

Hands, Mouth, and Mind: Distinct EEG Patterns of Speech, Motor, and Sign-Language Imagery

1st Woo-Yong Jung
Chungbuk Science High School
Cheongju, Republic of Korea
wooyongmeock@gmail.com

2nd Hyeong-Yeong Park
Dept. Computer Science
Chungbuk National University
Cheongju, Republic of Korea
hyeong.y.park@chungbuk.ac.kr

3rd Ji-Hoon Jeong*
Dept. Computer Science
Chungbuk National University
Cheongju, Republic of Korea
jh.jeong@chungbuk.ac.kr

Abstract—Brain-computer interface (BCI) technology has significant potential as an intuitive communication tool and as a platform for language rehabilitation. This study systematically compared three forms of imagined expression—speech imagery (SI), motor imagery (MI), and sign-language imagery (SLI)—under identical experimental conditions to examine their neural characteristics and decoding feasibility. EEG was recorded using a 16-channel system while a participant imagined four target words, and neurophysiological analyses including time–frequency mapping, sLORETA source localization, and phase-locking value (PLV) connectivity were applied to characterize cortical activation and network dynamics. Classification was performed using common spatial pattern (CSP) features and evaluated across five machine-learning models, with linear discriminant analysis (LDA) used for detailed analysis. SLI consistently achieved the highest performance across models, showing the highest accuracy in 4-class word decoding; moreover, SI, MI, and SLI were perfectly separable in 3-class imagery classification. These findings demonstrate that SLI produces robust and discriminative neural signatures that differ from both SI and MI, indicating its potential as a distinct and effective neural input modality for communication-oriented BCIs.

Index Terms—Brain-computer interface, electroencephalography, speech imagery, motor imagery

I. INTRODUCTION

Brain-computer interfaces (BCIs) enable direct communication between the brain and external devices by decoding neural activity. BCI paradigms are typically classified as exogenous or endogenous, with endogenous systems relying entirely on users’ voluntary mental imagery [1], [2]. As BCIs gain attention not only as assistive technologies but also as potential universal input methods in emerging spatial-computing environments, the demand for expressive and reliable endogenous control schemes continues to increase. Among the widely studied endogenous paradigms, speech imagery (SI) naturally

encodes linguistic meaning but produces weak and unstable EEG signals, whereas motor imagery (MI) yields more stable and reproducible patterns but lacks linguistic content [3]–[7]. These complementary strengths and limitations motivate the search for imagery paradigms that are both linguistically expressive and neurophysiologically robust.

To combine the advantages of SI and MI, hybrid frameworks that connect the two processes in a serial manner have been proposed [8]. Although such approaches improve classification performance, they require pairing each word with a predefined MI gesture, increasing task duration, reducing naturalness, and imposing additional cognitive load. As a result, serial hybrids remain inefficient for real-time communication scenarios where rapid and intuitive interaction is essential.

Another line of research has explored using sign-language imagery (SLI) as a communication-oriented BCI paradigm [9], [10]. These studies demonstrated that imagined signing can be decoded from EEG signals, suggesting that SLI may serve as a viable input modality. However, previous work has largely treated SLI as a variant of MI and focused mainly on hand-movement patterns while overlooking the linguistic properties of sign language. As a result, the neurophysiological interaction between semantic processing and motor planning, which is central to natural sign-language cognition, has not been adequately examined.

Neuroscientific evidence further suggests that sign language cannot be understood solely as a motor behavior. Electroencephalography studies have shown that signing recruits a dorsal fronto-parietal network involving perirolandic, superior parietal, and posterior temporal regions, which is distinct from the ventral speech-language pathway [11]. Likewise, fMRI studies report widespread activation across linguistic, premotor, and visuospatial parietal areas during sign-language perception and production [12]. These findings indicate that sign-language processing integrates linguistic, motor, and visuospatial components, implying that SLI may generate neural patterns that differ from both SI and MI.

In addition, EEG research has identified characteristic frequency bands that reflect cognitive and motor processes relevant to imagery-based BCIs. Activity around 10 to 15 Hz has been associated with linguistic, semantic, and internal-speech processing [13], [14], whereas oscillations in the 8 to

This work was partly supported by the National Research Foundation of Korea(NRF) grant funded by the Korea government(MSIT) (RS-2024-00456480), the Institute of Information & communications Technology Planning & Evaluation (IITP) grant, funded by the Korea government (MSIT) (RS-2021-II212068, Artificial Intelligence Innovation Hub), the Korea Institute for Advancement of Technology (KIAT) grant funded by the Korea Government (MOTIE) (No. P0025399), and Korea Institute of Planning and Evaluation for Technology in Food, Agriculture and Forestry(IPET) through Agriculture and Food Convergence Technologies Program for Research Manpower Development Program funded by Ministry of Agriculture, Food and Rural Affairs(MAFRA)(RS-2024-00398561).

12 Hz range correspond to the sensorimotor mu-rhythm linked to motor imagery and movement-related modulation [15], [16]. These established frequency signatures provide a principled basis for interpreting potential divergences among SI, MI, and SLI in the time-frequency domain.

Despite these insights, SI, MI, and SLI have rarely been compared directly under identical experimental conditions. Prior studies vary widely in stimuli, task structure, and participant groups, making it difficult to determine whether SLI offers more discriminative or robust neural signatures for communication-oriented BCIs. Furthermore, systematic neurophysiological analyses that clarify how SLI relates to or diverges from established imagery paradigms remain limited.

To address these gaps, the present study conceptualizes SLI not as a simple extension of MI but as a parallel integration of linguistic and motor processes. By examining SI, MI, and SLI within the same participant using identical stimuli and recording conditions, this study provides a controlled comparison of their neural characteristics and decoding performance. Through time-frequency analysis, source localization, functional connectivity, and machine-learning classification, we evaluate whether SLI can serve as a more effective and natural modality for imagined communication in BCI systems.

II. MATERIALS & METHODS

A. Participants & Experimental Protocols

A healthy 19-year-old participant without prior experience in sign-language participated in this study. The participant had normal vision and hearing. All procedures were carried out according to the Declaration of Helsinki and written informed consent was obtained prior to participation. The experimental protocol was approved by the Institutional Review Board (IRB) of Chungbuk National University (CBNU-202310-HRHR-0228).

EEG data were recorded using the OpenBCI Cyton + Daisy board (16 channels) and the Ultracortex Mark IV EEG headset. Signals were acquired at a sampling rate of 125 Hz following the international 10-20 system, with A1 and A2 used as reference electrodes. Data acquisition and stimulus presentation were implemented in Python via the BrainFlow interface. The experiment was conducted in a non-shielded room with constant illumination and temperature to minimize environmental variability. The participant remained seated comfortably in front of a monitor throughout the session and followed the on-screen task instructions without removing the headset to maintain stable electrode contact.

The experimental protocol consisted of sequential periods of rest, stimulus presentation, fixation, and imagery. A 4-second rest period allowed the participant to relax and prepare for the upcoming task, followed by a 4-second stimulus presentation during which one of four Korean words ("*Hello*", "*Help me*", "*Sorry*", and "*Thank you*") was displayed on the screen. A 1-second fixation period was then provided for visual adjustment, and the subsequent 3-second blank screen served as the imagery phase, during which the participant

performed the designated imagination task according to the given condition.

The paradigm included three conditions: SI, MI, and SLI. Each condition comprised 30 trials for each of the four words, resulting in a total of 120 trials per condition and 360 trials overall. The experiment consisted of three separate sessions, each corresponding to one imagery condition, and all sessions were conducted on the same day.

B. EEG Data Preprocessing

The raw EEG signals were band-pass filtered between 0.5 and 40 Hz and a notch filter at 60 Hz was applied to eliminate powerline interference. Continuous data were then segmented into epochs covering the resting and imagery periods for each trial. Artifacts related to eye blinks and muscle activity were automatically detected and removed using an independent component analysis (ICA) approach. Finally, all signals were re-referenced to a common average reference (CAR) to enhance spatial consistency across channels.

C. Neurophysiological Analysis

To examine neural activation patterns across the three imagery conditions, neurophysiological analyses were performed in both the time-frequency and spatial domains.

For the time-frequency analysis, Morlet-based time-frequency representations (TFRs) were computed and expressed as log power changes relative to a fixation baseline (100 ms to 0). Three representative electrodes (C3, T7, F7) associated with sensorimotor and language-related regions were analyzed, and trials were averaged for each word and condition. To identify condition-specific spectral differences, F-value time-frequency (FTF) analysis [17] was applied to compute pixel-wise F-statistics and highlight time-frequency regions where SI, MI, and SLI diverged.

For spatial analysis, standardized low-resolution brain electromagnetic tomography (sLORETA) was applied to estimate cortical activation associated with each imagery condition. The analysis used the common average-referenced EEG epochs from the imagery period, and the forward model was constructed using the standardized MNI152 template. For each condition, trial-averaged source estimates were obtained and contrasted to visualize the dominant cortical regions engaged during SI, MI, and SLI.

Inter-regional synchronization was evaluated using phase-locking value (PLV). EEG signals were band-pass filtered into canonical frequency bands (1–40 Hz), and instantaneous phase was extracted via the Hilbert transform. PLV was computed for each channel pair and baseline-corrected using the fixation window (100 ms to 0). For visualization, only edges with $PLV \geq 0.6$ were displayed, with edge thickness and color indicating PLV magnitude. Connectivity maps were generated from trial-averaged PLV matrices for each imagery condition.

These analyses collectively enabled characterization of both localized activation and network-level connectivity patterns during imagined speech, movement, and sign-language tasks.

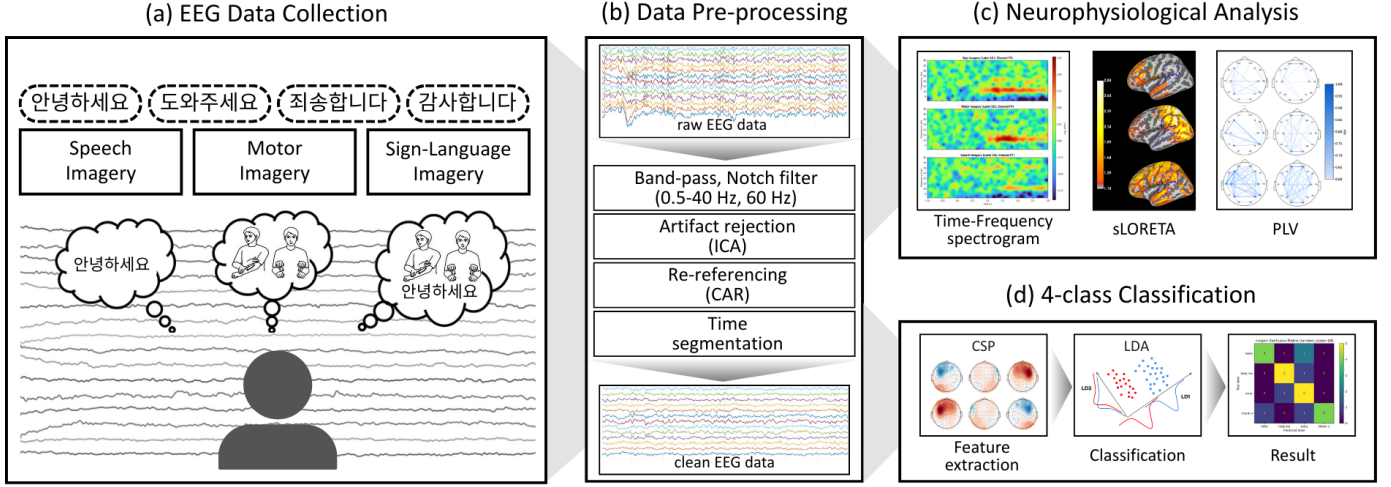


Fig. 1: Overall pipeline of the study. (a) EEG was recorded during speech imagery (SI), motor imagery (MI), and sign-language imagery (SLI). (b) Recorded signals were pre-processed through filtering, artifact rejection, re-referencing, and epoching. (c) Neurophysiological analyses included time–frequency analysis, sLORETA source localization, and PLV-based connectivity estimation. (d) Classification was performed using CSP feature extraction and LDA for 4-class word decoding.

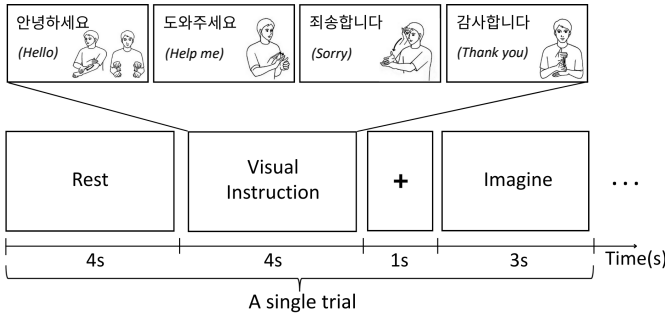


Fig. 2: Experimental paradigm for a single trial. Each trial consisted of a rest period (4 s), a visual instruction presenting one of four target words (4 s), a fixation interval (1 s), and an imagery period (3 s) during which the participant performed SI, MI, or SLI. This sequence was repeated for all words across the three imagery conditions.

D. Classification Method

To compare the decodability of the three imagery conditions (SI, MI, SLI), EEG trials were transformed into spatial features using the common spatial pattern (CSP) algorithm in a one-vs-rest configuration. Five classifiers were evaluated—LDA, Logistic Regression, SVM (RBF kernel), Random Forest, and KNN—using identical feature inputs and default hyperparameters to ensure consistent comparison.

Each condition was tested on two decoding tasks: (1) 4-class word classification, (2) 3-class imagery-type classification. Performance was estimated using 5-fold cross-validation repeated 20 times with randomized fold splits, and accuracy distributions were compared across conditions using Welch’s t-tests ($p < 0.05$).

Among the five models, LDA showed the most stable perfor-

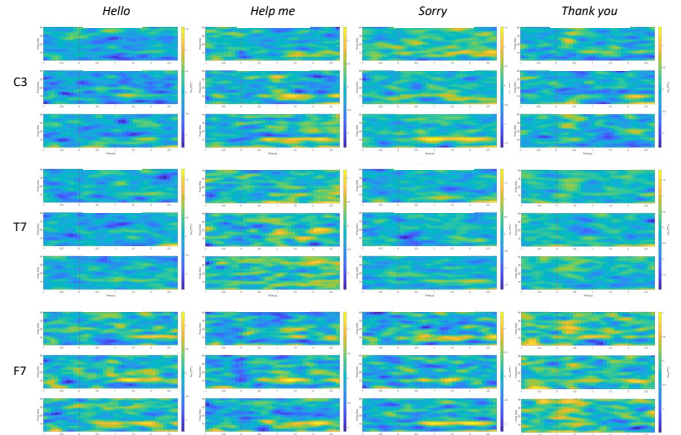


Fig. 3: Time–frequency representations (TFRs) for SI, MI, and SLI across three electrodes (C3, T7, F7) and four target words. The x-axis denotes time from stimulus onset, and the y-axis indicates frequency (Hz). Color scale represents log power change relative to baseline, where warmer colors indicate power increases and cooler colors indicate decreases.

mance; therefore, detailed analyses were conducted using LDA for all two decoding tasks. All procedures were implemented in Python using MNE and scikit-learn.

III. EXPERIMENTAL RESULTS

TFRs exhibited only modest power modulation across all imagery conditions (Fig. 3). At the level of individual channels and words, SI, MI, and SLI showed subtle but qualitatively distinguishable patterns, with SLI appearing to blend characteristics observed in both SI and MI rather than resembling either condition exclusively. This tendency became clearer in the global spectrograms obtained by averaging across channels

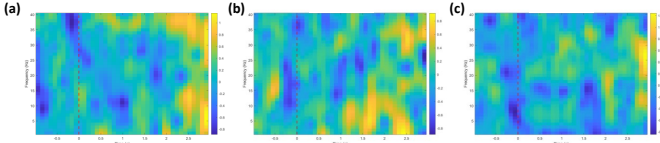


Fig. 4: Global TFRs averaged across all channels and words for (a) SI, (b) MI, and (c) SLI.

and words (Fig. 4), where SLI showed the overall weakest deviation from baseline, suggesting that its imagery-related spectral changes were more distributed and lower in magnitude compared to SI and MI.

Although these qualitative differences were visually observable, their small amplitude made it difficult to determine condition-specific spectral characteristics solely from the raw TFRs. To formally evaluate these distinctions, FTF analysis was employed to identify time–frequency regions where SI, MI, and SLI diverged significantly (Fig. 5).

FTF analysis revealed two prominent time–frequency regions in which the three imagery conditions diverged. A higher-frequency region around 10–15 Hz and a lower-frequency region around 8–12 Hz consistently appeared as major sources of separation across conditions. The SI–MI comparison (Fig. 5(a)) showed clear differences across both frequency regions, reaffirming that speech imagery and motor imagery rely on fundamentally distinct neural processes. In the SI–SLI comparison (Fig. 5(b)), differences emerged mainly in the lower-frequency region, suggesting that SLI incorporates motor-related components that are largely absent in SI while maintaining similar linguistic characteristics. Conversely, in the MI–SLI comparison (Fig. 5(c)), differences appeared predominantly in the higher-frequency region, indicating that SLI includes linguistic or semantic features not present in MI. Notably, these linguistic-related differences were narrower and weaker than those observed between SI and SLI, implying that SLI expresses a reduced or weaker form of SI-like linguistic activity. The FTF results demonstrate that SLI does not simply resemble SI or MI alone but instead exhibits an expanded response profile that blends features of both.

In Fig. 6, sLORETA source localization showed that SI primarily activated language-related regions, including the left inferior frontal gyrus (Broca’s area) and the superior temporal gyrus (Wernicke’s area). MI induced strong activation in the primary motor cortex and supplementary motor area, consistent with motor execution networks. In contrast, SLI exhibited widespread cortical activation encompassing the frontal, temporal, and parietal regions, indicating concurrent engagement of linguistic, motor, and visuospatial networks.

PLV analysis further revealed condition-specific patterns of functional connectivity across canonical frequency bands (Fig. 7). In SI, coherent connectivity was mainly observed in the delta, alpha, and gamma bands. MI, in contrast, showed little delta-band coupling and instead exhibited more focused connectivity in the alpha and gamma bands, consistent with

TABLE I: Test accuracies for SI, MI, and SLI across five machine-learning models, with Welch t-test p-values for SI–SLI and MI–SLI comparisons. SLI consistently achieved the highest test accuracy in most classifiers.

Model	SI	MI	SLI	p(SI–SLI)	p(MI–SLI)
LDA	0.3672	0.3927	0.4750	4.3E-09	2.6E-06
LogReg	0.2775	0.4263	0.4646	4.3E-35	2.2E-03
SVM	0.1925	0.2204	0.3013	4.3E-17	7.2E-11
RF	0.2392	0.2921	0.3221	1.9E-10	2.1E-02
KNN	0.2279	0.2700	0.2567	1.4E-02	2.3E-01

coordinated activity among motor-related regions. SLI combined these characteristics, displaying pronounced connectivity simultaneously in the delta, alpha, and gamma bands. Across these bands, SLI formed the densest and most spatially extended networks among the three conditions, indicating that sign-language imagery engages both the low-frequency interactions prominent in SI and the alpha–gamma coordination characteristic of MI. This hybrid connectivity pattern supports the view that SLI integrates neural processes associated with both speech- and motor-based imagery, in line with the FTF results showing that SLI shares substantial structure with MI while retaining additional components commonly observed in SI.

A. Classification Performance

Figure 8 and Table I summarize the decoding performance across the three imagery conditions. Across all five classification models, a consistent performance hierarchy emerged: SLI showed the highest accuracy, MI followed, and SI yielded the lowest performance. Statistical comparisons further confirmed these trends, with SLI significantly outperforming SI in every model and showing higher accuracy than MI in four of the five models. This robustness across model architectures suggests that SLI produces neural patterns that are both distinct and reliably separable, independent of classifier choice. Using LDA, which is the most stable model in our evaluation, 4-class word decoding revealed a clear performance advantage for SLI. The substantial gap between SLI and the other two conditions indicates that SLI contains richer and more discriminative neural features at the single-word level.

When classifying the imagery type itself (SI vs. MI vs. SLI), the model achieved 100% accuracy across repeated evaluations. The complete separability of the three categories supports the conclusion that SI, MI, and SLI elicit fundamentally different neural response structures, aligning with the distinctions observed in the time–frequency, source localization, and connectivity analyses.

These findings demonstrate that SLI provides the most robust and distinguishable EEG representations across multiple classification settings. Its consistently superior performance suggests that sign-language imagery constitutes a highly informative neural modality and a promising candidate for communication-oriented BCI systems.

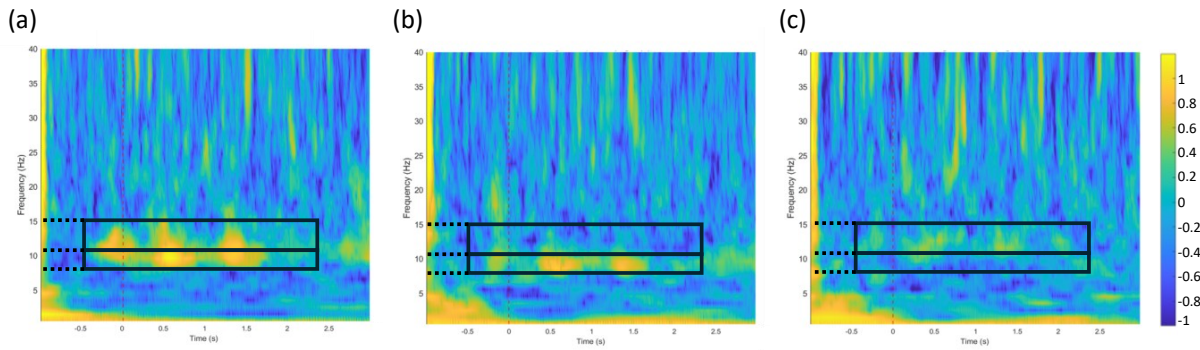


Fig. 5: F-value Time-Frequency (FTF) analysis comparing SI (a), MI (b), and SLI (c). The x-axis denotes time during imagery, and the y-axis denotes frequency (Hz). Color values represent F-statistics indicating the magnitude of spectral differences between conditions, with brighter regions reflecting stronger group separation. Highlighted boxes mark frequency bands where significant divergences were observed.

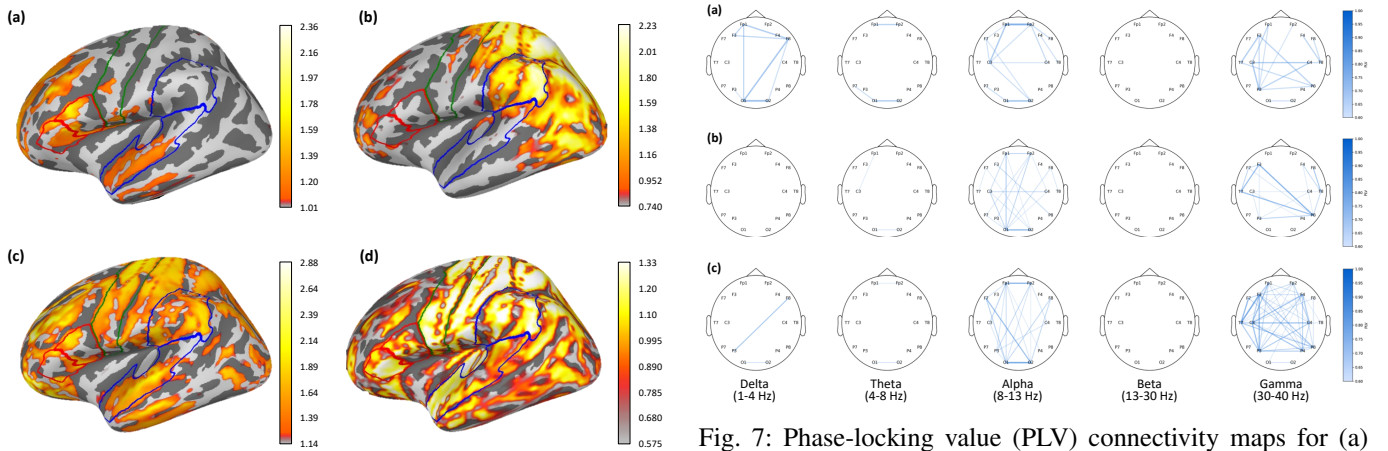


Fig. 6: sLORETA source localization for (a) SI, (b) MI, and (c-d) SLI. Warmer colors indicate higher estimated cortical activity relative to baseline. SI shows predominant activation in language-related frontal and temporal regions, MI engages motor and premotor cortices, and SLI exhibits widespread activation across frontal, temporal, and parietal areas.

IV. DISCUSSION

This study investigated the neural and decoding characteristics of speech imagery (SI), motor imagery (MI), and sign-language imagery (SLI) using EEG under identical experimental conditions. By directly comparing these three forms of imagined expression within the same paradigm, we examined how linguistic and motor processes contribute to the formation of distinct neural representations. The results revealed clear differences across the three conditions in cortical activation, functional connectivity, and classification performance.

Neurophysiological analyses showed that SLI engaged broader cortical regions than SI and MI, encompassing both language-related and motor-associated areas. Time-frequency analyses indicated that SLI exhibited a mixed spectral profile that combined characteristics of SI and MI, with statistically

Fig. 7: Phase-locking value (PLV) connectivity maps for (a) SI, (b) MI, and (c) SLI across five frequency bands (Delta, Theta, Alpha, Beta, Gamma). Nodes represent EEG electrode locations, and edges denote functional connectivity with PLV greater than 0.6. Edge thickness and color correspond to PLV magnitude, indicating the strength of phase synchronization between regions.

separable features emerging in both language-related and motor-related frequency regions. sLORETA further identified dominant activation in Broca’s and Wernicke’s areas during SI, in the motor cortex during MI, and across widespread frontal-temporal-parietal regions during SLI. PLV analysis revealed stronger and more distributed inter-regional synchronization for SLI across multiple frequency bands, suggesting a higher degree of neural integration in sign-language imagery than in the other two modalities.

Classification results provided additional converging evidence for these neurophysiological distinctions. Across five machine-learning models, SLI consistently achieved the highest test accuracy, outperforming SI in every model and surpassing MI in four out of five models. This cross-model robustness suggests that SLI produces neural features that are both more stable and more discriminative than those

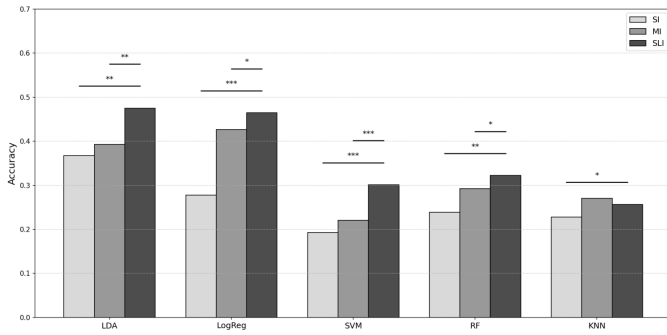


Fig. 8: Classification accuracies for SI, MI, and SLI across five machine-learning models (LDA, Logistic Regression, SVM, Random Forest, KNN). Bars represent mean test accuracy across repeated 5-fold cross-validation, and error bars indicate one standard deviation. Asterisks above brackets denote statistical significance of pairwise comparisons (* $p < 0.05$, ** $p < 1e-5$, *** $p < 1e-10$).

elicited by SI or MI alone. In the LDA-based analysis, SLI again demonstrated the strongest performance in 4-class word decoding. Furthermore, the three imagery conditions were perfectly separable in the 3-class imagery-type classification, achieving 100% accuracy, indicating that SI, MI, and SLI evoke fundamentally distinct neural response structures. These findings collectively support the idea that SLI is not merely an MI-derived gesture imagination task but a hybrid neural mode that integrates linguistic, motor, and visuospatial processes. As a result, SLI may offer a more expressive and robust input modality for communication-oriented BCIs, particularly in emerging spatial-computing environments where hands-free or silent communication channels are essential.

However, several limitations should be noted. This study involved a single participant and was conducted in a non-shielded environment, where external noise could not be fully controlled. Because SI, MI, and SLI were recorded in separate sessions, the perfect separability observed may partly reflect session-specific or temporal factors rather than purely neural differences. Moreover, the strong performance of SLI does not guarantee generalizability across users, proficiency levels, or real-time settings. Future studies with larger and more diverse participants, interleaved trial designs, and controlled environments are required to validate these findings. Additional work incorporating deep-learning models and online decoding will be necessary to determine whether the advantages of SLI persist in practical BCI applications.

V. CONCLUSION & FUTURE WORKS

This study compared SI, MI, and SLI under identical experimental conditions to examine their neural characteristics and decoding feasibility, and found that SLI elicited broader cortical activation, stronger inter-regional synchronization, and the highest word-level decoding accuracy. The three imagery conditions were fully separable, indicating that SLI constitutes a distinct neural mode integrating linguistic and motor pro-

cesses and offering promise as a communication-oriented BCI modality, particularly for users unable to rely on overt speech or movement. Future work should validate these findings in larger and more diverse cohorts under rigorously controlled protocols, and investigate deep learning-based classifiers and real-time decoding strategies. Systematic evaluation of factors such as sign-language proficiency, task complexity, and cognitive load will be essential for assessing the practical feasibility of SLI-based BCIs and further clarifying the mechanisms of imagined sign-language processing.

REFERENCES

- [1] U. Chaudhary, N. Birbaumer, and A. Ramos-Murguialday, "Brain-computer interfaces for communication and rehabilitation," *Nat. Rev. Neurol.*, vol. 12, no. 9, pp. 513–525, 2016.
- [2] L. F. Nicolas-Alonso and J. Gomez-Gil, "Brain computer interfaces, a review," *Sensors*, vol. 12, no. 2, pp. 1211–1279, 2012.
- [3] J.-H. Jeong, K.-H. Shim, D.-J. Kim, and S.-W. Lee, "Brain-controlled robotic arm system based on multi-directional CNN-BiLSTM network using EEG signals," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 5, pp. 1226–1238, 2020.
- [4] J.-H. Jeong, J.-H. Cho, B.-H. Lee, and S.-W. Lee, "Real-time deep neurolinguistic learning enhances noninvasive neural language decoding for brain-machine interaction," *IEEE Trans. Cybern.*, vol. 53, no. 12, pp. 7469–7482, 2022.
- [5] H.-Y. Park, S. Yu, S. Lee, and J.-H. Jeong, "Speech imagery decoding for emotional expression by exploring visual perception from eeg signals," in *2023 IEEE Int. Conf. Syst. Man. Cybern. (SMC), Hawaii, USA*, Oct. 2023.
- [6] M. Lee, H.-Y. Park, W. Park, K.-T. Kim, Y.-H. Kim, and J.-H. Jeong, "Multi-task heterogeneous ensemble learning-based cross-subject EEG classification under stroke patients," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 32, pp. 1767–1778, 2024.
- [7] S.-H. Yu, H.-Y. Park, E. Lee, T.-E. Kam, and J.-H. Jeong, "DeepSMR: Decoding high-complex motor imagery via subject-dependent multi-feature refinement in deep convolutional networks," *Comput. Biol. Med.*, vol. 197, p. 110920, 2025.
- [8] N. Padfield, T. Camilleri, S. Fabri, M. Bugeja, and K. Camilleri, "A combined EEG motor and speech imagery paradigm with automated successive halving for customizable command selection," *Brain-Computer Interfaces*, vol. 11, no. 3, pp. 125–142, 2024.
- [9] D. AlQattan and F. Sepulveda, "Towards sign language recognition using eeg-based motor imagery brain computer interface," in *2017 5th Int. Winter Conf. Brain-Computer Interface (BCI)*. IEEE, 2017, pp. 5–8.
- [10] P. Wang, Y. Zhou, Z. Li, S. Huang, and D. Zhang, "Neural decoding of chinese sign language with machine learning for brain-computer interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 2721–2732, 2021.
- [11] J. Shum, L. Fanda, P. Dugan, W. K. Doyle, O. Devinsky, and A. Flinker, "Neural correlates of sign language production revealed by electrocorticography," *Neurology*, vol. 95, no. 21, pp. e2880–e2889, 2020.
- [12] N. A. Mehta, T. Starner, M. M. Jackson, K. O. Babalola, and G. A. James, "Recognizing sign language from brain imaging," in *2010 20th Int. Conf. Pattern Recognit.* IEEE, 2010, pp. 3842–3845.
- [13] S. Weiss and H. M. Mueller, "Too many betas do not spoil the broth: The role of beta brain oscillations in language processing," *Front. Psychol.*, vol. 3, p. 201, 2012.
- [14] Y. Luo, Y. Zhang, X. Feng, and X. Zhou, "Electroencephalogram oscillations differentiate semantic and prosodic processes during sentence reading," *Neuroscience*, vol. 169, no. 2, pp. 654–664, 2010.
- [15] D. J. McFarland, L. A. Miner, T. M. Vaughan, and J. R. Wolpaw, "Mu and beta rhythm topographies during motor imagery and actual movements," *Brain Topography*, vol. 12, no. 3, pp. 177–186, 2000.
- [16] G. Pfurtscheller, C. Brunner, A. Schlögl, and F. H. Lopes da Silva, "Mu rhythm (de)synchronization and eeg single-trial classification of different motor imagery tasks," *NeuroImage*, vol. 31, no. 1, pp. 153–159, 2006.
- [17] H. G. Yeom and H. Jeong, "F-value time-frequency analysis: Between-within variance analysis," *Front. Neurosci.*, vol. 15, 2021.