A Language-Related Brain-Computer Interface: Turning Actions Words into control signals.

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Abstract. *Brain-Computer Interface (BCI) opened the possibility of communicating human beings with systems and devices using brain signals. This area inspired researchers to develop several applications such as medical rehabilitation of disabled people, robotic prostheses, games and assisted virtual reality (VR) scenarios. Motor imagery Brain-Computer Interface (MI-BCI) is a paradigm widely used for controlling external devices by imagining bodily movements. These actions modulate the power frequency in both alpha (8-12Hz) and beta (13-25Hz) bands creating cortical patterns known as Event-Related de-Synchronization and Synchronization (ERD/ERS). Likewise, cognitive linguistics research demonstrates a strong interplay between brain systems for action-perception and language in the semantic processing of Action Words (e.g., kick, grasp), eliciting similar patterns as Motor Imagery tasks. In this vein, the current proposal aims to develop and validate a BCI system that uses action words as a neurophysiological signal for controlling external devices. The framework includes a comparison among three paradigms: Motor Imagery, Movement Observation, and Action Words. The evaluation comprises a time-frequency analysis, classification rates using state of art methods (Support Vector Machine - SVM, Artificial Neural Network - ANN, Linear Discriminant Analysis - LDA), and an online feedback implementation. The author expects that, as Action Words are motor-related signals, a language-related BCI system can reduce the abstractness of motor imagery tasks because the proposed paradigm includes stimulus-locked (ERD/ERS) and time-locked (ERP) EEG components.*

1. Introduction

Throughout the last decades, human beings have sought different alternatives to communicate with machines or systems. In this context, Brain-Computer Interface (BCI) plays an important role, motivated by overcoming the difficulties experienced by impaired people [Neuper and Pfurtscheller 2010] or, just by developing a non-mechanical user interaction for robotic prostheses, games and assisted virtual reality (VR) scenarios [Neuper and Pfurtscheller 2010] [Brunner et al. 2011]. BCI is the technology that enables a bodiless communication with machines or devices; this is done using the translation of brain signals elicited during a specific task into command outputs. BCI commonly employs the electrical activity in the brain (EEG) elicited during a specific task. Depending on the nature of this activity, BCI is characterized as passive, active or reactive [Zander et al. 2010]. Passive systems use signals that arise without voluntary control. It is used fundamentally to asses mental states and enhance the human-computer interaction [Zander et al. 2010]. Active BCI works with the self-induced brain activity produced by the user independently of external events. It has been used as a control signal [Zander et al. 2010]. Finally, reactive BCI relies on the signals elicited by the reaction to specific external stimuli, which could also be used to control an application [Donchin et al. 2000].

Among reactive BCI applications, speller programs are one of the most well-known and widely developed. These systems allow subjects to communicate with machines through the visual typing of individual characters, words or even sentences by decoding the brain activity elicited by visual stimuli [Rezeika et al. 2018]. The BCI-speller can be categorized according to the type of brain response [Mora-Cortes et al. 2014], namely, visual evoked potentials (VEPs) and P300 evoked potentials. Contrary to reactive BCI, active BCI uses self-regulation brain rhythms without following any external stimuli. One of the most used control signals in this type of BCI system is Motor Imagery BCI (MI-BCI) [Wolpaw et al. 2002]. MI-BCI employs the amplitude changes voluntarily elicited by the mental rehearsal of physical motor actions since the activation patterns of imaginary body movements involves both brain regions (sensory and motor areas) and neural mechanisms similar to the executed movement [Jeannerod 1995]. Such variations are known as event-related de-synchronization and synchronization (ERD/ERS). These patterns have been successfully used for studying the neural mechanisms associated with motor actions, as well as a feature for classification in motor-related BCI systems [Pfurtscheller and Neuper 2001, Wolpaw et al. 2002, Gert et al. 2011, Neuper et al. 2003].

On the other hand, research in cognitive and behavioral neuroscience demonstrates the functional links between motor and language systems, specifically, the contributions of motor cortex to action word processing [Pulvermuller et al. 2005]. Action Words refer to words with action or body-related content that activates for their semantic processing both motor and language cortical areas. For example, Action Words that are semantically related to arm or hand movements (e.g, pick) activate neuronal ensembles in both perisylvian cell assemblies and semantic circuits in different regions of the lateral motor cortex [Hauk et al. 2004]. Moreover, EEG approaches found neuronal oscillations in alpha (8–12Hz) and beta (13–30Hz) frequencies when users read Action Words [Niccolai et al. 2014]. These patterns are similar to the ones related to Motor Imagery [Pfurtscheller 1999] and Motor Observation [Neuper et al. 2009]. Likewise, studying Actions Words drive us to explore the implications of embodied-related mental representations in conceptual processing.

Therefore, the current research proposal is addressed towards the development of augmentative and alternative communication (AAC) devices, in this case, a language-based BCI that includes Action Words as a control signal. For this purpose, the new paradigm will be compared with Motor Imagery and Motor Observation-based BCI systems in terms of the effectiveness of producing motor patterns and classification rates. The typical EEG MI-BCI pipeline will be used in order to analyze the oscillatory (ERD/ERS) and temporal (ERP) activity elicited by each paradigm; meanwhile, the extracted features (via CSP filters) will separately train three common BCI classifiers [Lotte et al. 2018]: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Linear Discriminant Analysis (LDA). After the offline analysis, the best classifier per user is used for online implementation. Thus, checking and evaluating the feasibility of the proposed method,

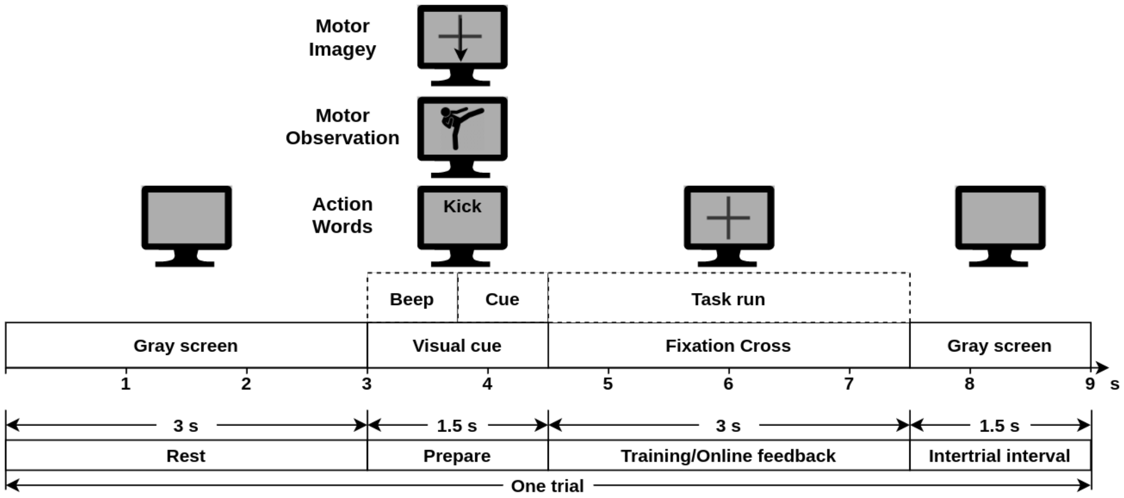

Figure 1. BCI timing protocol and visual cues for each paradigm.

the authors would introduce a new paradigm for BCI systems. Additionally, with the inclusion of Action Words inside BCI, this work offers new accounts regarding the specific effects of language-motor interaction in semantic processing.

2. Methodology

Using Electroencephalography (EEG) and following the usual procedure for analyzing sensory-motor rhythms in BCI systems [Leeb et al. 2006], this proposal aims to collect data from three groups of five users under three counterbalanced conditions 1:

a) ***Motor Imagery - MI***: consists of the mental rehearsal of a motor action without actually performing any movement. The user in this condition has to perform either the motor imagination of a hand or foot movement. An arrow (visual cue) indicates the task (upward refers to hand, downward to foot). The instruction here is that the users perform the kinesthetic experience during the execution of motor imagery tasks (first-person imagery), i.e., imagining the sensation of performing the motor tasks [Neuper et al. 2005].

b) ***Motor Observation - MO***: consists in the triggering of mirror neurons structures from action observation without actually performing any movement. The user in this condition has to observe either the motor action of a hand or foot movement. An animation (visual cue) indicates the task (grasping animation refers to hand, kicking to foot). The instruction here is that the users perform the visual experience during the execution of motor imagery tasks (third-person imagery), i.e., imagining the visual representation of the movement [Neuper et al. 2009].

c) ***Action Words - AW***: consists of reading an Action Word without actually performing any movement. The user in this condition has to read an AW related to either the motor imagination of a hand or foot movement. An AW (visual cue) indicates the task ('grasping' refers to hand, 'kicking' to foot). The instruction here is that the users perform the inner voice experience during the execution of motor imagery tasks, i.e., the mental repetition of the Action Word [Niccolai et al. 2014].

The aforementioned conditions follow the same timing protocol [Pfurtscheller and Neuper 2001]: starting with a gray screen (resting-state), at time

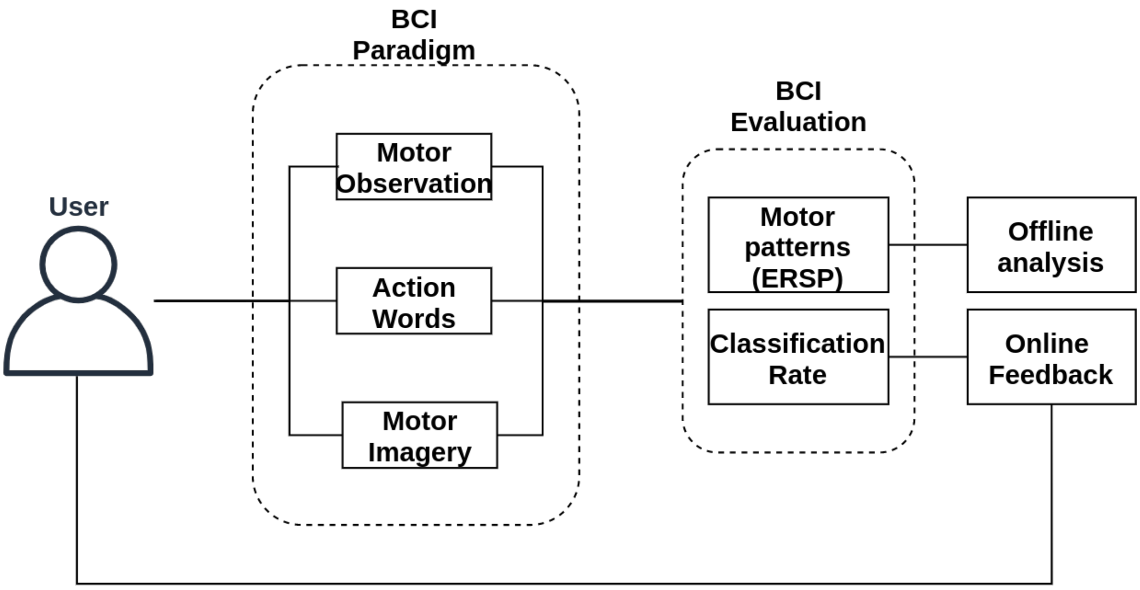

Figure 2. Experiment paradigm. The visual stimulus of the task's cue are corresponding for both conditions. Top: *Hands* condition. Middle: *Graz* condition. Bottom: timing of the trials.

3s, a visual cue at the center of the scene was displayed with a short warning tone ('beep') which indicates to the user to pay attention to the visual cue presented. At time 4.5s, a fixation cross appears at the center of the scene, and the user has to perform the task for three seconds. Finally, at time 7.5, the cross disappears and users come back to resting-state 1. The users have to perform, for each condition, 30 trials of each task randomly selected (hand or foot action) with a duration of 9 seconds each. There is a resting space in the interval among the conditions (five minutes). In order to avoid the carry-over bias, the experimental conditions were counterbalanced across participants (i.e. five subjects start with *MI* condition, other ones with *MO* condition, and the rest with *AW*).

For the EEG analysis, the author plans to use EEGLAB (14.1) [Delorme and Makeig 2004a] (under Matlab 2017b) as well as LabStreamingLayer [Kothe 2013] for synchronizing EEG data with trials). After the filtering process, the Filter Bank Common Spatial Pattern (FBCSP) will be used for extracting the EEG features for classification. The FBCSP approach has demonstrated successful performance in BCI applications [Ang et al. 2008]. This method extracts the most relevant spectral and spatial features using a CSP filter for each frequency band. Hence, these features are used to separately train three common BCI classifiers [Lotte et al. 2018]: Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Linear Discriminant Analysis (LDA). These models have to distinguish between hand and foot movements. Initially, the user's data is recorded for training the classifier model; later in a final running, the training step is replaced by online feedback composed of a progress bar indicating the user's performance.

Finally, the event-related spectral perturbation (ERSP) is a generalization of the ERD/ERS patterns. ERSP computes the changes of the spectral powers in time-frequency domains, relative to the stimuli [Delorme and Makeig 2004b]. Thus, with this approach, the changes of the EEG signals elicited by motor imagery task can be detected alongside of the spectral band and epoch. The ERS/ERD patterns are predominant in alpha (8-12 Hz), and beta (13-30 Hz) rhythms and in its onset goes from 500ms up to three seconds after the movement execution [Pfurtscheller 1999]. Therefore, the time-frequency analysis will be computed at the sensory-motor electrodes using the filtered data in every mental task (hand or feet) for each condition, with a time window from -500 to 2500 ms, and frequency between 5 and 30 Hz. See the Figure 2 for a comprehensive summary of the experimental framework.

It is important to mention that the current project must receive the approval from Ethical Committee before running the experiments.

3. Expected results

With the current proposal, the author aims to contribute to the BCI literature with a novelty paradigm using Action Words. This language-related BCI systems can open countless opportunities for the traditional paradigms. In the MI-BCI, Action Words could be used in a training step for enhancing the modulation of the motor EEG signals; in Speller-BCI, Action Words could replace letters or words on the interface for improving the decodification of the user's intention. The main findings of this research consist on the evaluation and validation of the proposed paradigm (Action Words BCI) comparing its effectiveness in signal modulation and classification rates against two established methods (Motor Imagery and Motor Observation).

In addition, this work can offer novel data from a language-motor interaction experiment where the applicability of Action Words is demonstrated. Likewise, the findings can contribute to the debate concerning the embodied language processing [Fischer and Zwaan 2008, Hauk and Tschentscher 2013], supporting the conceptual grounding argument, which states that language processing in some degree can be based on sensorimotor experiences rather than only a symbolic representation [Mollo et al. 2016, Klepp et al. 2019].

Two research publications are expected from this proposal. The first one related to the dataset of the experiment in the journal Data in Brief, the second one is about the main findings of the EEG analysis for the proposed paradigm and the comparison of it against the two others in terms of classification rates and signal modulation.

References

Ang, K. K., Chin, Z. Y., Zhang, H., and Guan, C. (2008). Filter bank common spatial pattern (fbcsp) in brain-computer interface. In *2008 IEEE International Joint Conference on Neural Networks*, pages 2390–2397.

Brunner, P., Bianchi, L., Guger, C., Cincotti, F., and Schalk, G. (2011). Current trends in hardware and software for brain–computer interfaces (BCIs). *Journal of Neural Engineering*, 8(2):025001.

Delorme, A. and Makeig, S. (2004a). Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1):9 – 21.

Delorme, A. and Makeig, S. (2004b). Eeglab: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1):9 – 21.

Donchin, E., Spencer, K. M., and Wijesinghe, R. (2000). The mental prosthesis: assessing the speed of a p300-based brain-computer interface. *IEEE Transactions on Rehabilitation Engineering*, 8(2):174–179.

Fischer, M. H. and Zwaan, R. A. (2008). Embodied language: A review of the role of the motor system in language comprehension. *The Quarterly Journal of Experimental Psychology*, 61(6):825–850.

Gert, P., Leeb, R., Faller, J., and Neuper, C. (2011). Brain-computer interface systems used for virtual reality control. In Kim, J.-J., editor, *Virtual Reality*, chapter 7, pages 1–19. InTech.

Hauk, O., Johnsrude, I., and Pulvermüller, F. (2004). Somatotopic representation of action words in human motor and premotor cortex. *Neuron*, 41(2):301 – 307.

Hauk, O. and Tschentscher, N. (2013). The body of evidence: What can neuroscience tell us about embodied semantics? *Frontiers in Psychology*, 4:50.

Jeannerod, M. (1995). Mental imagery in the motor context. *Neuropsychologia*, 33(11):1419 – 1432. The Neuropsychology of Mental Imagery.

Klepp, A., van Dijk, H., Niccolai, V., Schnitzler, A., and Biermann-Ruben, K. (2019). Action verb processing specifically modulates motor behaviour and sensorimotor neuronal oscillations. *Scientific Reports*, 9(1):15985.

Kothe, C. A. (2013). lab streaming layer.

Leeb, R., Keinrath, C., Friedman, D., Guger, C., Scherer, R., Neuper, C., Garau, M., Antley, A., Steed, A., Slater, M., and Pfurtscheller, G. (2006). Walking by thinking: The brainwaves are crucial, not the muscles! *Presence*, 15(5):500–514.

Lotte, F., Bougrain, L., Cichocki, A., Clerc, M., Congedo, M., Rakotomamonjy, A., and Yger, F. (2018). A review of classification algorithms for eeg-based brain–computer interfaces: a 10 year update. *Journal of Neural Engineering*, 15(3):031005.

Mollo, G., Pulvermüller, F., and Hauk, O. (2016). Movement priming of eeg/meg brain responses for action-words characterizes the link between language and action. *Cortex; a journal devoted to the study of the nervous system and behavior*, 74:262–276. 26706997[pmid].

Mora-Cortes, A., Manyakov, N., Chumerin, N., and Van Hulle, M. (2014). Language model applications to spelling with brain-computer interfaces. *Sensors*, 14(4):5967–5993.

Neuper, C., Muller, G., Kubler, A., Birbaumer, N., and Pfurtscheller, G. (2003). Clinical application of an eeg-based brain-computer interface: a case study in a patient with severe motor impairment. *Clinical Neurophysiology*, 114(3):399 – 409.

Neuper, C. and Pfurtscheller, G. (2010). *Neurofeedback Training for BCI Control*, pages 65–78. Springer Berlin Heidelberg, Berlin, Heidelberg.

Neuper, C., Scherer, R., Reiner, M., and Pfurtscheller, G. (2005). Imagery of motor actions: differential effects of kinesthetic and visual-motor mode of imagery in single-trial eeg. *Cognitive Brain Research*, 25(3):668 – 677.

Neuper, C., Scherer, R., Wriessnegger, S., and Pfurtscheller, G. (2009). Motor imagery and action observation: Modulation of sensorimotor brain rhythms during mental control of a brain-computer interface. *Clinical Neurophysiology*, 120(2):239 – 247.

Niccolai, V., Klepp, A., Weissler, H., Hoogenboom, N., Schnitzler, A., and Biermann-Ruben, K. (2014). Grasping hand verbs: Oscillatory beta and alpha correlates of action-word processing. *PLOS ONE*, 9(9):1–10.

Pfurtscheller, G. (1999). *Quantification of ERD and ERS in the time domain*, pages 89–105. Elsevier B.V., Netherlands, revised edition vol. 6 edition.

Pfurtscheller, G. and Neuper, C. (2001). Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89(7):1123–1134.

Pulvermuller, F., Hauk, O., Nikulin, V. V., and Ilmoniemi, R. J. (2005). Functional links between motor and language systems. *European Journal of Neuroscience*, 21(3):793–797.

Rezeika, A., Benda, M., Stawicki, P., Gembler, F., Saboor, A., and Volosyak, I. (2018). Brain-computer interface spellers: A review. *Brain sciences*, 8(4):57. 29601538[pmid].

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., and Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. *Clinical Neurophysiology*, 113(6):767 – 791.

Zander, T. O., Kothe, C., Jatzev, S., and Gaertner, M. (2010). *Enhancing Human-Computer Interaction withInput from Active and Passive Brain-Computer Interfaces*, pages 181–199. Springer London, London.