

EEG classifier cross-task transfer to avoid training sessions in robot-assisted rehabilitation

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Abstract

Background: For an individualized support of patients during rehabilitation, learning of individual machine learning models from the human electroencephalogram (EEG) is required. Our approach allows labeled training data to be recorded without the need for a specific training session, which is important for the feasibility of using EEG to support exoskeleton-assisted therapy. For this, the planned exoskeleton-assisted rehabilitation enables bilateral mirror therapy, in which movement intentions can be inferred from the activity of the unaffected arm. During this therapy, labeled EEG data can be collected to enable movement predictions of only the affected arm of a patient based on the EEG and a proposed transfer learning approach in the second step.

Methods: A study was conducted with 8 healthy subjects and the performance of the classifier transfer approach was evaluated. Each subject performed 3 runs of 40 self-intended unilateral and bilateral reaching movements toward a target while recording EEG data from 64 channels, EMG data from 16 channels, and motion tracking data. A support vector machine (SVM) classifier was trained under both movement conditions to make predictions for the same type of movement. Furthermore, the classifier was trained under the bilateral condition and then transferred to predict motion intention under the unilateral condition. The approach was evaluated comparing a custom EEG channel selection method to a standard electrode constellation under varying the number of EEG channels.

Results: The results show that the performance of the classifier trained on selected EEG channels evoked by bilateral movement intentions is not significantly reduced compared to a classifier trained directly on EEG data including unilateral movement intentions. Comparisons with standard channel constellations show that the comparable performance was enabled by our knowledge-based channel selection. Moreover, the results show that our approach also works with only 8 or even 4 channels.

Conclusion: It was shown that the proposed classifier transfer approach enables motion prediction without explicit collection of training data. Since the approach can be applied even with a small number of EEG channels, this speaks for the feasibility of the approach in real therapy sessions with patients and motivates further investigations with stroke patients.

Keywords: EEG; movement prediction; rehabilitation; classifier transfer; robot assisted therapy; lateralized readiness potential (LRP); event related potential (ERP); BCI; transfer learning

Background

With the demographic change, concepts for maintaining the health of an increasingly aging population must be rethought. As shown in a statistic by [1] the cost of stroke in 2017 was €60 billion in the 32 European countries alone. Necessary changes affect the entire range of health care from prevention and acute treatment to rehabilitation and reintegration of persons who are ill or injured into everyday life. One of the approaches pursued is the use of robots in rehabilitation therapy, which was clinically tested, for example, as early as 1994 with the MIT-MANUS [2] and meanwhile proven to improve arm and hand function and muscle strength [3] and to enable more effective therapy if combined with traditional physiotherapy [4].

The goals of using such complex technologies are manifold and range from reducing costs to increasing the efficiency of therapy and relieving the burden on the therapists, to achieve high repetitions in interactive and self-initiated therapy as well as to extend therapy options [5].

On the other hand therapy strategies for the rehabilitation and restoration of functions in humans, as for example discussed in [6] in order to maximally restore functions of patients with spinal cord injury (SCI), can be very intense to achieve optimal results. Regarding physiotherapy it was shown that patients receiving intensive peer mentoring during and after rehabilitation had greater gains in self-efficacy [7], which is highly important in rehabilitation [8]. It further decreases the time for unplanned rehospitalizations [7].

For support at home, robotic solutions provide assistance in daily living (ADL), which can range from

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helping a patient balance [9] while walking and standing to complex assistance with reaching [10] and grasping [11].

Active exoskeletons [12] are commonly used for such assistance, as well as for rehabilitation therapies, and have shown to be effective in neuromotor rehabilitation, especially after stroke [13, 14, 15].

The application of new robotic technologies, such as exoskeletons, gives us hope to cope up with higher demands caused by demographic changes, the orientation to more intensive therapy, self-efficacy of patients, relieve of therapists, extension of therapeutic options and reduction of cost, all together reducing the total disease burden by 6 to 10 per cent by 2040 [16].

However, for an individualized support, learning of individual models from human data is required. To acquire such data without the demand of a person to attend long training and calibration sessions is very relevant. Here, we show that we can successfully combine rehabilitation sessions with data acquisition to train models that infer movement intentions in humans, which in turn, can then be supported by an assistive robotic device.

Exoskeletons and physiological measures in therapy

To provide support when needed [17, 18, 19], physiological measurements such as the electromyogram (EMG), which can for example be recorded from a healthy leg to control a disabled leg using an exoskeleton [20], or the electroencephalogram (EEG) which allows conclusions to be drawn about a user's intention to move, are of great importance for successful neurorehabilitation [13, 14]. In particular, EEG can be used to infer movement intentions [21, 12], for example, where a patient wants to move [22, 23]. There are many examples of how human EEG can be used to control exoskeletons using a brain computer interface (BCI) [24, 22, 23, 25, 13, 14, 26]. However, BCIs are often not used to decode brain activity that correlates with the brain processes that control movement intention, planning, and execution; instead, other brain signals are used, such as the activity evoked in the visual cortex by flickering light, known as steady state visual evoked potentials (SSVEP) [22, 23, 27] to rather artificially make use of the patient's EEG as a control input. To bridge the gap between brain and body caused by brain injury and to promote rehabilitation, such an approach is not the preferred one. Instead, brain activity that drives movement intention, planning, and execution should be used as a natural or intrinsic bridge between the brain and the body [28, 29], using both, the physiological data that directly encodes the humans intention and the autonomous capabilities of the robotic system, i.e., an exoskeleton.

Transfer learning and classifier transfer in BCIs

In the field of BCIs, long training sessions are often required to record a large amount of training data [30, 31]. However, transfer learning (TL) can be applied in BCI applications to reduce the calibration effort and training duration. This can be achieved by using prior knowledge or data that does not originate from the target session, subject or even measurement device or task [32]. TL has recently proven its potential to improve classification performance and reduce calibration times in several investigations, e.g., [33, 34, 35, 36, 37]. This is of high importance for enhancing the usability of BCIs in real-world applications.

In addition to cross-session as well as cross-subject paradigms, a cross-task TL approach could achieve complete avoidance of calibration sessions and even enable learning in the first place if labeled data is available only for a training task but not for a test task, as in this work. However, in comparison, cross-task classification approaches based on EEG data and TL have been less comprehensively investigated [32]. Nevertheless, across different fields of BCI research, transfer approaches for cross-task EEG classification have been proposed. In our previous work, we showed that a classifier trained on EEG data from an observation scenario could be transferred to detect erroneous behavior of a robot during an interaction scenario [38, 39, 40, 41]. Therefore, the elicited event-related potential (ERP), namely the error-related potential (ErrP), could be classified in the transfer case although the tasks and ERP shapes differed between training and testing. The transferrability of a classifier for the detection of errors across tasks was also shown in [42], where a deep convolutional neural network was used to detect errors for two different error paradigms from intracranial EEG data. Another application of a classifier transfer is the detection of target and *missed target* events from EEG while the classifier was trained on EEG data evoked by target and *standard* events (oddball paradigm) to enhance the amount of available training data and, hence, to enable classification of EEG trials evoked during recognition of targets and the failure of recognition of those [43, 44, 45]. Further examples of applied cross-task EEG classification can be found in literature in the area of workload recognition [46, 47, 48], where the performed workload task differed between training and testing a classifier or model. For example in [46], a domain adaptation approach was applied that improved the workload classification performance for the transfer case compared to a non-transfer case. Besides cross-task EEG classification, where a classifier is strictly trained on one task and tested on another task, fusion approaches were

applied in which data from different tasks were combined for training a classifier [49, 50]. However, classifier transfer and TL approaches for the detection of movement intentions in motor imagery or motor execution paradigms have been little investigated so far. A few examples are the decoding of forearm movements that were improved by combining data from motor imagery and motor execution tasks [51] as well as the investigation of cross-subject and cross-task motor imagery classification [52].

Nevertheless, to our knowledge, the transferability of a classifier between bilateral and unilateral movements (upper body reaching movement tasks), especially conceptualised to support rehabilitation therapy, has not been proposed or investigated so far.

Approach and goal of the paper

In this work, we focus on how to generate training data for EEG-based intention recognition to guide support using an active exoskeleton [53] for unilateral arm movements of the affected arm after stroke. Our approach eliminates any time spent by the patient generating training data, as data collection is integrated into the therapy training itself.

For motion intention detection in human EEG, training data is needed to train a classifier or model for the prediction task. Even if a patient is able to complete such long training sessions, this is not desirable since all time available should be used for therapy in the early post-stroke period in which the brain is very plastic [54]. Waste of time in this very sensitive time by plainly recording data to train a classifier must be avoided as far as possible.

Here we present our approach to train a classifier during a therapy session that does not require intention recognition from EEG activity but makes use of the intelligence of the robotic system to timely map movement intention to movement execution. This is done by making use of the exoskeletons mirror mode in which a movement of the unaffected arm is transferred to the affected arm by the exoskeleton [53]. Hence the exoskeleton supports mirrored dual arm movements intended by the patient. While the patient is exercising in this mode, EEG data can be recorded. The recorded EEG contains activities associated with the planning and execution of bilateral arm movements and can be used to train a classifier to infer movement intention of both arms. The usability of such classifier to determine the motion intention of the affected arm alone, will be explained in the following methods section. To develop such a classifier-transfer approach and evaluate its feasibility in principle, we conducted a study with healthy subjects and report and discuss the results here.

Methods

Proposed Classifier Training Method

Table 1 Definition of concept for training and testing the EEG classifier.

		training	testing
A	no transfer	unilateral	unilateral
B	no transfer	bilateral	bilateral
C	transfer	bilateral	unilateral

To train an EEG-classifier to predict movement intentions only for the affected arm of stroke patients, the following two-step concept was developed. In the first step, the EEG classifier is trained during the execution of bilateral movements (in a mirror mode rehabilitation session). The onsets of the bilateral movements are inferred from the non-affected arm to generate reliable labels to train the classifier. In the second step, the classifier is transferred to predict unilateral movements of the affected arm. The transfer approach consists of training on EEG data derived from bilateral movement executions and applying a custom EEG-channel selection to improve the transferability of the classifier by data adaptation. Since the LRP (Lateralized Readiness Potential) [55, 56], that is associated with movement planning, can be observed from EEG-channels of the motor cortex side contralateral to the moved upper limb [57], we focus on the differences and similarities in the EEG data between bilateral and unilateral movement intentions. Therefore, we customly select EEG-channels for the data processing, that are related to the planning of unilateral movements with the affected limb. Hence, the abilities of the non-affected limb are used to generate reliable training labels and the classifier can be customly trained on the provided EEG-data, containing information about movement intentions of the affected arm. The proposed method was evaluated by conducting experiments, involving bilateral and unilateral movement tasks, executed by healthy subjects. The training and testing conditions of the evaluation are illustrated in Table 1.

Experimental Setup and Procedure

Eight healthy subjects (4 male, 4 female) at the age of 25.5 ± 4.0 years participated in the conducted study. Only healthy right-handed subjects with no history of neurological or muscular diseases were recruited for the experiments. All subjects were advised to be well-rested for the experiment. The subjects were seated in a comfortable chair inside a shielded cabin. In front of the subjects a custom-build board, including hand-switches and a button was placed on a table. The subjects were asked to perform a reaching task, by pressing the button with their thumb. The button was placed

at a height of approximately 25 cm and at a distance of 30 cm away from the resting position. The resting position was defined by the hand switches, where the subjects were asked to place their hands during the resting period. The position of the button was adjusted to the arm length of the subjects. Start and endpoint of the movements were standardized by ensuring a 90-degree forearm-upper arm angle at rest and 0 degree when pressing the button.

The experiment consisted of two different movement tasks which were 1) unilateral reaching movements and 2) bilateral reaching movements. The sequence of the task was varied between subjects (counterbalanced) in order to avoid possible learning effects. For the unilateral task, only the dominant right arm was moved whereby in the bilateral task a synchronous movement of both arms (both thumbs pressing the button) was executed. Each task included 3 sets of 40 self-initiated movements. Therefore, each subject performed a total of 120 trials for each task. Each trial consisted of a resting period of at least 5 seconds followed by a self-initiated and self-paced reaching movement. Trials with a resting period under 5 seconds were excluded from the evaluation and an error symbol was presented on a monitor for a duration of 200 ms. The error symbol consisted of a fixation cross that turned from a green to a red background colour. During the hole experiment, a fixation cross with a green background was continuously shown on the monitor. After each set, the subjects were asked to relax for at least 5 minutes to avoid any fatigue. The whole experiment was designed and controlled by using the Presentation software [Neurobehavioral Systems, Inc., Albany, USA]. The experimental setup is illustrated in Figure 1.

Data Acquisition

EEG data was recorded using a LiveAmp64 amplifier and an actiCap montage with 64 active electrodes [Brain Products GmbH, Munich, Germany]. The electrodes were located according to the extended 10-20 system with FCz as reference electrode. All impedances were kept below a threshold of 5 k Ω and were controlled after each measurement set. The data was acquired at a sampling rate of 500 Hz and pre-filtered by the measurement device to a bandwidth of 0.1 – 131 Hz. To avoid possible artifacts during the recording, the subjects were asked to avoid head and eye movements as far as possible.

EMG signals were recorded bipolar (Ag/AgCl electrodes) by a WavePlus wireless system and picoEMG sensors by Cometa [Cometa srl., Barregio, Italy]. The EMG was sampled at 2000 Hz and reduced to a bandwidth of 10-500 Hz by filters of the measurement device. The signals were recorded from 8 muscles for the

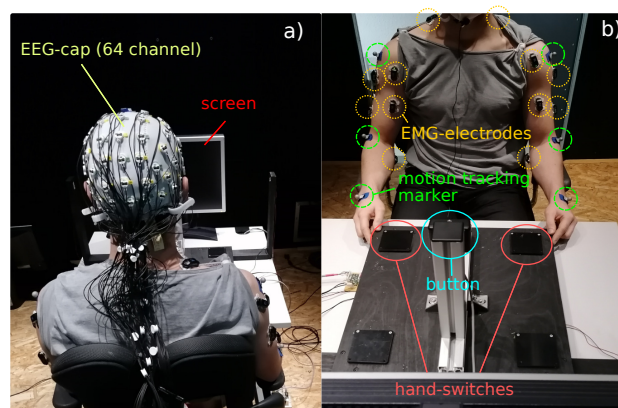


Figure 1 Experimental setup of the study. In a) a subject is shown sitting in front of a screen wearing an EEG-cap with 64 electrodes. In b) the custom build experimental board including hand-switches (orange) and a button (blue) as well as the placed EMG-sensors (yellow) and motion tracking marker (green) are illustrated.

right and left side of the body which were: M. biceps brachii medial, M. triceps brachii medial, M. triceps brachii lateral, M. deltoideus lateral, M. deltoideus anterior, M. deltoideus posterior, M. trapezius pars descendens (upper trapezius) and M. flexor carpi radialis. The skin was prepared with alcohol and electrodes were placed according to anatomical landmarks [58].

To mark the physical movement onsets, an infrared motion tracking system [Qualisys AB, Gothenburg, Sweden] was used in addition to the mechanical hand-switches. In total, 4 motion tracking cameras (Oqus 300+) were placed in the shielded cabin to record motion data. To track the motions, 3 reflecting markers were placed on the back of the hand, the elbow (next to the lateral epicondyle) and the deltoideus (muscle belly) on each side of the body. The motion tracking data was acquired at a sampling rate of 500 Hz.

All events during the experiments, such as pressing/releasing the hand-switches and the button as well as invalid trials (shown error symbols) were tracked by the EEG system. Additionally, the start and stop of the recordings of each measurement system was recorded by the trigger channels of the EEG system to synchronize all data in the offline analysis.

Estimation of Physical Movement Onset

For estimating the physical (ground truth) movement onset, the position data tracked by the motion capture system were analyzed and processed in an offline evaluation. Since the executed reaching tasks consisted of moving the hand from a resting position towards the button, the data from the reflective marker of the moved hand was used for the estimation. Note that in a later rehabilitation session, movement onsets will

be measured by the exoskeleton [26, 59]. Since only healthy subjects participated in the study, it was assumed for the evaluations, that the right arm is affected whereby the left arm is not affected. Therefore, for bilateral movements only the position data of the left hand was selected for estimating the ground truth movement onset.

In a first processing step, the EEG and motion capture data were synchronized. Afterwards the position data was re-initialized to the resting position by subtracting the mean position data, calculated from the first second (resting period) of each experiment. In the next step, the absolute distance to the resting position was calculated by computing the euclidean distance from the three-dimensional position data. Additionally, the velocity of the hand was calculated for each timepoint by taking the difference between two consecutive samples of the euclidean distance. The velocity was filtered by a lowpass filter with a cutoff frequency of 4 Hz (butterworth, 4. order) and normalized to the maximum value of the current trial. The distance and velocity were then combined by multiplication in order to provide an exact estimate of the movement onset. This procedure was chosen to calculate the onset, independent from small position fluctuations (producing high velocity values) or slight variations of the resting position between trials.

Starting from the movement period towards the resting period, it was searched backwards for a datapoint with a magnitude below a defined threshold. The search started at the time where the mechanical hand-switch was released since this is assumed to be the movement onset plus the mechanical delay of the device. The threshold was set to 0.6 mm and specified with respect to the resolution of the motion tracking system after calibration. The movement onsets were marked in the EEG data.

Channel Selection and Reduction

In order to provide a proper transferability of the classifier, we custom selected EEG channels by means of the knowledge about the surface distribution of relevant EEG activity with respect to individual EEG channels. Due to the fact that the LRP can be observed in the hemisphere contralateral to the side of the moved limb (right arm), we custom selected channels for the classifications that were located on the left hemisphere, especially in the area of the motor cortex. By this approach, we aim for enhancing the transferability of the classifier, that is trained on evoked EEG potentials from bilateral movement planning to predict unilateral movement intentions by selecting EEG channels related to right arm movements.

Besides enhancing the performance of the transferred classifier, we also aim to reduce the number of channels

to provide an approach that is feasible to be used with persons suffering from stroke. Therefore, we systematically reduced the number of channels used for the classification task in order to reduce the preparation effort in a real rehabilitation session. Due to this we evaluated the use of 32, 21, 16, 8 and 4 custom selected channels for the classification task. For all numbers of channels, the selection was made considering the C1 channel as a center of EEG activity related to movement planning, with the other channels located around it. Therefore, by reducing the number of channels the area around this center was further reduced in size. The specified EEG channels for the custom selection are illustrated in Figure 2.

In order to evaluate the relevance of custom channel selection, we further compared the custom selection to standard electrode constellations based on the extended 10-20 system. Since such a standard constellation comprises at least 16 EEG channels, we evaluated and compared 32, 21 and 16 channels for the standard constellation as a baseline to our custom channel selection. The standard channel constellations for the different numbers of channels is illustrated in Figure 3.

EEG Processing and Classification

For the processing and classification of the EEG signals, the signal processing and classification platform pySPACE [60] was used. A previously developed machine learning pipeline [21], specialized to detect the LRP, was adapted.

Preprocessing and Windowing

The EEG signals were processed window-wise by cutting out overlapping windows with a length of 1 s and a stepsize of 0.05 s. For each trial, a total of 81 windows, starting from window $[-5.00, -4.00]$ s to $[-1.00, 0.00]$ s were cut out with respect to the labeled physical movement onset at 0 s.

First, a subset of EEG channels corresponding to the evaluated channel selection methods, was included in further processing steps (see Channel Selection and Reduction). Afterwards the data was standardized channel-wise (zero mean, SD of one) and decimated to 20 Hz. Next, a FFT bandpass filter with a passband of 0.1-4.0 Hz was applied.

Feature Extraction and Classification

The channel dimension was reduced by applying an xDAWN spatial filter [61] with 4 remaining pseudo-channels, that was designed to enhance event related potentials. Afterwards, the last 4 samples of each window, that correspond to the last 0.2 s, were extracted as time domain features. Therefore, a total of 16 features were extracted for each window. The features

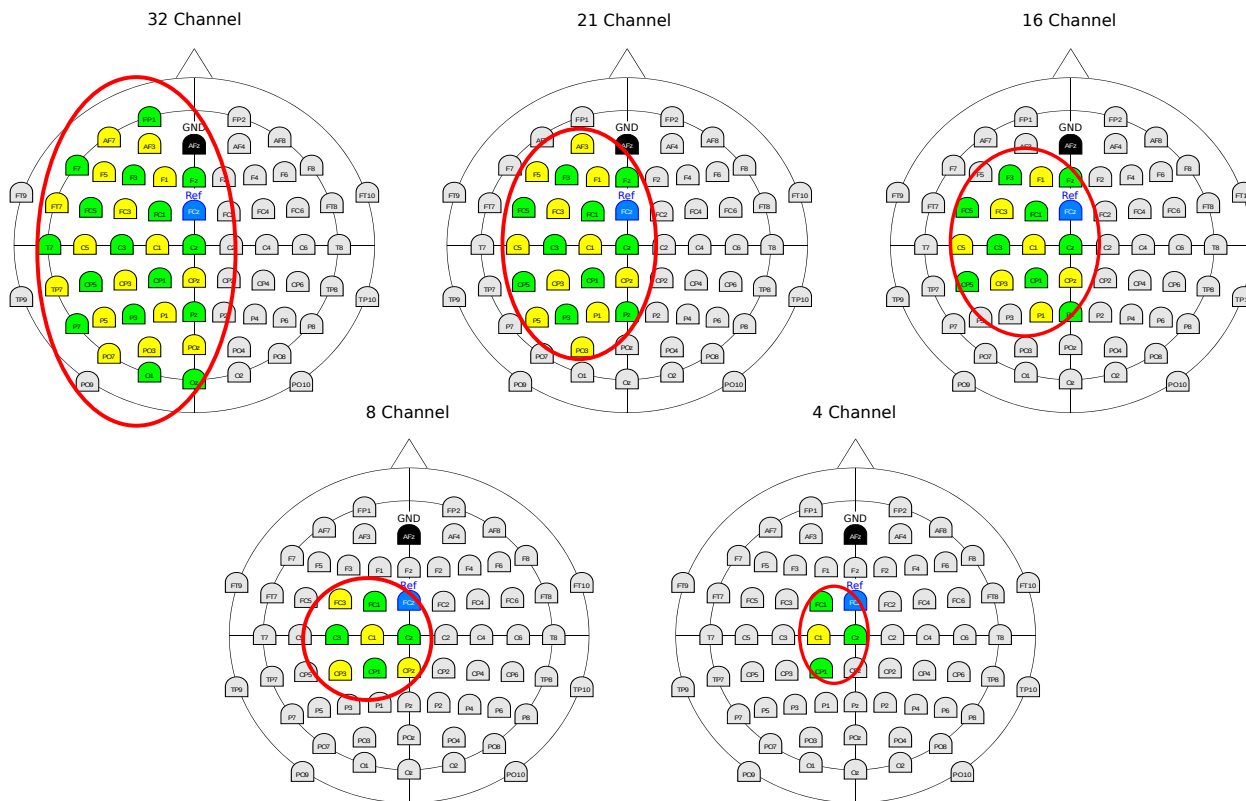


Figure 2 Custom selected channels from the left hemisphere. Channels used for the study are marked by a red circle.

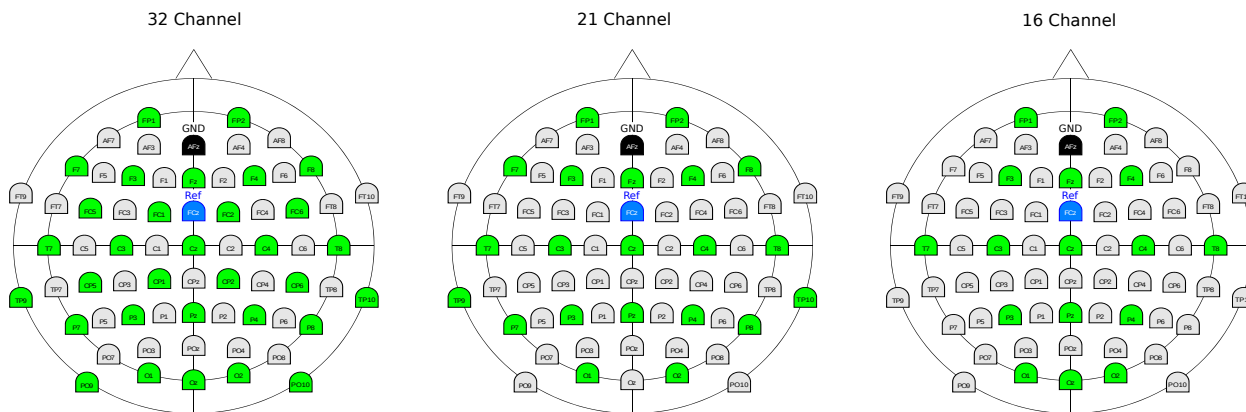


Figure 3 Standard channel constellation based on the extended 10-20 system. Channels used for this study are marked in green.

were then normalized by applying a gaussian feature normalization (zero mean, variance one). After feature extraction, an SVM with L1-norm regularization was trained for a binary classification task. The class labels were NoLRP (resting) and LRP (movement intention). The complexity parameter of the SVM was optimized by applying a grid search with 7 equal spaced values in a range of 10^{-6} to 10^0 . The class weights of the SVM were set to a ratio of 1 : 2 (NoLRP:LRP). The windows $[-1.10, -0.10]$ s and $[-1.00, 0.00]$ s were used as training instances of the LRP class and the windows

$[-3.05, -2.05]$ s, $[-3.25, -2.25]$ s and $[-3.50, -2.50]$ s were selected as training instances of the NoLRP class. After training, the classifier was used to predict all windows of a separated test set. This was done to simulate a real online application scenario, where a classifier is continuously deciding between a resting period and movement intention. The SVM scores were then transformed into a probability by using platts sigmoid function [62]. A probability greater than 0.5 corresponded to a detected movement intention (LRP

class), otherwise a resting period (NoLRP class) was detected.

Performance Evaluation and Metrics

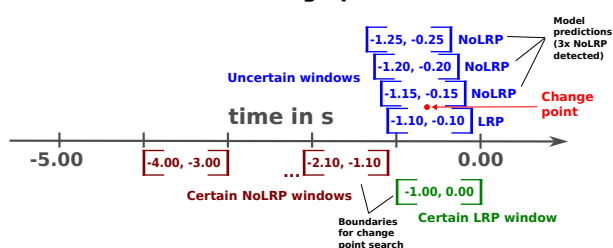
Since the class ratios (NoLRP:LRP) are unbalanced for a continuous detection of movement intentions (longer resting periods than movement planning) the balanced accuracy (BA) was used as a performance metric. The balanced accuracy calculates the performance with respect to the individual class rates for both classes and is defined as the mean of the true negative rate (TNR) and the true positive rate (TPR). During the evaluation, care was taken that the TNRs and TPRs are not imbalanced in order to avoid a disbalance or bias between the prediction of the NoLRP and LRP classes.

To emulate an online application scenario, the classifier was evaluated by creating set wise train and test pairs. For each condition, 2 sets were used for training and the remaining was used as a test set to evaluate the performance. For each condition a total of 24 performance results were produced due to 3 train/test permutations for all 8 subjects.

To evaluate the performance results in respect to the characteristics of the LRP, a relabelling technique was applied to the classification outcome in order to generate ground truth labels for performance evaluation. Since the individual planning and execution of a movement, for example depending on the waiting time, is affecting the temporal characteristics of the LRP [63], a variability between single trials must be considered. Since the actual start of the movement planning remains unknown, ground truth labels of the windows were computed based on the classification outcome for each individual trial considering an online application. In the following, the procedure is described in detail.

First, a change point of classes (class boundaries) was computed, which gives an estimate of a started movement planning phase following the resting period and therefore the starting point of the LRP class in time. This change point was defined as a point between two consecutive windows that is determined inside an interval ranging from window $[-2.00, -1.00]$ s to window $[-1.00, 0.00]$ s. This is the range where the movement planning is to be expected when continuously classifying windows in an online application scenario. The windows at the boundary of the defined interval correspond to windows where the true label is known with high certainty for the NoLRP ($[-2.00, -1.00]$ s) and LRP ($[-1.00, 0.00]$ s) class. The choice of the class boundaries was also discussed in our previous work in [21]. If three consecutive NoLRP windows were counted backwards in time (starting from window $[-1.00, 0.00]$ s backwards) within this range,

A) Determine label change point



B) Set ground truth labels

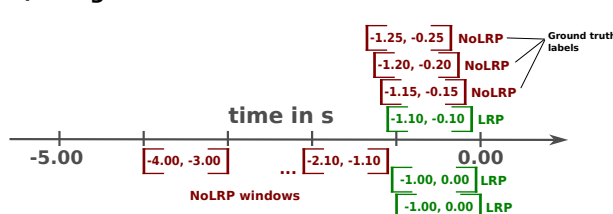


Figure 4 Illustration of the relabeling technique. In **A)** the determination of the label change point between two consecutive windows is shown while in **B)** the ground truth label after applying the method are illustrated.

the label change point was detected and the labels of all windows prior to this point were set to the NoLRP class and past this point to the LRP class. In case no change point was found inside this range, all windows within this range were defined as instances of the LRP class corresponding to a detected long movement planning phase. However, for windows where the true label is known (from the experimental design), the class label remained fixed for each movement trial. Therefore, all windows prior to window $[-2.00, -1.00]$ s were always instances of the NoLRP class while window $[-1.00, 0.00]$ s was always an instance of the LRP class.

In conclusion, this technique was used to provide ground truth labels for each sliding window based on the nature of the LRP under predefined constraints where the detection of a movement intention was allowed. To illustrate the procedure, the applied method is shown in Figure 4.

Statistical Analysis

For the main analysis, the classification performances were analyzed by two-way repeated measures ANOVA with *number of channels* and *train-test condition* as within-subjects factors to investigate the effect of transfer depending on the number of channels: *transfer* vs. *no transfer* (see Fig. 5). Additionally, we performed two-way repeated measures ANOVA with *channel constellation* and *train-test condition* as within-subjects factors to compare both standard constellation and custom channel selection for each *train-test condition* (see Fig. 6).

Results

Figure 5 shows the classification performance between both *train-test* conditions: (A) *unilateral-unilateral* (no transfer) and (C) *bilateral-unilateral* (transfer). We found no significant differences between both *train-test* conditions (A vs. C) for all setups of channel numbers (32, 21, 16, 8, 4). That means, the classification performance was for the *transfer* case slightly reduced, but did not significantly differ from the *no transfer* case.

Figure 6 shows the classification performance between both types of channel constellations: standard constellations vs. custom channel selection. The custom channel selection improved the classification performance. This was evident for the case *transfer* [standard constellations vs. custom channel constellations: *n.s.* for all setups of channels, see condition (C) in Fig. 6]. The case *no transfer* also benefited from the selection of custom channels when the number of channels was reduced (see condition (A) in Fig. 6). However, when EEGs from bilateral movements were used for training and test, we found no differences between both channel constellations, although in the custom channel selection only channels from the left hemisphere were used. Moreover, the classification performance was not affected by channel reduction (see, condition (B) in Fig. 6).

Discussion

In this work, we proposed a novel approach to generate labeled EEG data from bilateral movement executions to train a classifier to predict unilateral movement intentions with a high performance. The results show, that unilateral movement intentions can be predicted with a balanced accuracy up to 0.845 (for 32 channel, see Fig. 5) using the proposed approach for transferring the classifier. This implies that recorded EEG data from a bilateral interaction session, i.e., from a mirror mode rehabilitation session with an exoskeleton, can be used to predict unilateral movement intentions with a high performance.

Most interestingly, the results showed that there were no significant differences between classification performances of the condition *unilateral-unilateral* (A) and *bilateral-unilateral* (C) using the custom channel selection although a reduced number of channels was used for the classifications for the transfer condition (C) (see Fig. 5). This means, that the proposed transfer approach yields comparable performances to the no-transfer case for a unilateral movement prediction task based on EEG data.

As expected, the results showed that the performance of the classifier systematically decreases with the number of used channels for all conditions. Nevertheless, the results show that the number of channels

can be reduced, for example, from 32 to 21 channels without a significant performance loss in case of classifier transfer (condition C in Fig. 5). This means that a subset of channels covering to some extent relevant brain regions provide sufficiently relevant features for the detection of movement intentions. Even more interesting was, that we did not find significant differences between the transfer condition *bilateral-unilateral* (C) and baseline condition *unilateral-unilateral* (A) even though the number of channels was reduced for example from 32 to 21 included channels (see Fig. 5). This strongly motivates the applicability of the proposed approach, due to a clear reduction of preparation time when using a reduced number of EEG channels. Nevertheless, the channels must be carefully selected and were specifically chosen in the conducted study depending on the motion task in order to allow the channel reduction without much loss in performance. Therefore, the same number and selection of EEG channels may not be adequate for a different movement task (e.g., hand movements) and an alternative manual or automatic technique can be required when reducing the number of used EEG channels.

Most importantly, we found that a custom selection of EEG channels outperformed the use of a standard channel constellation for training and transferring the EEG classifier (see Fig. 6). Therefore, the custom channel selection outperformed the standard channel constellation, especially for the transfer case. This results indicate, that the custom channel selection allows the possibility to provide a proper transferability of the classifier to predict unilateral movements although only bilateral movements were executed in the training session. Although, preliminary measurements with stroke patients showed that movement intention can be inferred with similar performance compared to healthy subjects, brain activity patterns are different due to the disturbance after stroke. Therefore, the approach has to be further evaluated with EEG data from persons suffering from stroke.

Conclusion

We proposed a novel approach to train an EEG classifier on EEG data recorded during bilateral reaching movements that is afterwards transferred to predict unilateral reaching movements. Classifier transfer was supported by our knowledge-based selection of EEG channels as a data adaptation technique. The approach was evaluated with data from healthy subjects recorded in the conducted study. It was shown that the proposed transfer approach can predict *unilateral* movement intentions with a high performance although the classifier is trained only on EEG data recorded during *bilateral* movements even when using only a small amount of channels.

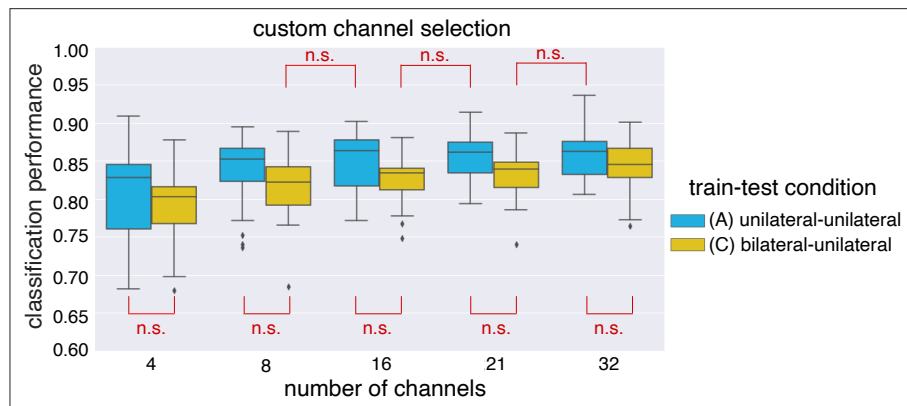


Figure 5 Transfer effect: classification performance between both *train-test* conditions: (A) no transfer (*unilateral-unilateral*) and (C) transfer (*bilateral-unilateral*). Details for *train-test* conditions, see Table 1. The *n.s.* stands for no significant difference

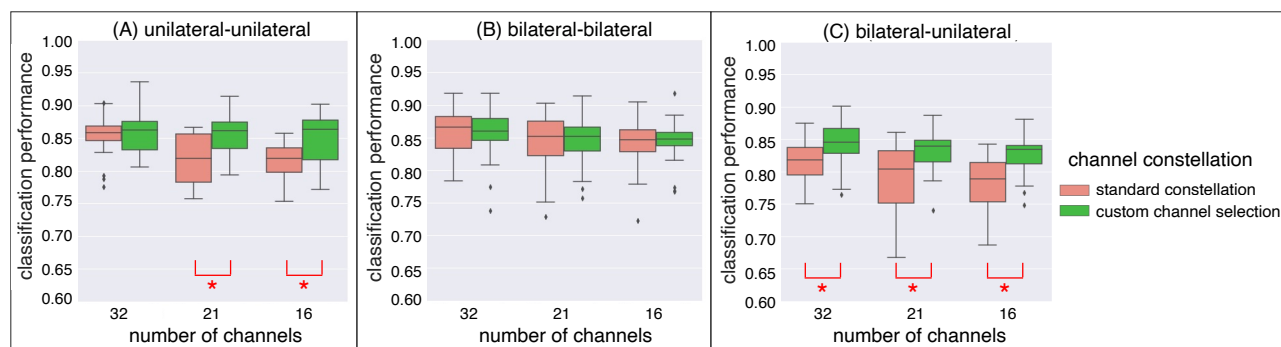


Figure 6 Effect of electrode distribution: classification performance between standard constellation and custom channel selection for all *train-test* conditions. Details for *train-test* conditions, see Table 1. The * stands for significant difference

Due to the promising results, we are planning further investigations with patients suffering from stroke to evaluate the proposed approach to improve stroke rehabilitation. In future work, we will use our approach in robot-supported rehabilitation using an upper body exoskeleton. In such an application bilateral movements of a hemiplegic patient allows to detect movement onsets from the non-affected arm while the assistive robotic device moves the affected arm synchronously with the unaffected arm (mirror mode). Hence, rehabilitation therapy can take place while EEGs are recorded and labeled to generate training data. After training a classifier on this data, unilateral movement intentions of the affected arm can be detected from it and supported by an exoskeleton. However, we expect that in the case of patients suffering from stroke channel selection must be adapted. To this end, an automated approach considering the type and effect of lesion would be preferable.

We believe that our envisioned novel robot assisted rehabilitation approach can improve future rehabilitation therapy coping with effects of demographic changes such as the rising life expectancy and the ac-

companying need for more support for the aging population.

Declarations

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Abbreviations

ADL: Assistance in daily living; EMG: Electromyogram; EEG: Electroencephalogram; BCI: Brain computer interface; SSVEP: Steady state visual evoked potentials; TL: Transfer learning; LRP: Lateralized readiness potential; SVM: Support vector machine; BA: Balanced accuracy; TNR: True negative rate; TPR: True positive rate; ErrP: Error-related potential; ERP: Event-related potential

Availability of data and materials

The datasets generated and/or analysed during the current study are available in the following Zenodo repository: <https://doi.org/10.5281/zenodo.10229480>.

Ethics approval and consent to participate

The conducted study was examined and found to be harmless by the University of Bielefeld according to the ethical guidelines of the German

Society for Psychology and the Professional Association of German Psychologists.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

The person on the images used in this manuscript gave a written consent (consent form) for publication.

Authors' contributions

N.K. recorded and analyzed the data, conducted the study, and performed the evaluation for classifying the data. E.K. and S.K. designed and supervised the study. S.K. performed the statistical analysis. N.K., E.K., and S.K. have discussed and proposed the classifier training approach and equally contributed in writing the manuscript.

All authors read and approved the final manuscript.

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References

- Luengo-Fernandez, R., Violato, M., Candio, P., Leal, J.: Economic burden of stroke across Europe: A population-based cost analysis. *European stroke journal* **5**(1), 17–25 (2020)
- Krebs, H.I., Hogan, N., Aisen, M.L., Volpe, B.T.: Robot-aided neurorehabilitation. *IEEE transactions on rehabilitation engineering* **6**(1), 75–87 (1998)
- Mehrholz, J., Pohl, M., Platz, T., Kugler, J., Elsner, B.: Electromechanical and robot-assisted arm training for improving activities of daily living, arm function, and arm muscle strength after stroke. *Cochrane database of systematic reviews* (9) (2018)
- Fazekas, G., Tavaszi, I.: The future role of robots in neuro-rehabilitation. *Expert Review of Neurotherapeutics* **19**(6), 471–473 (2019)
- Poli, P., Morone, G., Rosati, G., Masiero, S.: Robotic technologies and rehabilitation: new tools for stroke patients' therapy. *BioMed Research International* **2013** (2013)
- Huang, H., Young, W., Skaper, S., Chen, L., Moviglia, G., Saberi, H., Al-Zoubi, Z., Sharma, H.S., Muresanu, D., Sharma, A., et al.: Clinical neurorestorative therapeutic guidelines for spinal cord injury (ianr/canr version 2019). *Journal of Orthopaedic Translation* **20**, 14–24 (2020)
- Gassaway, J., Jones, M.L., Sweatman, W.M., Hong, M., Anziano, P., DeVault, K.: Effects of peer mentoring on self-efficacy and hospital readmission after inpatient rehabilitation of individuals with spinal cord injury: a randomized controlled trial. *Archives of physical medicine and rehabilitation* **98**(8), 1526–1534 (2017)
- Kornhaber, R., Mclean, L., Betihavas, V., Cleary, M.: Resilience and the rehabilitation of adult spinal cord injury survivors: a qualitative systematic review. *Journal of advanced nursing* **74**(1), 23–33 (2018)
- Kerdraon, J., Previnaire, J.G., Tucker, M., Coignard, P., Allegre, W., Knappen, E., Ames, A.: Evaluation of safety and performance of the self balancing walking system atalante in patients with complete motor spinal cord injury. *Spinal cord series and cases* **7**(1), 1–8 (2021)
- Grimm, F., Gharabaghi, A.: Closed-loop neuroprosthesis for reach-to-grasp assistance: combining adaptive multi-channel neuromuscular stimulation with a multi-joint arm exoskeleton. *Frontiers in neuroscience* **10**, 284 (2016)
- Gerez, L., Dwivedi, A., Liarakapis, M.: A hybrid, soft exoskeleton glove equipped with a telescopic extra thumb and abduction capabilities. In: 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 9100–9106 (2020). IEEE
- Kirchner, E.A., Bütefür, J.: Towards bidirectional and coadaptive robotic exoskeletons for neuromotor rehabilitation and assisted daily living: a review. *Current Robotics Reports*, 1–12 (2022)
- Noda, T., Sugimoto, N., Furukawa, J., Sato, M.-a., Hyon, S.-H., Morimoto, J.: Brain-controlled exoskeleton robot for bmi rehabilitation. In: 2012 12th IEEE International Conference on Humanoid Robots (humanoids 2012), pp. 21–27 (2012). IEEE
- Hortal, E., Planelles, D., Resquin, F., Climent, J.M., Azorin, J.M., Pons, J.L.: Using a brain-machine interface to control a hybrid upper limb exoskeleton during rehabilitation of patients with neurological conditions. *Journal of neuroengineering and rehabilitation* **12**(1), 1–16 (2015)
- Singh, N., Saini, M., Kumar, N., Srivastava, M., Mehndiratta, A.: Evidence of neuroplasticity with robotic hand exoskeleton for post-stroke rehabilitation: a randomized controlled trial. *Journal of neuroengineering and rehabilitation* **18**(1), 1–15 (2021)
- Remes, J., Linzer, K., Singhal, S., Dewhurst, M., Dash, P., Woetzel, J., Smit, S., Evers, M., Wilson, M., Rutter, D.K.-A., Ramdorai, A.: Ten innovations that can improve global health. Website. Online; last access 02-01-2023 (2022). <https://www.mckinsey.com/industries/healthcare/our-insights/ten-innovations-that-can-improve-global-health>
- Pehlivan, A.U., Losey, D.P., O'Malley, M.K.: Minimal assist-as-needed controller for upper limb robotic rehabilitation. *IEEE Transactions on Robotics* **32**(1), 113–124 (2015)
- Mounis, S.Y.A., Azlan, N.Z., Sado, F.: Assist-as-needed control strategy for upper-limb rehabilitation based on subject's functional ability. *Measurement and Control* **52**(9-10), 1354–1361 (2019)
- Prange, G.B., Jannink, M., Groothuis-Oudshoorn, C., Hermens, H.J., IJzerman, M.J.: Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke (2009)
- Zhang, C., Liu, G., Li, C., Zhao, J., Yu, H., Zhu, Y.: Development of a lower limb rehabilitation exoskeleton based on real-time gait detection and gait tracking. *Advances in Mechanical Engineering* **8**(1), 1687814015627982 (2016)
- Kirchner, E.A., Tabie, M., Seeland, A.: Multimodal movement prediction-towards an individual assistance of patients. *PloS one* **9**(1), 85060 (2014)
- Kwak, N.-S., Müller, K.-R., Lee, S.-W.: A lower limb exoskeleton control system based on steady state visual evoked potentials. *Journal of neural engineering* **12**(5), 056009 (2015)
- Lee, K., Liu, D., Perroud, L., Chavarriaga, R., del R. Millán, J.: A brain-controlled exoskeleton with cascaded event-related desynchronization classifiers. *Robotics and Autonomous Systems* **90**, 15–23 (2017). doi:10.1016/j.robot.2016.10.005. Special Issue on New Research Frontiers for Intelligent Autonomous Systems
- Wolpaw, J.R., Birbaumer, N., McFarland, D.J., Pfurtscheller, G., Vaughan, T.M.: Brain-computer interfaces for communication and control. *Clinical Neurophysiology* **113**(6), 767–791 (2002). doi:10.1016/S1388-2457(02)00057-3
- Soekadar, S.R., Witkowski, M., Vitiello, N., Birbaumer, N.: An eeg/eog-based hybrid brain-neural computer interaction (bnici) system to control an exoskeleton for the paralyzed hand. *Biomedical Engineering / Biomedizinische Technik* **60**(3), 199–205 (2015). doi:10.1515/bmt-2014-0126
- Folgheraiter, M., Jordan, M., Straube, S., Seeland, A., Kim, S.K.,

- Kirchner, E.A.: Measuring the improvement of the interaction comfort of a wearable exoskeleton. *International Journal of Social Robotics* **4**(3), 285–302 (2012)
27. Lew, E., Chavarriaga, R., Silvoni, S., Millán, J.d.R.: Detection of self-paced reaching movement intention from eeg signals. *Frontiers in Neuroengineering* **5** (2012). doi:10.3389/fneng.2012.00013
 28. Kirchner, E.A., Albiez, J.C., Seeland, A., Jordan, M., Kirchner, F.: Towards assistive robotics for home rehabilitation. In: *Biodevices*, pp. 168–177 (2013)
 29. Kirchner, E.A., Kim, S.K., Straube, S., Seeland, A., Wöhrle, H., Krell, M.M., Tabie, M., Fahle, M.: On the applicability of brain reading for predictive human-machine interfaces in robotics. *PLoS One* **8**(12), 81732 (2013)
 30. Gemein, L.A., Schirrmester, R.T., Chrabąszcz, P., Wilson, D., Boedecker, J., Schulze-Bonhage, A., Hutter, F., Ball, T.: Machine-learning-based diagnostics of eeg pathology. *NeuroImage* **220**, 117021 (2020)
 31. Roy, Y., Banville, H., Albuquerque, I., Gramfort, A., Falk, T.H., Faubert, J.: Deep learning-based electroencephalography analysis: a systematic review. *Journal of Neural Engineering* **16**(5), 051001 (2019). doi:10.1088/1741-2552/ab260c
 32. Wu, D., Xu, Y., Lu, B.-L.: Transfer learning for eeg-based brain-computer interfaces: A review of progress made since 2016. *IEEE Transactions on Cognitive and Developmental Systems* **14**(1), 4–19 (2020)
 33. Zhang, K., Xu, G., Zheng, X., Li, H., Zhang, S., Yu, Y., Liang, R.: Application of transfer learning in eeg decoding based on brain-computer interfaces: a review. *Sensors* **20**(21), 6321 (2020)
 34. Zou, Y., Zhao, X., Chu, Y., Zhao, Y., Xu, W., Han, J.: An inter-subject model to reduce the calibration time for motion imagination-based brain-computer interface. *Medical & biological engineering & computing* **57**, 939–952 (2019)
 35. Wei, C.-S., Lin, Y.-P., Wang, Y.-T., Lin, C.-T., Jung, T.-P.: Transfer learning with large-scale data in brain-computer interfaces. In: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4666–4669 (2016). IEEE
 36. Li, F., Xia, Y., Wang, F., Zhang, D., Li, X., He, F.: Transfer learning algorithm of p300-eeg signal based on xdown spatial filter and riemannian geometry classifier. *Applied Sciences* **10**(5), 1804 (2020)
 37. Peterson, V., Nieto, N., Wyser, D., Lambercy, O., Gassert, R., Milone, D.H., Spies, R.D.: Transfer learning based on optimal transport for motor imagery brain-computer interfaces. *IEEE Transactions on Biomedical Engineering* **69**(2), 807–817 (2021)
 38. Kim, S.K., Kirchner, E.A.: Classifier transferability in the detection of error related potentials from observation to interaction. In: 2013 IEEE International Conference on Systems, Man, and Cybernetics, pp. 3360–3365 (2013). IEEE
 39. Kim, S.K., Kirchner, E.A.: Handling few training data: classifier transfer between different types of error-related potentials. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **24**(3), 320–332 (2015)
 40. Kim, S.K., Kirchner, E.A., Stefes, A., Kirchner, F.: Intrinsic interactive reinforcement learning—using error-related potentials for real world human-robot interaction. *Scientific reports* **7**(1), 1–16 (2017)
 41. Kim, S.K., Kirchner, E.A., Kirchner, F.: Flexible online adaptation of learning strategy using eeg-based reinforcement signals in real-world robotic applications. In: 2020 IEEE International Conference on Robotics and Automation (ICRA), pp. 4885–4891 (2020). IEEE
 42. Behncke, J., Schirrmester, R.T., Volker, M., Hammer, J., Marusic, P., Schulze-Bonhage, A., Burgard, W., Ball, T.: Cross-paradigm pretraining of convolutional networks improves intracranial eeg decoding. In: 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 1046–1053 (2018). IEEE
 43. Woehrl, H., Kirchner, E.A.: Online detection of p300 related target recognition processes during a demanding teleoperation task-classifier transfer for the detection of missed targets. In: *International Conference on Physiological Computing Systems*, vol. 2, pp. 13–19 (2014). ScitePress
 44. Kirchner, E.A., Kim, S.K.: Transfer approach for the detection of missed task-relevant events in p300-based brain-computer interfaces. In: 2019 9th International IEEE/EMBS Conference on Neural Engineering (NER), pp. 134–138 (2019). IEEE
 45. Kirchner, E.A., Kim, S.K., Straube, S., Seeland, A., Wöhrle, H., Krell, M.M., Tabie, M., Fahle, M.: On the applicability of brain reading for predictive human-machine interfaces in robotics. *PLoS One* **8**(12), 81732 (2013)
 46. Zhou, Y., Xu, Z., Niu, Y., Wang, P., Wen, X., Wu, X., Zhang, D.: Cross-task cognitive workload recognition based on eeg and domain adaptation. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **30**, 50–60 (2022)
 47. Kakkos, I., Dimitrakopoulos, G.N., Sun, Y., Yuan, J., Matsopoulos, G.K., Bezerianos, A., Sun, Y.: Eeg fingerprints of task-independent mental workload discrimination. *IEEE Journal of Biomedical and Health Informatics* **25**(10), 3824–3833 (2021)
 48. Baldwin, C.L., Penaranda, B.: Adaptive training using an artificial neural network and eeg metrics for within-and cross-task workload classification. *NeuroImage* **59**(1), 48–56 (2012)
 49. Yang, J., Zhang, Z., Fu, Z., Li, B., Xiong, P., Liu, X.: Cross-subject classification of depression by using multiparadigm eeg feature fusion. *Computer Methods and Programs in Biomedicine* **233**, 107360 (2023)
 50. Chen, Y., Ke, Y., Meng, G., Jiang, J., Qi, H., Jiao, X., Xu, M., Zhou, P., He, F., Ming, D.: Enhancing performance of p300-speller under mental workload by incorporating dual-task data during classifier training. *Computer Methods and Programs in Biomedicine* **152**, 35–43 (2017)
 51. Lee, D.-Y., Jeong, J.-H., Shim, K.-H., Lee, S.-W.: Decoding movement imagination and execution from eeg signals using bci-transfer learning method based on relation network. In: *ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 1354–1358 (2020). IEEE
 52. He, H., Wu, D.: Different set domain adaptation for brain-computer interfaces: A label alignment approach. *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **28**(5), 1091–1108 (2020)
 53. Kumar, S., Wöhrle, H., Trampler, M., Simnofske, M., Peters, H., Mallwitz, M., Kirchner, E.A., Kirchner, F.: Modular design and decentralized control of the recupera exoskeleton for stroke rehabilitation. *Applied Sciences* **9**(4) (2019). doi:10.3390/app9040626
 54. Fazekas, G., Tavasz, I.: The future role of robots in neuro-rehabilitation. *Expert Review of Neurotherapeutics* **19**(6), 471–473 (2019)
 55. de Jong, R., Wierda, M., Mulder, G., Mulder, L.J.: Use of partial stimulus information in response processing. *Journal of Experimental psychology: Human perception and performance* **14**(4), 682 (1988)
 56. Gratton, G., Coles, M.G., Sirevaag, E.J., Eriksen, C.W., Donchin, E.: Pre-and poststimulus activation of response channels: a psychophysiological analysis. *Journal of Experimental Psychology: Human perception and performance* **14**(3), 331 (1988)
 57. Kutas, M., Donchin, E.: Preparation to respond as manifested by movement-related brain potentials. *Brain research* **202**(1), 95–115 (1980)
 58. Barbero, M., Merletti, R., Rainoldi, A.: *Atlas of Muscle Innervation Zones: Understanding Surface Electromyography and Its Applications* vol. 1, pp. 95–113. Springer, ??? (2012). doi:10.1007/978-88-470-2463-2
 59. Tabie, M., Seeland, A., Kim, S.-K., Kirchner, E.A.: Labelling of movement onsets based on exoskeleton joint data. In: *The First Biannual Neuroadaptive Technology Conference*, p. 162 (2017)
 60. Krell, M.M., Straube, S., Seeland, A., Wöhrle, H., Teiwes, J., Metzger, J.H., Kirchner, E.A., Kirchner, F.: pypspace—a signal processing and classification environment in python. *Frontiers in Neuroinformatics* **7**, 40 (2013)
 61. Rivet, B., Soulioumiac, A., Attina, V., Gibert, G.: xdown algorithm to enhance evoked potentials: application to brain-computer interface. *IEEE Transactions on Biomedical Engineering* **56**(8), 2035–2043 (2009)
 62. Platt, J., et al.: Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods. *Advances in large margin classifiers* **10**(3), 61–74 (1999)
 63. Schurger, A.: Specific relationship between the shape of the readiness potential, subjective decision time, and waiting time predicted by an accumulator model with temporally autocorrelated input noise. *Eneuro* **5**(1) (2018)