2025 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE) | 979-8-3315-0279-9/25/$31.00 ©2025 IEEE | DOI: 10.1109/METROXRAINE66377.2025.11340347

Stay quiet: Investigating the effect of overt speech on EEG classification performance

1st Patrick Bings
Robotics Innovation Center
German Research Center for Artificial Intelligence (DFKI)
Bremen, Germany
patrick.bings@dfki.de
Institute of Medical Technology Systems
University of Duisburg-Essen
Duisburg, Germany

2nd Niklas Kueper
Robotics Innovation Center
German Research Center for Artificial Intelligence (DFKI)
Bremen, Germany
niklas.kueper@dfki.de
Institute of Medical Technology Systems
University of Duisburg-Essen
Duisburg, Germany

3rd Elsa Andrea Kirchner
Institute of Medical Technology Systems
University of Duisburg-Essen
Duisburg, Germany
elsa.kirchner@uni-due.de
Robotics Innovation Center
German Research Center for Artificial Intelligence (DFKI)
Bremen, Germany

***Abstract*—The detection of movement intentions for controlling robotic systems is becoming increasingly important in human-robot interaction especially for exoskeleton-supported rehabilitation. This movement intention can be expressed by a speech command, which can be used, for example, to generate training labels in electroencephalography (EEG)-based brain-computer interface (BCI) applications. However, the production of overt speech during BCI applications is strictly avoided in many studies due to the potential artifacts that affect the signal quality of the EEG and is a major limitation for out-of-the-lab use of BCI systems for various applications. In such applications, it cannot be strictly prohibited for the user to remain silent while using the BCI.**

In this work, the influence of overt speech commands on the detection of a person's arm movement intentions was investigated. Our objective was to reduce the influence of overt speech artifacts in EEG-based classification. EEG data were recorded from six healthy subjects under three experimental conditions: unilateral arm movements (Uni), isolated speech commands (Sp), and unilateral arm movements with speech commands (UniSp), where subjects indicated their intention to move by saying the word *begin* before the onset of the arm movement. To investigate the effect of overt speech on the EEG classifier performance, we performed a classifier transfer between UniSp and Uni condition. Additionally, an independent component analysis (ICA)-approach was also applied to reduce artifacts caused by overt speech on the transferred classifier.

For the Uni condition (baseline and no transfer), an accuracy of 0.828 was achieved. In contrast, the accuracy for the UniSp (no transfer) condition increased to 0.953. However, a naive classifier transfer from the UniSp condition to the Uni condition yielded a strongly reduced accuracy of 0.544 and this transfer combined with the ICA approach resulted in a slightly reduced accuracy of 0.534. These results indicate that the increase in performance in the UniSp condition compared to the Uni condition (baseline) resulted from specific patterns in the EEG data originating from overt speech. These patterns can also arise from muscle activity and speech-related movement artifacts. The poor classification accuracy of 0.544 and 0.534 (chance level 0.5) observed in the classifier transfer approach support the hypothesis that the artifact contamination in the EEG produced from overt speech result in a major decrease in classification performance. Therefore, very different patterns might have been learned by the classifier for the UniSp condition compared to the Uni condition. Finally, the results demonstrated that no increase in performance could be observed when applying an ICA-based approach to reduce the effect of overt speech on EEG classification performance. These findings strongly motivate the need for improved preprocessing and transfer learning strategies for more robust EEG classifications for an out-of-the-lab use of BCIs.

***Index Terms*—BCI, overt speech, EEG, machine learning, classifier transfer, movement prediction**

I. Introduction

In the field of human-robot interaction (HRI), active exoskeletons [1] can extend therapy options for stroke patients [2] and are effective in improving post-stroke neuromotor rehabilitation [3]–[5]. There are many examples of how such exoskeletons can be used to support rehabilitation after stroke for lower and upper limb movement therapy [1], [6]. However, to enable an intuitive and natural interaction between the human and the robotic system, it is essential to decode the user's movement intention for providing personalised exoskeleton support. This can be achieved by EEG-based BCIs [7]–[10] and can be applied for the post-stroke rehabilitation [3], [11]–[13].

979-8-3315-0279-9/25/$31.00 ©2025 IEEE

Beyond approaches that rely solely on EEG as a single modality, multimodal approaches combining EEG and EMG signals within a hybrid BCI framework, have shown to improve prediction performances [7], [14]–[19]. However, additional modalities such as the EMG can be used not only for a combined multimodal prediction but also as a feedback signal to recalibrate an EEG classifier for example shown in [20]. In addition to EMG, modalities such as speech can also be used as an additional type of interaction in HRI scenarios combined with BCIs [21]. An example of such a scenario would be the use of speech commands for the explicit indication of a movement intention by a severely affected stroke patient. Such speech commands could then be directly used to trigger exoskeleton support as well as to generate labels for training an EEG classifier. This would enable a more intuitive and natural interaction as compared to the explicit usage of the speech modality through implicit movement intention decoding.

However, the production of speech commands, is a known source of noise and artifacts in EEG recordings [22]. Therefore, the production of speech is mostly avoided in EEG-based BCI studies, especially in the field of speech production research itself [23]. Nevertheless, in real world out-of-the-lab applications of BCIs, it may not be feasible to strictly avoid speech production.

Therefore, in this work, we investigated an approach to label EEG data with speech commands for a motor execution paradigm and to analyse the effect of overt speech on this paradigm in general. This was done by applying a classifier transfer approach for the detection of movement intentions in an upper-limb reaching task. To the best of our knowledge, the effect of overt speech on a motor execution paradigm, as well as an approach to label movement-related EEG data with overt speech in this context, has not been investigated so far.

II. Methods

A. Experimental Setup and Procedure

Six healthy subjects (2 male and 4 female), with an average age of 23.8 $\pm$ 0.75 years, participated in the study. All subjects were right-handed, healthy, and reported no history of neurological or muscular disorders. They were seated comfortably in front of a custom-built apparatus consisting of tactile hand switches and a centrally positioned button as shown in Fig 1. The experimental setup was developed for the reaching task. In the reaching task, the subjects were instructed to stretch their right arm to reach the red button from the defined resting position (on the tactile switch) towards the central button and to press it with their right thumb. Further experimental details can be found in our previous work [8].

Three different experimental conditions were investigated: (1) Speech-command (Sp) condition, (2) Unilateral movement (Uni) condition, and (3) Combined (UniSP) condition containing both Speech-command (Sp) condition and Unilateral movement (Uni) condition. To ensure counterbalancing, the order of condition execution varied across subjects. During the Sp condition, subjects remained in the resting position and articulated only the the voice command *begin* without performing the reaching task. For the Uni condition, subjects performed only the reaching task. The UniSp condition required subjects to first issue the voice command *begin* immediately followed by the reaching task.

Each experimental condition consisted of three sets containing 40 trials each, totaling 120 trials per condition. Trials were self-initiated, with movements executed at the subject's own pace. A mandatory resting period of at least 5 s was enforced between trials. Trials preceded by resting intervals shorter than 5 s were excluded from analysis and accompanied by a 200 ms visual error signal displayed to the subjects. A fixation cross, displayed on the screen, was visible continuously throughout the experimental session. The whole experiment was designed and controlled using the *Presentation* software.

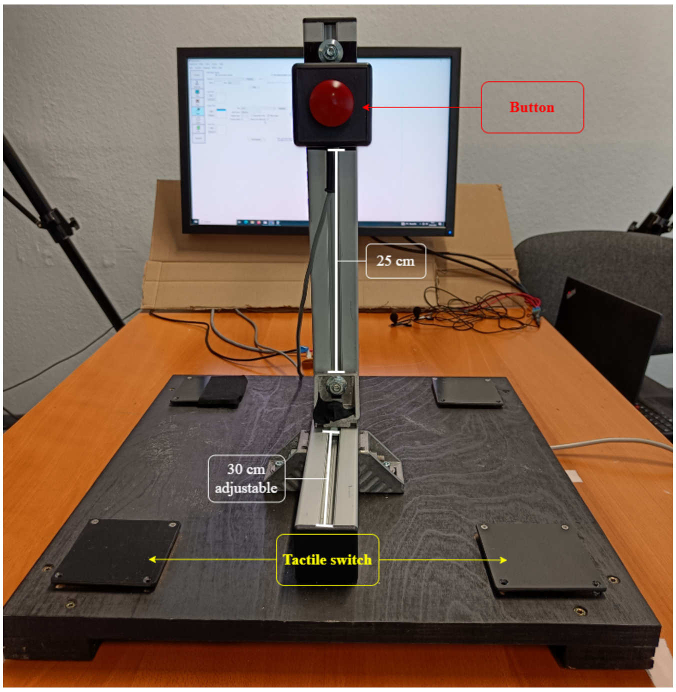

Fig. 1. Experimental setup of the study. The setup contains two tactile switches, one each for right and left hand resting positions and a button fitted on an adjustable aluminum profile for the subjects to reach and press.

B. Data Aquisition

For EEG measurements, the actiCap system equipped with 64 electrodes was used in conjunction with the LiveAmp 64 recording device, both from Brainproducts. Electrode placement adhered to the extended 10-20 system [24]. The LiveAmp functioned as both a recording device and a wireless interface with the recording computer. EEG data were recorded using the BrainVision Recorder software at a sampling rate of 500 Hz with a bandpass filter set between 0.1 and 131 Hz.

Audio recordings were performed using a custom-developed Python script that controlled a mono-channel clipon microphone from Delock. The audio was sampled at $44\,100\,\mathrm{Hz}$ and was synchronized with the EEG recordings by emitting trigger signals at the beginning and end of each measurement. In addition, a video of the experiment was recorded for further control.

All participants provided their informed consent in writing prior to participating in the experiment.

C. Speech Data Processing

A three-step procedure was followed for the processing of audio signals. First, the raw audio signals were trimmed to isolate relevant segments. Next, the signals were filtered to remove artifacts and enhance signal quality. Finally, an algorithm was applied to accurately detect the onset and offset of speech events.

After isolating the relevant segments, the raw signals underwent high-pass filtering (Butterworth, second-order, zero-phase) with a cutoff frequency of $10\,\mathrm{Hz}$ to remove baseline fluctuations. Subsequently, the signals were rectified and low-pass filtered (Butterworth, second-order, zero-phase) with a cutoff frequency of $15\,\mathrm{Hz}$ for smoothing. Finally, an adaptive thresholding method, based on 3% of the maximum signal amplitude, was applied separately from signal onset to offset and vice versa to accurately detect speech command boundaries as shown in Fig. 2.

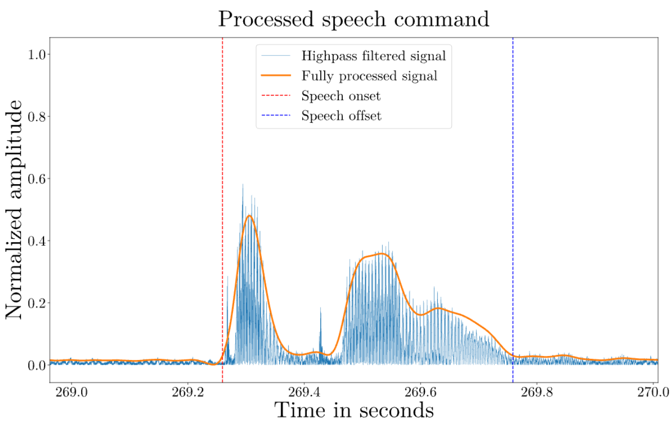

Fig. 2. Processed audio signal with speech onset and offset. The figure shows the high-pass filtered and rectified audio signal (blue) and the fully processed signal (orange), as well as the speech onset (vertical red line) and the speech offset (vertical blue line).

D. Processing of EEG Signals

For processing and classification of EEG signals, a self-developed python platform based on the MNE library was used. In addition, a machine learning pipeline using EEGNet as classifier was adopted. The different signal processing steps used in this work are as follows:

1) ERP analysis: Event related potentials (ERP) are time-locked EEG responses that reflect the brain's processing of specific internal or external events. ERPs can capture complex cognitive and motor processes, such as voluntary arm movement preparation, through characteristic patterns like the readiness potential and lateralized readiness potential (LRP) [25]. For the ERP analysis, EEG data were processed using a Python pipeline based on the MNE library. Raw EEG recordings were rereferenced to the common average, and bandpass filtered between $0.5\,\mathrm{Hz}$-$4\,\mathrm{Hz}$.

The EEG data were then segmented into epochs ranging from $-1.0\,\mathrm{s}$ to $0.5\,\mathrm{s}$ pre- and post-movement onset. Baseline correction was applied using a pre-movement interval of $-1.5\,\mathrm{s}$ to $-1\,\mathrm{s}$. The grand average ERPs were subsequently obtained by averaging across all subjects.

2) EEGNet Preprocessing: EEG data were processed window-wise by cutting overlapping windows of length $1\,\mathrm{s}$ with a stepsize of $50\,\mathrm{ms}$ resulting in an overlap of 95%. This was done starting from $-5.0\,\mathrm{s}$ to $0\,\mathrm{s}$, where $0\,\mathrm{s}$ denotes the labeled movement onset. The label for the movement onset was derived from the right hand tactile switch and corresponds to the time point at which the hand leaves the switch. This yielded a total of 81 windows for each movement trial.

For the next processing steps, an average rereferencing was performed and a bandpass filter was applied between $0.5\,\mathrm{Hz}$-$40\,\mathrm{Hz}$. Subsequently, a subset of 12 channels (FC1, FC2, CZ, C1, C2, C3, C4, CPZ, CP1, CP2, CP3, CP4), located around the central motor cortex, were selected for further analysis. The restriction to central channels over the motor cortex is intended to maximize the focus on motor-related activity. This spatial limitation targeted to support isolate neural signals primarily associated with motor function, thereby reducing confounding contributions from language processing regions.

3) ICA-based filtering: ICA enables the decomposition of multichannel EEG signals into statistically independent components, facilitating the separation of temporally and spatially overlapping signal sources. These components can be used to isolate and identify activity originating from distinct neural sources [26].

Based on this principle, a signal processing pipeline was established in which speech-related components were initially identified and removed using a template-matching algorithm based on ICA components.

First the EEG data was epoched from $-5.0\,\mathrm{s}$ to $0.0\,\mathrm{s}$ and an average rereferencing was performed. Subsequently, a bandpass filter between $0.5\,\mathrm{Hz}$ and $40\,\mathrm{Hz}$ was applied. Thereafter, a manual ICA component selection, based on a previous ERP analysis of topography plots of the Sp condition to identify speech-related activity, was conducted. These components were saved and later used as templates. Afterwards, an ICA on the UniSp condition was applied and the corresponding components were saved. Finally, the template-matching algorithm automatically detected the corresponding components between Sp and UniSp condition. If components in the UniSp data exhibited a correlation with the templates of the Sp data, exceeding an adaptively determined threshold (ranging from 0.6 to 0.95), with the template components, they were automatically labeled as speech-related artifacts and were excluded from further analysis. To account for inter-subject variability in ICA components, the automatic adaptive thresholding option of the `corrmap()` function from the MNE-Python library was employed.

E. Model Training and Classification

To train the classifier, two of the three recorded measurement sets, comprising a total of 80 trials, were used as training data. The remaining set, containing 40 trials, was reserved for validation and testing, with 20 trials each (leave-one-set-out validation). The windows $[-5.0\,,\ -2.5\,]$s, $[-2.5\,,\ -1.9\,]$s, $[-1.9\,,\ -1.5\,]$s and $[-1.5\,,\ -1.2\,]$s were used as training instances for the resting class, whereas the windows $[-0.20\,,\ -0.15\,]$s, $[-0.15\,,\ -0.10\,]$s, $[-0.10\,,\ -0.05\,]$s and $[-0.05\,,\ 0.00\,]$s were used as training instances for the movement preperation class. Accordingly, a binary classification was performed to distinguish between resting state and movement intention.

The model was preset for 300 training epochs and an early stopping condition was applied to reduce overfitting. The number of filters of the EEGNet layers was set to F1 = 8, F2 = 16 and the depth multiplier was set to D = 2 as presented in [27].

F. Performance Evaluation

The classification task was formulated as a binary classification problem, distinguishing between resting state and movement intention. Accuracy was used as the primary performance metric to evaluate and compare the effects of different evaluation strategies. Specifically, four evaluation conditions were assessed: (1) a baseline condition without speech and without transfer (Uni to Uni), (2) a movement condition including speech with no-transfer (UniSp to UniSp), (3) a naive transfer condition (UniSp to Uni), and (4) an ICA-based transfer condition (UniSp with ICA to Uni).

Model training and evaluation followed the above described leave-one-set-out cross-validation procedure. This resulted in three cross-validation folds per subject. Across all six subjects, this yielded a total of 18 classification results per evaluation condition, each based on 20 test trials.

III. Results

Initially, the classifier was trained and tested on the Uni scenario, yielding a median accuracy of 0.828. Subsequently, an additional classifier was trained and evaluated on the UniSp scenario, achieving a median accuracy of 0.953. Then, the classifier trained on UniSp scenario was directly transferred to the Uni scenario, resulting in a median accuracy of 0.544. Finally, applying ICA filtering using templates from the speech scenario resulting in a median accuracy of 0.534. This corresponds to a performance reduction of 0.01 (1.84%) as shown in Fig. 3.

Figure 4 presents a comparison of the grand average ERPs for the UniSp and Uni conditions at channel C1, which is associated with motor-related activity preceding and after onset of arm movements at 0.0 s. In the Uni condition, a negative shift in the averaged ERP activity is observed to begin around -1.0 s, with a more pronounced decline starting at approximately -0.3 s. In contrast, the UniSp condition shows negative shift in the averaged ERP activity from approximately -1.2 s to -0.8 s, followed by a positive shift between -0.6 s and -0.2 s, and a subsequent negative shift between -0.2 s to 0.0 s. In both the conditions, a clear positive shift in the averaged ERP activity is evident starting at the movement onset at 0.0 s, with the increase being more pronounced in the Uni condition.

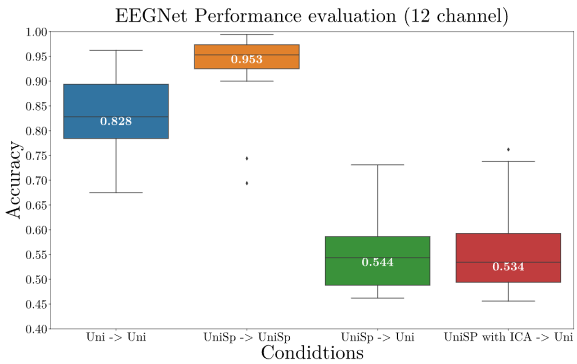

Fig. 3. Comparison of the conditions. The figure shows the performance of the four evaluation conditions: Uni to Uni (left), UniSp to UniSp (mid-left), UniSp to Uni (mid-right) and UniSp with ICA to Uni (right).

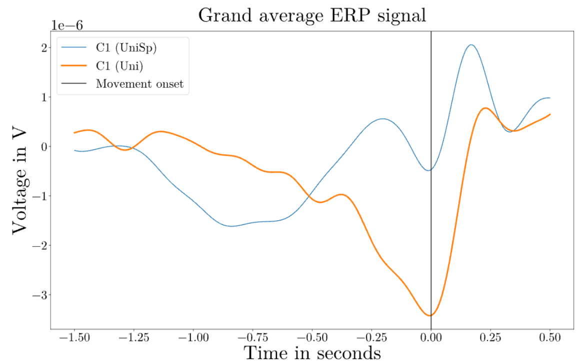

Fig. 4. Grand average ERP curves for the UniSp condition and the Uni condition. The EEG signals were rereferenced (average across all electrodes), bandpass filtered (0.5 Hz-4 Hz), and baseline corrected (average over -1.5 s to -1 s before movement onset). The displayed EEG signals were averaged over N = 720 epochs.

IV. Discussion

The results of the ERP analysis reveal clear motor-related ERP activity in the Uni condition, characterized by an initial slight negative shift in amplitude (readiness potential), followed by a pronounced negative deflection immediately preceding movement onset (LRP). In the UniSp condition, this movement-related LRP remains observable; however, the early readiness potential appears to be superimposed by another ERP component likely associated with speech-related activity or artifacts. Moreover, the observation that both conditions exhibit similar ERP amplitudes following movement onset supports the interpretation that the differences observed prior to movement are primarily driven by the overlapping speech-related EEG activity, as the speech command was given prior to the movement onset.

The classification results clearly demonstrate a decline in performance when using a naive transfer approach, compared to the baseline condition involving only unilateral movements. This performance drop suggests that the classifier, when trained in the presence of overt speech commands, may have primarily learned to rely on overlaying overt speech command features rather than neural patterns associated with motor preparation for arm movements.

Furthermore, the comparison between the naive transfer approach and the ICA-based adaptation method revealed no improvement in performance. This implies that ICA, as applied in this study, may be insufficient for isolating and removing EEG components associated with overt speech production. While ICA is effective in identifying stereotypical artifacts (ocular or muscle-related), its ability to disentangle temporally and spatially overlapping patterns, such as those originating from simultaneous speech and motor planning, appears to be limited in this context. However, it cannot be ruled out that the limited performance of the ICA-based filtering approach may be attributed to the preceding manual selection of components, which is a general challenge when applying ICA for component removal, as only clearly distinguishable components, such as those related to ocular artifacts, can be reliably identified and removed.

V. Conclusion

This study investigated the impact of overt speech on EEG-based classification of movement intentions and explored classifier transferability under conditions involving speech. The findings highlight the need for more advanced preprocessing and adaptation techniques. A key challenge lies in the fact that both processes (speech production and arm movement planning) activate overlapping cortical regions, making it difficult to isolate arm movement-related activity when speech-related activities are simultaneously present. This signal overlap complicates signal interpretation and highlights the importance of robust methods capable of disentangling these closely related neural sources.

Interestingly, the classification performance in the UniSp condition, when trained and tested on EEG containing both speech-related EEG activity and EEG activity related to unilateral movement planning, exceeded that of the baseline. This improvement may reflect the model's exploitation of both motor-related and speech-related EEG components, which are temporally aligned to each other. In this case, the presence of overt speech, rather than acting solely as a confounding factor, may have introduced additional, class-discriminative features that enhanced the model performance. However, the transfer of such a classifier to classify only arm movement-related motor activity was not successful. This highlights the complexity of interpreting EEG signals in multimodal conditions and reinforces the need for more complex transfer learning approaches and improved model interpretability.

Acknowledgment

We thank Sivalaxsaan Sivarasa for refining the experimental setup and data acquisition and Kartik Chari for proofreading the manuscript.

References

[1] E. A. Kirchner and J. Bütefür, "Towards Bidirectional and Coadaptive Robotic Exoskeletons for Neuromotor Rehabilitation and Assisted Daily Living: A Review," *Current Robotics Reports*, Apr. 2022.

[2] P. Poli, G. Morone, G. Rosati, and S. Masiero, "Robotic technologies and rehabilitation: new tools for stroke patients' therapy," *BioMed research international*, vol. 2013, no. 1, p. 153872, 2013.

[3] T. Noda, N. Sugimoto, J. Furukawa, M.-a. Sato, S.-H. Hyon, and J. Morimoto, "Brain-controlled exoskeleton robot for bmi rehabilitation," in *2012 12th ieee-ras international conference on humanoid robots (humanoids 2012)*, pp. 21–27, IEEE, 2012.

[4] E. Hortal, D. Planelles, F. Resquin, J. M. Climent, J. M. Azorín, and J. L. Pons, "Using a brain-machine interface to control a hybrid upper limb exoskeleton during rehabilitation of patients with neurological conditions," *Journal of neuroengineering and rehabilitation*, vol. 12, pp. 1–16, 2015.

[5] N. Singh, M. Saini, N. Kumar, M. P. Srivastava, and A. Mehndiratta, "Evidence of neuroplasticity with robotic hand exoskeleton for post-stroke rehabilitation: a randomized controlled trial," *Journal of neuroengineering and rehabilitation*, vol. 18, no. 1, p. 76, 2021.

[6] S. Kumar, H. Wöhrle, M. Trampler, M. Simnofske, H. Peters, M. Mallwitz, E. A. Kirchner, and F. Kirchner, "Modular Design and Decentralized Control of the Recupera Exoskeleton for Stroke Rehabilitation," *Applied Sciences*, vol. 9, no. 4, 2019.

[7] E. A. Kirchner, M. Tabie, and A. Seeland, "Multimodal Movement Prediction - Towards an Individual Assistance of Patients," *PLOS ONE*, vol. 9, p. e85060, Aug. 2014.

[8] N. Kueper, S. K. Kim, and E. A. Kirchner, "Avoidance of specific calibration sessions in motor intention recognition for exoskeleton-supported rehabilitation through transfer learning on EEG data," *Scientific Reports*, vol. 14, p. 16690, July 2024.

[9] O. Bai, V. Rathi, P. Lin, D. Huang, H. Battapady, D.-Y. Fei, L. Schneider, E. Houdayer, X. Chen, and M. Hallett, "Prediction of human voluntary movement before it occurs," *Clinical neurophysiology : official journal of the International Federation of Clinical Neurophysiology*, vol. 122, pp. 364–372, Feb. 2011.

[10] E. López-Larraz, L. Montesano, A. Gil-Agudo, and J. Minguez, "Continuous decoding of movement intention of upper limb self-initiated analytic movements from pre-movement EEG correlates.," *Journal of Neuroengineering and Rehabilitation*, vol. 11, pp. 153–153, Nov. 2014.

[11] E. López-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday, "Brain-machine interfaces for rehabilitation in stroke: A review," *NeuroRehabilitation*, vol. 43, pp. 77–97, Jan. 2018.

[12] A. Sarasola-Sanz, A. M. Ray, A. Insausti-Delgado, N. Irastorza-Landa, W. J. Mahmoud, D. Brötz, C. Bibián-Nogueras, F. Helmhold, C. Zrenner, U. Ziemann, E. López-Larraz, and A. Ramos-Murguialday, "A hybrid brain-muscle-machine interface for stroke rehabilitation: Usability and functionality validation in a 2-week intensive intervention," *Frontiers in Bioengineering and Biotechnology*, vol. 12, Apr. 2024.

[13] H. Yang, J. Wan, Y. Jin, X. Yu, and Y. Fang, "EEG- and EMG-Driven Poststroke Rehabilitation: A Review," *IEEE Sensors Journal*, vol. 22, pp. 23649–23660, Dec. 2022.

[14] R. Leeb, H. Sagha, R. Chavarriaga, and J. del. R. Millán, "Multimodal Fusion of Muscle and Brain Signals for a Hybrid-BCI," in *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology*, pp. 4343–4346, Aug. 2010.

[15] C. Cui, G.-B. Bian, Z.-G. Hou, J. Zhao, and H. Zhou, "A Multimodal Framework Based on Integration of Cortical and Muscular Activities for Decoding Human Intentions About Lower Limb Motions," *IEEE Transactions on Biomedical Circuits and Systems*, vol. 11, pp. 889–899, Aug. 2017.

[16] M. S. Al-Quraishi, I. Elamvazuthi, T. B. Tang, M. Al-Qurishi, S. Parasuraman, and A. Borboni, "Multimodal Fusion Approach Based on EEG and EMG Signals for Lower Limb Movement Recognition," *IEEE Sensors Journal*, vol. 21, pp. 27640–27650, Dec. 2021.

[17] J. Zhang, B. Wang, C. Zhang, Y. Xiao, and M. Y. Wang, "An EEG/EMG/EOG-Based Multimodal Human-Machine Interface to Real-Time Control of a Soft Robot Hand," *Frontiers in Neurorobotics*, vol. 13, Mar. 2019.

[18] H. Yang, J. Wan, Y. Jin, X. Yu, and Y. Fang, "EEG- and EMG-Driven Poststroke Rehabilitation: A Review," *IEEE Sensors Journal*, vol. 22, pp. 23649–23660, Dec. 2022.

[19] S. Tortora, L. Tonin, C. Chisari, S. Micera, E. Menegatti, and F. Artoni, "Hybrid Human-Machine Interface for Gait Decoding Through Bayesian Fusion of EEG and EMG Classifiers," *Frontiers in Neurorobotics*, vol. 14, Nov. 2020.

[20] M. Tabie, H. Woehrle, and E. A. Kirchner, "Runtime calibration of online eeg based movement prediction using emg signals.," in *BIOSIGNALS*, pp. 284–288, 2014.

[21] N. Kleer, M. Rekrut, J. Wolter, T. Schwartz, and M. Feld, "A Multimodal Teach-in Approach to the Pick-and-Place Problem in Human-Robot Collaboration," in *Companion of the 2023 ACM/IEEE International Conference on Human-Robot Interaction*, (Stockholm Sweden), pp. 81–85, ACM, Mar. 2023.

[22] G. Ouyang, W. Sommer, C. Zhou, S. Aristei, T. Pinkpank, and R. Abdel Rahman, "Articulation artifacts during overt language production in event-related brain potentials: Description and correction," *Brain topography*, vol. 29, pp. 791–813, 2016.

[23] L. Ganushchak, I. Christoffels, and N. Schiller, "The Use of Electroencephalography in Language Production Research: A Review," *Frontiers in Psychology*, vol. 2, 2011.

[24] M. Seeck, L. Koessler, T. Bast, F. Leijten, C. Michel, C. Baumgartner, B. He, and S. Beniczky, "The standardized EEG electrode array of the IFCN," *Clinical Neurophysiology*, vol. 128, pp. 2070–2077, Oct. 2017.

[25] M. Bleich, A. Draguhn, H. Ehmke, and D. Singer, *Physiologie [Physiology]*. Stuttgart New York: Georg Thieme Verlag, 10., vollständig überarbeitete auflage ed., 2023.

[26] A. Tharwat, "Independent component analysis: An introduction," *Applied Computing and Informatics*, vol. 17, pp. 222–249, Jan. 2020.

[27] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: A Compact Convolutional Network for EEG-based Brain-Computer Interfaces," *Journal of Neural Engineering*, vol. 15, p. 056013, Oct. 2018.