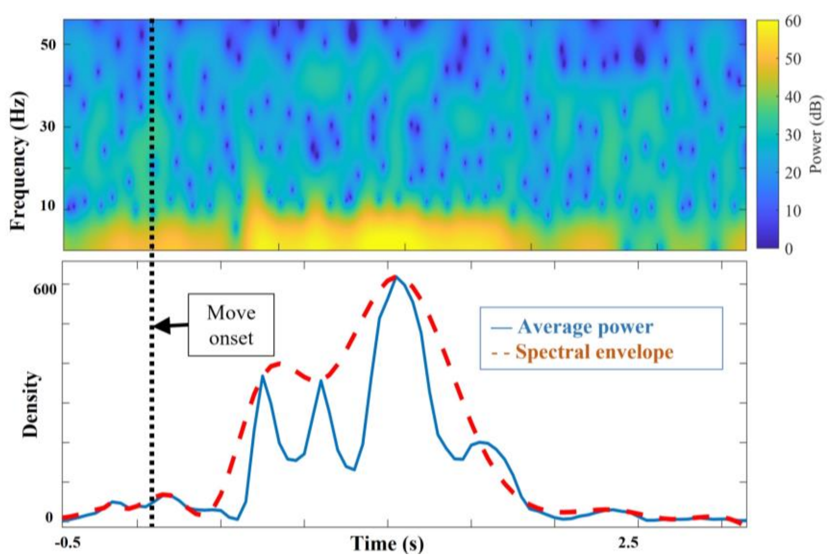

Figure. 1. Spectral envelope. The spectrogram was estimated from each EEG electrode, and then the spectral envelope was calculated by averaging power across all frequencies. This figure shows the spectrogram and spectral envelope from the frequency band 0.1-58 Hz.

2.4 Neural decoding

The neural decoding model was implemented using multivariate linear regression to determine the relationship between neural features and synergy weights from the training set [5,6,23]. The training set was used to derive the kinematic synergies and model the linear correlation matrix between the synergy weights and corresponding neural features. The weights of synergies from the testing set were calculated using corresponding neural features through this multivariate linear regression model, and the hand kinematics were then reconstructed by linearly combining the decoded synergy weights and the kinematic synergies extracted from the training set. The decoding procedure is briefly illustrated in Figure. 2. Decoding accuracy between the recorded kinematics and neural decoded kinematics was measured using the Pearson correlation coefficient β, and the decoding error was defined as 1—β. To avoid bias from a certain set of repetitions, this model was evaluated with 8-fold cross-validation with shuffled repetitions in the training set and testing set in each fold.

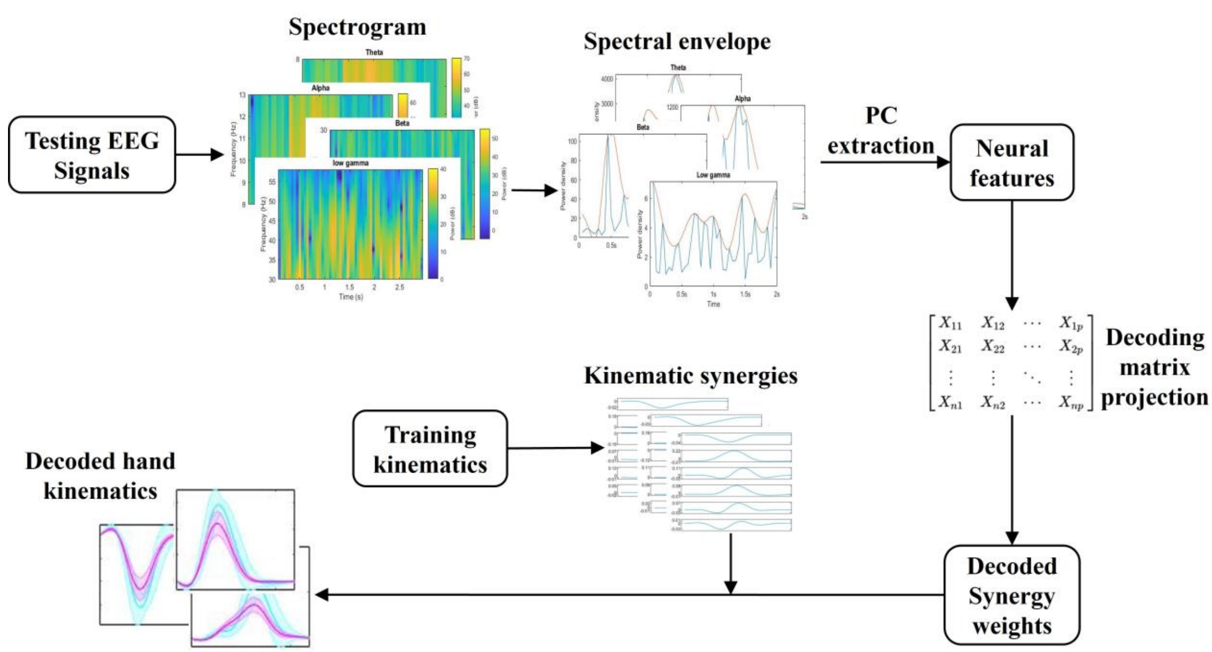

Figure. 2. Neural decoding process of the testing set. The neural features were extracted from the principal components of the spectral envelope of EEG signals. Synergy weights for the testing set were then calculated using these features through the multivariate linear regression model. Finally, hand kinematics were decoded by linearly combining the decoded synergy weights and the pre-extracted kinematic synergies.

3. Results

Motor-related EEG activity reveals distinct modulations in specific regions, effectively visualized through EEG spectral power tomography, as illustrated in Figure. 3. Averaged over all frequencies, the EEG spectral power offers valuable insights into the dynamic changes occurring during movement execution; brain activity exhibits a notable increase post-stimulus, reaching its peak during the active movement phase, and gradually settling down towards the holding phase.

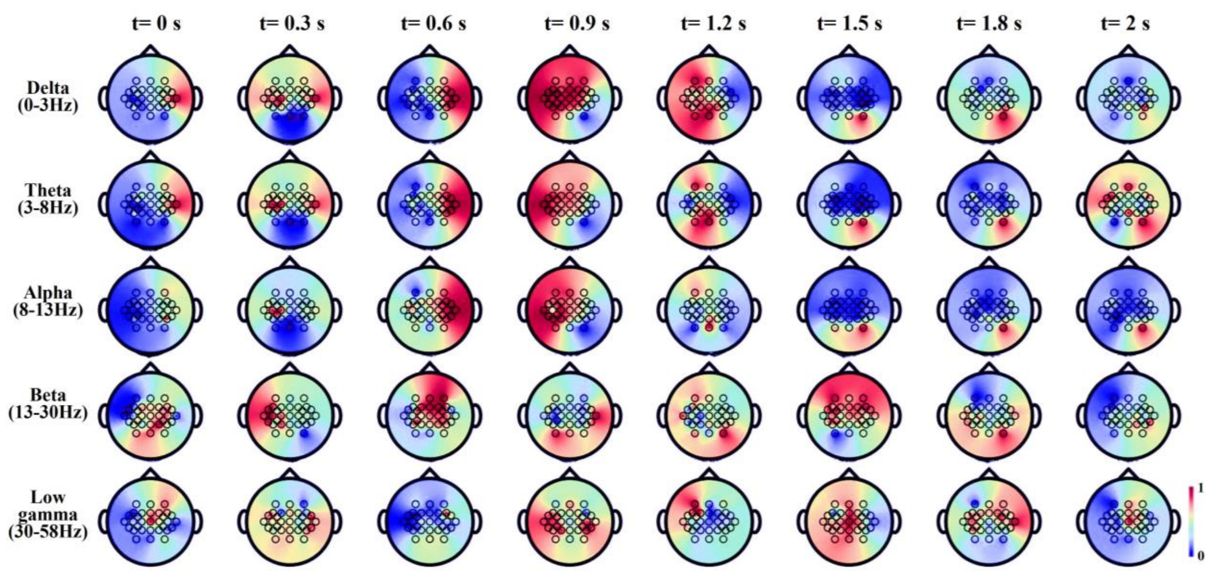

Figure. 3. Tomography of spectral power changes during grasp on various frequency bands. The activity in the motor cortex first decreases after the auditory stimulus, then increases to its peak during the movement, and gradually settles down.

Intriguingly, similar dynamic changes are observed in the low-frequency bands (delta, theta, and alpha). Following the auditory stimulus, the contralateral hemisphere of motor-related areas initially exhibits post-stimulus desynchronization, while the ipsilateral side exhibits synchronization. Conversely, relatively fluctuated dynamic changes were observed bilaterally across the hemisphere in the low gamma power. Furthermore, beta waves exhibit earlier synchronization, with the spectral power demonstrating greater activation in the bilateral primary motor cortex. This is followed by a more gradual decline compared to other frequencies.

The average decoding accuracy rates across all subjects achieved 79.1±0.14%. Figure. 4 displays the averaged decoding errors based on two types of grasps and different EEG frequency bands. Overall, whole-hand grasp performance slightly surpasses that of precision grasp, with lower average errors, particularly in the low gamma band (30-56 Hz). Notably, the low gamma waves displayed exceptional decoding performance for both grasps, particularly for whole hand grasp, where they exhibited the lowest error and deviation. In contrast, alpha waves (8-13 Hz) performed best for the precision grasp.

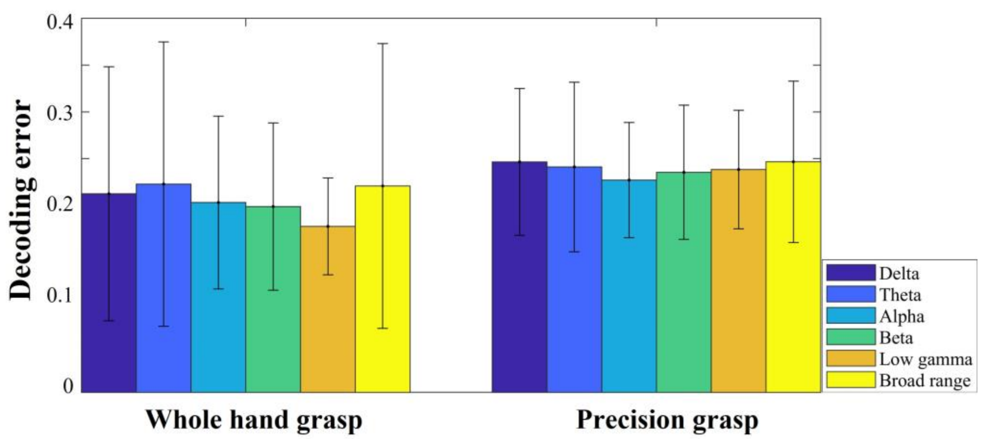

Figure. 4. Decoding error of two types of hand grasp using various EEG waves. The relatively lower decoding errors are observed in the low gamma band (30-56 Hz) for both types of hand grasp. The whole-hand grasp exhibits slightly better overall performance compared to the precision grasp.

Additionally, the precision grasp exhibited smaller standard deviations across movement repetitions, suggesting slightly more consistent decoding compared to the whole hand grasps, which showed greater variability. These findings highlight specific frequency bands offering superior decoding accuracy for different grasp types, emphasizing the potential of exploring alternative EEG rhythms in developing and optimizing BMI systems for hand movement.

The decoding model demonstrated its capability to finely adjust weights according to different movements, leading to successful decoding of the angular velocity patterns across typical hand grasps. Figure. 5 (from Subject 9, low gamma waves) presents comparisons between recorded and decoded kinematic patterns of ten joints from whole hand grasps (illustrated in Figure.5(A)) and precision hand grasps (illustrated in Figure.5(B)). The results show the averaged trajectories across the testing set, where shaded areas indicate the variability among different repetitions. Consistent with previous observations, the decoding performance appears more robust in whole-hand grasps. Additionally, the model achieved higher accuracy in predicting the kinematic trajectories of the MCP joints compared to the PIP joints, particularly evident in the index finger. This observation aligns with the understanding that the index finger plays a crucial role in employing various dexterity strategies during grasp movements.

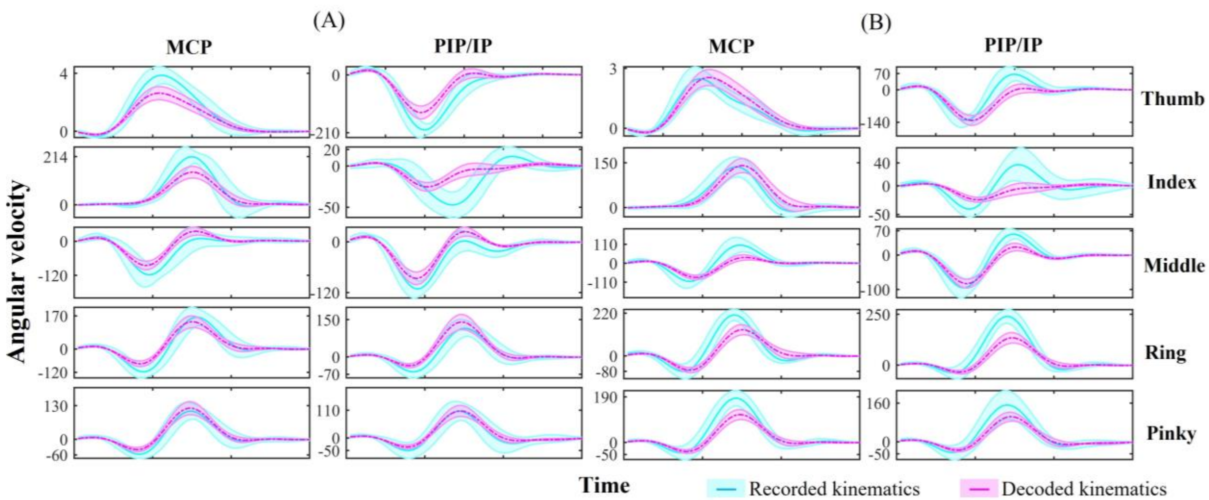

Figure. 5. Reconstruction plots of the whole hand grasp in (A) and the precision grasp in (B) from 10 joints. The recorded kinematics (in green solid line) and neural decoded kinematics (in pink dashed line) are averaged across all repetitions for Subject 9, low gamma (30-58 Hz) band and the shaded regions represent standard deviations. T: thumb, I: index, M: middle, R: ring, P: pinky.

4. Discussion and Conclusion

This study implemented a linear model between the neural features and hand kinematics to successfully predict two types of synergy-based hand grasps from different frequency ranges of EEG and achieved promising results. Activity in the contralateral motor cortex (in Fig. 3) associated with the dominant hand movements was observed from low-frequency EEG rhythms (delta, theta, and alpha rhythms), while bilateral activity revealed from beta and low gamma rhythms could compensate for the influence of contralesional motor cortex in individuals with stroke. Furthermore, the high performance of hand movement decoding using different EEG rhythms reveals the probability of decoding the movement using alternative cortical activities, leading to the potential of exploration of robust and dexterous hand movement decoding for individuals with stroke.

Despite the diversity of the motor cortex activations observed from healthy individuals, stroke patients with moderate to severe hand movement deficits [19] show potential for utilizing alternative mechanisms, such as the ipsilateral system, to compensate for unusual cortical potential changes. Increased ipsilateral cortical activity associated with hand movements after stroke [24] suggests that neural decoding from these areas could reveal different information compared to the damaged regions, although previous studies have shown the feasibility of decoding upper limb movements from the ipsilateral sensorimotor area for BMI systems [25]. Remarkably, even in individuals with brain lesions from stroke, the ipsilateral hemisphere retains the ability to represent motor effort. This finding suggests the potential for a robust decoding system based on our approach for individuals with stroke. Furthermore, the analysis of bilateral cortical activity in alternative EEG rhythms, such as beta and low gamma bands, may play a significant role in mediating motor-related activities in both healthy individuals and individuals with stroke. These findings suggest that distinct neural mechanisms contribute to motor task processing, potentially impacting our understanding of motor control and its application in BMI. The exceptional performance of low gamma waves in decoding both types of grasps, particularly in the case of the whole hand grasp, underlines the importance of exploring alternative EEG rhythms for optimizing BMI development for hand movement applications. Moreover, the correlation between neural features and kinematic synergy weights reveals the value of mapping and analyzing the CNS and motor primitives, offering crucial insights into the complex interaction between neural representations and motor tasks.

Motor function impairments may challenge the development of the correlation between brain activity and hand synergies due to the changes in synergy patterns in stroke individuals [26]. Healthy synergies have demonstrated the promising potential for stroke rehabilitation [27,28], which could also be considered as compensation for the way of reconstruction of healthy and near-natural movements. Previous research has demonstrated that a BMI-based rehabilitation system for stroke patients yields significantly superior outcomes compared to traditional rehabilitation methods used in the control group [29]. Moreover, clinical evidence has provided compelling support for the substantial functional improvement in stroke rehabilitation across various stroke stages through rehabilitation [30]. Additionally, the inclusion of brain activation training practices in the rehabilitation process has emerged as a promising and effective strategy [31]. The incorporation of brain activation training enhances the rehabilitation methodology by leveraging the brain's adaptive capabilities and promoting neuroplasticity, ultimately contributing to improved recovery outcomes.

Beyond decoding movement intentions, BMIs that capture brain activity associated with movement synergies offer additional potential. They could assist in near-natural hand movements through robotic or exoskeletal interfaces or facilitate the rehabilitation process through targeted electrical stimulation. The proposed idea involved in this study contributes to a deeper understanding of the intricacies of neural decoding to realize dexterous hand reconstruction in various daily activities. Consequently, it holds significant promise for future therapeutic interventions, including EEG-based motor rehabilitation and assistive BMI systems for individuals with motor impairments.

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