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Robust Online Movement Prediction from EEG Data for Post-Stroke Rehabilitation

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Abstract

Stroke is one of the leading causes of long-term disabilities and requires effective sensory motor rehabilitation in the early post stroke period to provide rehabilitation therapy as required. While the use of the non-invasive electroencephalogram (EEG) in Brain-Computer Interfaces (BCIs) has been studied already for decades, approaches that enable reliable detection of movement intentions from EEG are still missing or unsatisfactory. Therefore, we developed two approaches to improve reliability and practical applicability in the detection of human movement intentions from EEG signals to extend robot-driven post-stroke rehabilitation approaches. The first approach was developed for the continuous detection of EEG-based movement intentions to support post-stroke rehabilitation using the RECUPERA exoskeleton developed at our institute. In this approach, two neural network models were applied for a robust online detection of human movement intentions from EEG. The second approach was developed to avoid a dedicated calibration session, which is usually required to train an EEG classifier during a therapy session. In this approach, we used transfer learning to improve the practical applicability of the BCI in real therapy sessions. Both approaches were combined and integrated into a realistic virtual kitchen scenario to provide a comprehensive therapy approach with gamification providing a contextual environment and enabling reliable interpretation of non-invasive EEG. Although the presented approach yields promising first results, the approach has only been tested with healthy subjects so far.

Introduction

Stroke is the leading cause of disabilities, with 38% of stroke survivors suffering from such disabilities in their everyday life [1]. 94 million people are living with the serious effects of stroke and the number of new strokes occurring every year with 12 million people is tremendous [2]. Due to this, there is a huge need for improved and extended therapy possibilities for efficient and effective sensorimotor rehabilitation after stroke. To enable such effective sensorimotor post-stroke rehabilitation, traditional physiotherapy can be combined with robot-assisted therapy [3, 4, 5]. For this purpose, active exoskeletons [6] can be used to relieve the burden on the therapists by enabling the support of executed movements during therapy sessions and by extending therapy options [7].

Therefore, we developed the RECUPERA Reha exoskeleton system, which is an active upper-body exoskeleton designed to assist patients during post-stroke rehabilitation [8]. To support movement therapy, RECUPERA has three distinct operational modes: 1) gravity compensation, 2) teach and replay, and 3) mirror mode. In gravity compensation mode, the weight of the exoskeleton arm is compensated so that the wearer does not feel the extra load. In teach and replay mode, a pre-trained movement is repeated multiple times. Such a taught movement can be triggered, for example by the output of a non-invasive EEG-based BCI. In mirror mode, the system allows for simultaneous bilateral movements of both arms, mirroring the movement of the unaffected arm to the affected arm of patients. This results in the possibility to provide a special form of mirror therapy [9] by adding real movement execution to an otherwise illusion therapy. This, in turn, has the potential of enhancing therapy outcome by providing not only visual feedback but also proprioceptive feedback from the affected limb's movements.

By leveraging these capabilities of our system, we aim to create a natural interaction between the user and the system by decoding the movement intentions from their EEG signals [10, 11]. This allows for the implicit decoding of the person's movement intentions while the person is interacting with the system by executing movements of daily living. There are many examples of how the intention to move can be detected from EEG signals, e.g. [12, 13, 14]. However, to achieve this, a reliable and practical method for online movement intention detection from EEG data is required. In particular, the continuous asynchronous detection of such movement intentions is very challenging [15, 16], and the chances of false positive classifications occurring are much higher as compared to a synchronous classification as e.g. described in [17]. There is a clear need for improving continuous asynchronous detection of movement intentions based on the EEG.

Furthermore, beyond reliably detecting movement intentions, such an approach must demonstrate strong practical applicability for real therapy sessions by minimizing any time overhead unrelated to the therapy itself (see also [10]). Such overhead could be the preparation time of a gel-based EEG, and the additional time spent recording training data to calibrate the classifier. Those factors limit the practicality of EEG based BCI applications.

In addition to detecting the person's movement intention solely by analyzing or classifying the EEG signals, the knowledge about the context of interaction in such a rehabilitation scenario can help to improve the interpretability of the person's intentions [18, 19]. This context can be embedded into a controlled virtual reality (VR) environment that enables intuitive and realistic interactions. The adjunctive use of VR to provide intuitive and motivating training in rich sensory stimulating environments [20] can promote reorganization and restructuring of neuronal circuits [21]. VR offers self-embodiment using virtual avatars [22], enriched visual, auditory and tactile feedback [23] and playful training in serious gaming environments, which have all been proven advantageous in the rehabilitation of stroke patients and can also be of aid for eliciting better discriminable EEG patterns for BCIs [24], without impeding EEG signal quality [25].

In our work, we developed a comprehensive stroke rehabilitation scenario that consists of a robust online EEG processing pipeline which utilizes neural network models for robust asynchronous detection of movement intentions. Additionally, this was combined with a novel classifier transfer approach to eliminate the need for a specific calibration session (see [10]). Finally, these improved EEG classification methods were integrated into a VR kitchen environment. Movements and interactions were supported by the exoskeleton's functionalities triggered by the detected movement intentions from the EEG and the contextual information provided by the VR environment as described in more detail below.

Robust Prediction of Movement Intentions

Robust and accurate predictions of movement intentions from the EEG signals are of utmost importance especially when these classification results trigger exoskeleton movements. A single misclassification could lead to unexpected behavior of the robot (e.g., an exoskeleton). Such behavior can be early, or unwanted movement starts, which must be avoided at all costs. This is particularly challenging when detecting movement intentions for a person's self-paced movements, as the EEG data needs to be classified continuously and asynchronously throughout the session irrespective of whether certain events such as stimuli occur. Thus, in most EEG-based BCIs, predictions are not continuously made in an asynchronous fashion to detect movement intentions. Instead, only single EEG windows are cut and evaluated after a stimulus to distinguish between two or more classes, as for example in [26, 27]. In such cases, the chances of a correct classification would be at 50% for two classes but much lower for a continuous detection of a movement onset (i.e. movement intention) from sliding windows. This is because multiple windows need to be correctly classified consecutively to achieve a correct final output to trigger the support of the exoskeleton as required. Such classifications are challenging and require advanced methods to ensure robust predictions.

To tackle these challenges, we developed an EEG processing pipeline that combines two neural networks, namely the EEGNet [28] and a Multilayer Perceptron (MLP) model. This combination enhances the robustness and performance of continuous classifications by minimizing false (positive) detections, which would result in an undesired early movement of the exoskeleton when aiming to detect movement onsets. This would lead to the patient becoming suspicious of the system due to undesired behavior.

Due to the promising results of the approach, we applied this method in a live demo with the exoskeleton, where movements were triggered solely by the detected movement intentions from the classification of non-invasive EEG signals. In the following Figure 1, the subject of the live demo is shown during the interaction with the exoskeleton, where movement onsets are continuously classified from the EEG.

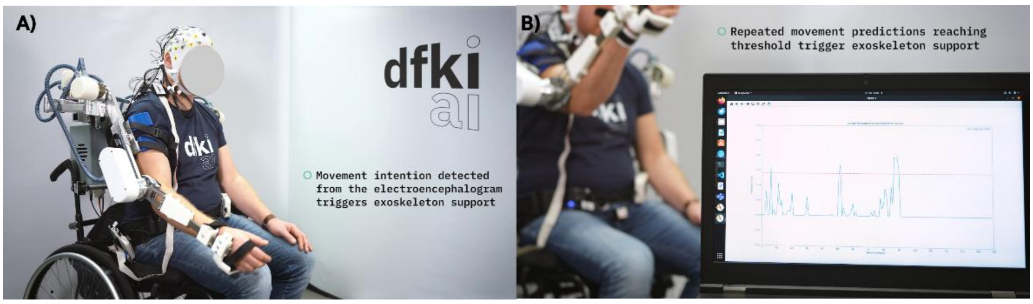

Figure 1: Online EEG-based movement prediction with a healthy subject to trigger exoskeleton support. In A) the subject remains in a resting period. In B) a movement intention is detected by the EEG classifiers (EEGNet and MLP

models), and the support of the exoskeleton is triggered after the prediction score exceeds a thresholding value shown on the monitor on the right.

Avoidance of Calibration Sessions

Another critical factor in enhancing the practical applicability of BCIs for robot-assisted stroke therapy is the reduction of preparation times of EEG-based movement intention recognition. To address this issue, we have proposed a novel approach that eliminated the need for a dedicated calibration session. This approach applies a classifier transfer between two movement tasks - unilateral movements and bilateral movements [10]. In this approach, EEG data is recorded during bilateral movement therapy, which is a part of the rehabilitation session itself. Subsequently, a classifier is trained and transferred to predict the unilateral movement intentions of a patient's affected arm. This concept is illustrated in Figure 2.

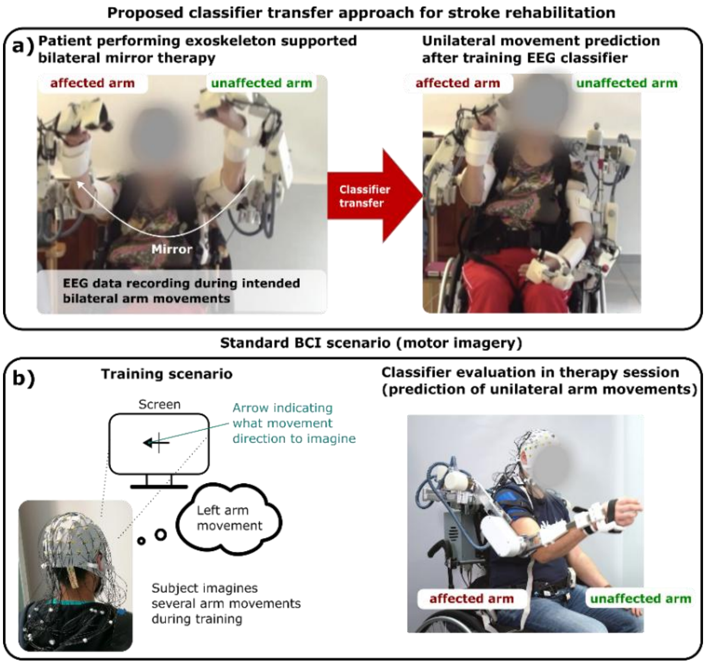

Figure 2: Comparison between the classifier transfer approach for stroke rehabilitation and the motor imagery (MI) scenario used in rehabilitation. In a) a patient is shown performing bilateral movements (mirror mode) while EEG data is being recorded. The classifier is transferred after training to predict unilateral movement intentions of the affected arm. In b) a standard MI training scenario with an evaluation of the classifier for stroke rehabilitation is shown. Figure from [10].

The following sections describe a summary of the proposed approach as mentioned in [10].

Methods

Eight healthy subjects (25.5 ± 4.0 years) performed self-paced and self-intended unilateral and bilateral arm movements and gave their written informed consent to participate in the study. Each participant performed a total of 120 movement trials under both conditions (unilateral and bilateral) and each trial consisted of a resting period of at least 5 seconds followed by an executed reaching movement to a button, placed in front of the subject.

EEG data was recorded from 64 channels (extended 10-20 system) using the LiveAmp system from Brain Products GmbH with active electrodes. The data was limited to a bandwidth of 0.1 - 131.0 Hz by the measurement hardware. The EEG data was cut into 1-second windows and preprocessed window-wise by applying a channel-wise standardization, decimation to 20 Hz, and bandpass filtering using an FFT bandpass filter from 0.1 - 4.0 Hz. Afterwards, an xDAWN spatial filter [29] was applied to reduce the spatial dimensionality, and the last 200 ms (4 samples) of the four pseudo channels that remained after spatial filtering were used as features for classification. The features were normalized with a Gaussian feature normalization and fed into an L1 regularized SVM.

To investigate the effect of the proposed classifier transfer approach on classification performance (balanced accuracy), we performed a two-way repeated measures ANOVA with *number of channels* and *train-test condition* as within-subjects factors. Here, we performed pair-wise comparisons under each within-subjects factor: comparisons between four different numbers of channels (N = 32, 21, 16, 8, 4) and comparisons between three different train-test conditions: (A) *unilateral-unilateral* (no transfer), (B) *bilateral-bilateral* (no transfer), and (C) *bilateral-unilateral* (cross-task transfer). In addition, we performed a two-way repeated measures ANOVA with *channel constellation* and *train-test condition* as within-subjects factors. Here, we performed pair-wise comparisons under each within-subjects factor: comparisons between two types of *channel constellation* (standard vs. custom) and comparisons between three different train-test conditions.

Results

There were no significant differences between the train-test conditions A (baseline) and the proposed transfer approach C (cross task transfer) for all numbers of evaluated EEG channels which were 32, 21, 16, 8, and 4.

In addition, the use of the custom channel selection significantly improved the performance of the transferred classifier (condition C) for 32, 21, and 16 EEG channels which clearly indicates the effectiveness of the proposed knowledge-driven channel selection method when applying the classifier transfer.

Integration into a Virtual Reality Environment

In addition to the exoskeleton, which physically supports the movements of stroke patients, a virtual reality (VR) environment can be used to assist patients in practicing typical activities of daily living enabled by the exoskeleton [30]. Therefore, we developed a virtual kitchen scenario that offers the patient the opportunity to perform supported unilateral as well as bilateral interactions. In our scenario, objects that are used in everyday life can be picked up and placed at target locations. Furthermore, the used HTC Vive pro Head-Mounted Display (HMD), is also equipped with a Tobii eye tracker, that allows for a selection of objects in the virtual environment from the eye gaze of a person. The main advantage of a VR approach embedded in a robot-assisted rehabilitation scenario is that it provides a controlled environment where the current state of action is always known. This means, for example, that information about positions of target objects that should be grasped or moved, as well as objects that can be selected with the eye gaze is always available.

The VR scenario provided the possibility to perform unilateral or bilateral interaction, while the movements of the exoskeleton were synchronized with the interaction in VR. Furthermore, a game logic was integrated, which shows the subject/patient a sequence of tasks to perform. The VR scenario described is illustrated in Figure 3.

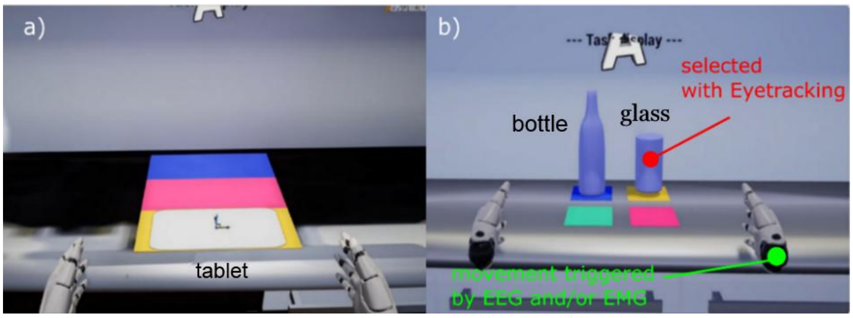

Figure 3: Developed VR kitchen scenario for targeted stroke rehabilitation. In a) the scenario for bilateral interaction with a tablet is shown, while in b) the scenario for unilateral interaction with a glass and bottle is illustrated.

Stroke Rehabilitation Scenario

As mentioned above, the developed multimodal stroke rehabilitation scenario consists of three parts - *robust online prediction of movement intentions, avoidance of calibration sessions,* and *virtual reality scenario,* integrated into a single application. In this, the virtual environment and game logic provide the base for performing unilateral and bilateral movements with the help of the exoskeleton. Here, the tasks to be performed are shown through the VR glasses (see Figure 4 right).

In this scenario, we assumed that the healthy test subject suffers from a monoparetic stroke, where the right arm is mostly disabled but the hand function still intact to some degree. Therefore, the applied custom EEG channel selection from the *avoidance of calibration sessions approach* was directly applied so that the subject was prepared with an EEG cap with 14 custom selected electrodes placed on the left side of the motor cortex. Later, the HMD headset was placed over the EEG cap (compare Figure 4). As in [10], we recorded the EEG signals during the bilateral interaction of the subject in the virtual kitchen scenario with the help of the exoskeleton's mirror mode. The onsets of the arm’s movements were computed from the exoskeleton’s sensor data using a thresholding technique [31]. After recording the training data (80 movement trials) during the bilateral interaction according to the displayed task, both neural network models, namely the EEGNet and the MLP, were trained and transferred to predict unilateral movement intentions.

During the unilateral movement scenario (see Figure 3b) the subject first selected a target object with the eye tracker. Thereafter, the exoskeleton’s movement was triggered by the EEG classification score which was computed from the prediction scores of both models using AND logic. After the movement was triggered, the exoskeleton moved to the target location. It should be mentioned that all EEG classification results were ignored before an object is selected with the eye gaze. Using this contextual information from the game allows for the reduction of false positive classifications.

At this point, the object could be grasped, which was triggered by the EMG signal of the flexor carpi radialis that was processed using a thresholding method for grasping detection (movement onset) [32]. It should be noted that the trigger for grasping could also result from the EEG classification. After releasing the object, which was again triggered by EMG, the same sequence continued with a different task shown on the screen. Therefore, a comprehensive stroke rehabilitation scenario was realized by integrating multiple modalities into a realistic robot-supported BCI application.

Figure 4: Multimodal robot assisted stroke rehabilitation scenario. The subject on the left is attached to the exoskeleton performing bilateral movements in the mirror mode of the exoskeleton and is wearing an HMD and EEG cap. On the right, the synchronized virtual kitchen is shown during placement of the tablet.

Discussion and Outlook

Here, we presented a stroke rehabilitation scenario which is based on three methodological approaches - *robust online prediction of movement intentions, avoidance of calibration sessions* approach, and *virtual reality integration*. The main improvements of this approach are enhanced robustness and applicability of the EEG-based detection of movement intentions that were integrated into the VR application. Nevertheless, the demonstrated scenario was only evaluated with one healthy subject, and further evaluations with stroke patients are required. To this end, we recorded an EEG data set of 9 stroke patients who performed unilateral and bilateral movements or movement attempts under realistic conditions to evaluate the presented approaches. Furthermore, approaches such as the integration of dry EEG caps or the consideration of variabilities in BCI's need to be further investigated to boost practical applicability and reliability in the future.

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