On the prediction accuracy of movement speed and force from single-trial EEG recordings of healthy volunteers and stroke patients

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Abstract.
Objective. Building efficient movement decoding models from brain signals is crucial for many biomedical applications. Moreover, decoding specific movement features, such as speed and force, may provide useful information at the expense of increasing the complexity of the decoding problem. Recent attempts to predict movement kinetics from the electroencephalogram (EEG) achieved classification accuracy levels not better than chance, stressing the demand for more accurate prediction strategies. Thus, the aim of this study was to determine the prediction accuracy of movement kinetics that can be achieved from single-trial EEG signals recorded from healthy volunteers and stroke patients. *Approach.* A strategy based on convolutional neural networks (ConvNet) was tested, since it has recently shown good performance in the classification of EEG signals. EEG data were minimally pre-processed, in order to mimic online classification scenarios. *Main results.* Overall accuracy for the 4-class classification problem using ConvNets was close to 80% for healthy volunteers and around 60% for stroke patients. *Significance:* These results represent a substantial improvement over previously reported results, suggesting that movement kinetics can be accurately predicted from single-trial EEG using ConvNets.

1. Introduction

The decoding of brain signals to predict movements is useful in many research areas, such as neuromechanics, neuroscience and robotics [1]. Furthermore, it has gained relevance in neurological rehabilitation, since it has potential to facilitate the assessment of the central nervous system in patients, promote neural plasticity, improve motor dysfunction and allow the control of assistive devices through brain-computer interfaces (BCI) [2]. Brain signals are commonly recorded in the electroencephalogram (EEG) and specific oscillatory patterns in the EEG, such as sensorimotor rhythms and slow cortical potentials, can be analysed to extract motor commands prior to or during movement execution [3, 4]. Indeed, EEG waves carry information about anticipatory behaviour [5], which makes it possible to predict movement, i.e., to detect and classify a particular movement before it is actually executed. This is commonly performed by analysing components of movement-related cortical potentials (MRCPs), such as the readiness potential and contingent negative variation, during self-paced or cue-based movement, respectively [6].

The movement decoding process is generally focused on detecting a predetermined final state and lacks attention regarding the quality of the action, resulting in rough commands [7] that do not correspond to the actual movement [8, 9]. Research on fine movements of body structures, such as individual fingers from one hand [10], or complex movement control [11] is comparatively scarce. It is straightforward to hypothesize that better commands can be achieved if movement kinematics and kinetics are taken into account in the decoding process [12]. Indeed, the decoding of hand movement velocities [13, 14] and 3D trajectories [15] as well as the prediction of force and speed from a specific movement [16, 11] showed promising results. However, recent attempts to predict speed and force from a hand grasping tasks resulted in a classification accuracy not better than chance level [17, 18, 19], stressing the demand for more accurate prediction strategies.

Each pattern in the EEG related to motor control has a different neurophysiological basis, since the brain uses distinct and specialised strategies to generate commands. Thus, pattern recognition systems used to decode and predict movements require careful engineering and domain expertise to transform raw EEG signals (usually by means of a feature extraction subsystem) into a suitable representation for the classification stage [20]. In this regard, several techniques have been proposed for feature extraction, e.g., independent component analysis, common spatial patterns and joint time-frequency analysis, and also for classification, e.g., linear discriminant analysis, support vector machines (SVMs), nearest neighbour classifiers and combinations, among others [21]. An alternative is to use representation learning methods that automatically perform feature extraction and classification through optimisation algorithms. Deep learning is a paradigmatic example, with multiple levels of representation obtained by combining simple but non-linear modules that transform the input into increasingly more abstract levels [20]. Recently, a decoding model based on deep learning implemented through convolutional neural networks (ConvNets) was proposed to improve state-of-the-art classification performance across several tasks and across subjects using different EEG paradigms [22].

The aim of the present study was to determine the prediction accuracy of movement kinetic that can be achieved from single-trial EEG signals recorded from healthy volunteers and stroke patients. Subjects executed an isometric right hand palmar grasp task using two predefined levels of force (20% and 60% of the maximum voluntary contraction, MVC) and speed (a 3-s slow grasp and a 0.5-s fast grasp). EEG data were minimally pre-processed, in order to mimic online classification scenarios. A prediction strategy using ConvNets was implemented and contrasted with results obtained using SVM on the same datasets. Overall classification accuracy, precision and recall were quantified in order to evaluate the performance of the proposed prediction strategies.

Materials and methods

Dataset

A dataset consisting of EEG recordings of sixteen healthy volunteers and five stroke patients was employed [17]. Written informed consent was obtained from all subjects prior to participation and the Declaration of Helsinki was respected. The study was approved by the local ethical committee of Region NordJylland (approval no. N-20100067). EEG was recorded during four isometric right hand palmar grasp tasks with different execution speeds and force levels (expressed as percentage of MVC), categorized as follows: *Slow20*, 3 s to reach 20% MVC; *Slow60*, 3 s to reach 60% MVC; *Fast20*, 0.5 s to reach 20% MVC and *Fast60*, 0.5 s to reach 60% MVC. Forty externally cued repetitions (trials) were performed for each task. A Neuroscan NuAmp Express amplifier was used to record the EEG (Compumedics Ltd., Victoria, Australia) from the electrode locations shown in Fig. 1, in accordance to the 10/10 system. The corresponding EEG channels were referenced to the right earlobe and grounded at nasion. During the experiment, the impedance of all electrodes was kept below 5 kΩ, continuously sampled at 500 Hz and stored for offline analysis. For the full description of the experimental procedure, please refer to [17].

Prediction strategies

Pre-processing. EEG was notch-filtered (50 Hz) in order to reduce power line interference. No further pre-processing or filtering was applied to the EEG signals, and noisy epochs were not removed, in order to test the prediction schemes in settings that resemble as much as possible an online prediction scenario. Forty trials per task were executed, resulting in 160 trials per subject. All trials were baseline corrected using a 1-s interval before the cue as reference. Trials were subsequently segmented into 500-ms epochs, from 600 ms to 100 ms before movement onset (Fig. 2). EEG epochs were finally arranged in a $5 \times 4 \times 250$ matrix with a two-dimensional spatial distribution and the time samples in the third dimension (Fig. 1). Data were divided in 128 trials (80%) for training and validation and 32 trials (20%) for testing. The training and validation set was further split into 102 trials (80%) for training and 18 trials (20%) for validation.

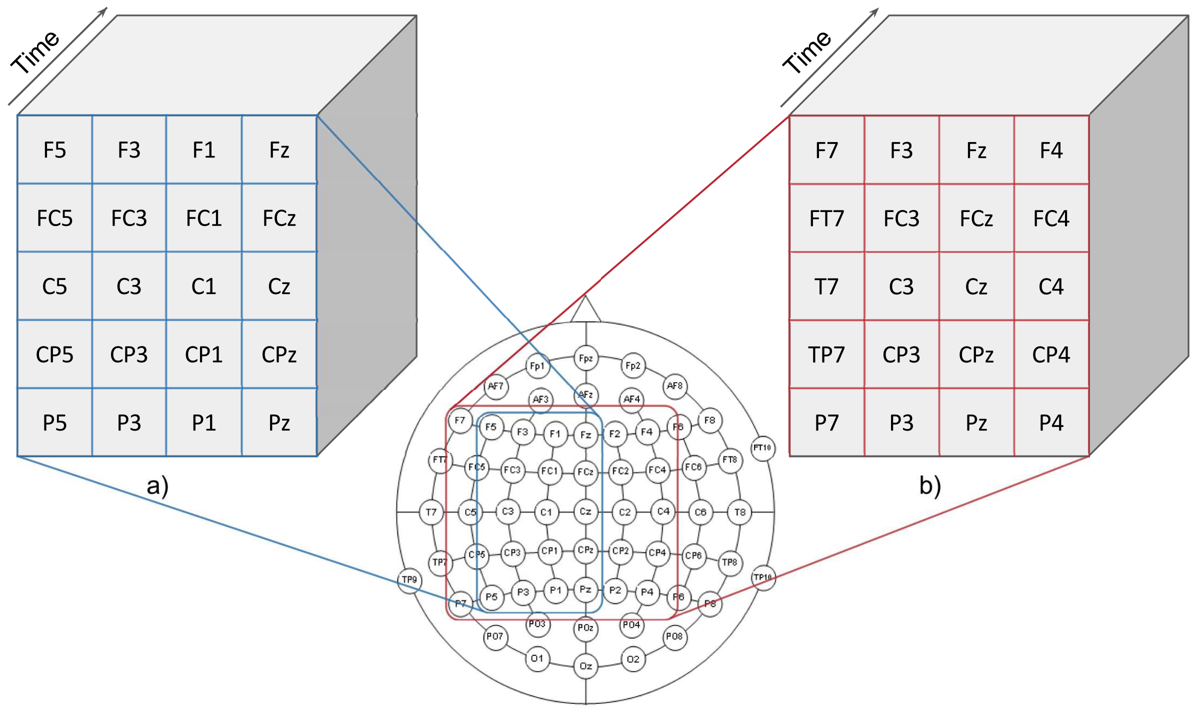

Figure 1: Input data arrangement for the ConvNet based on the spatial distribution of the recorded channels in healthy volunteers (a) and stroke patients (b).

Convolutional Neural Network The model was based on the EEGnet described in Lawhern et al. (2016) [22]. The ConvNet was built in Keras 2.0.5 [23] using the TensorFlow 1.2.1 back-end [24] and trained on an Dell Precision 7910 workstation with an NVIDIA Titan Xp GPU, using CUDA 8 and cuDNN 8.

The model consisted of four layers (Table 1). The input of the first layer was a pre-processed three-dimensional (3D) matrix for each trial, which was reshaped so the 16 convolutional kernels (size 2×2) were applied to each time sample, generating linear combinations of four neighbouring channels in the spatial dimension (spatial filter). Kernel weights were initialized with a Glorot uniform technique and were regularized with an elastic-net (L1 + L2) penalties, with L1 = L2 = 0.01, because the weights were expected to be small and sparse. Padding was not applied and stride was set to 1 for all dimensions. Exponential Linear Unit (ELU) activation with alpha = 1 was applied afterwards, followed by a batch normalization and drop-out with a rate of 0.25.

In the second layer, both spatial and temporal dimensions were taken into account, using eight convolutional kernels (size $2 \times 2 \times 27$) for each map. In this case, the spatial dimension size was kept constant through zero padding. Henceforth, a 3D max pooling step was applied to the layers (stride set to 1, no padding), which selected the maximum value from a kernel with a size of $2 \times 3 \times 4$. ELU activation, batch normalization, and drop-out were applied using the same hyperparameters as in the first layer.

The third layer consisted of four convolutional kernels (size $2 \times 2 \times 27$) for each

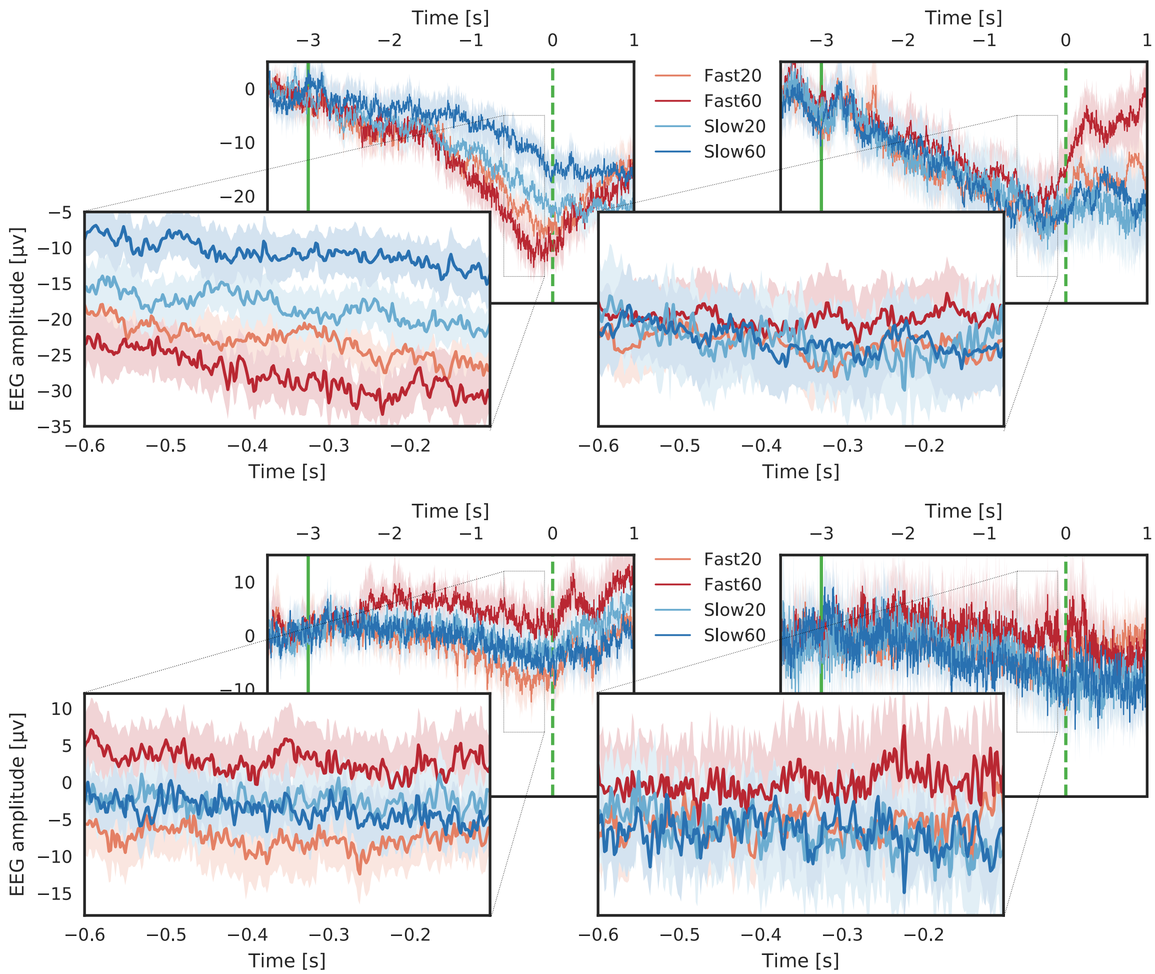

Figure 2: Representative examples of 3 s EEG trials (back) and the corresponding 500 ms epochs (front) for healthy volunteers (top) and stroke patients (bottom), relative to movement onset. The solid trace and shading represent mean and 95% confidence intervals for each class, respectively, derived using 5000 bootstrap iterations. Vertical lines represent cue (solid) and movement onset (dashed) times.

map, corresponding to the four classes of the problem. The max pooling kernel size in this layer was $2 \times 1 \times 4$. A 3D global average pooling was applied at the end of this layer. Finally, the four resulting scores were transformed to probabilities in the last layer by means of a softmax activation.

The learning process consisted of a fixed number of learning steps using mini-batch of 16 randomly selected trials and the Adam optimization. The final number of steps was set to 150 after analysing the learning curves for all subjects. The accuracy obtained from the validation set was used as metric, and the model was updated through a model check point if the accuracy improved compared to the last saved model. To prevent model overfitting, only the model with the best validation accuracy was kept. This regularization procedure is similar to that obtained by early stopping, with the

Table 1: ConvNet architecture

Layer	Type	Output size	Parameters #
1	Input	$(C_y \times C_x \times T)$	0
	Reshape	$(C_y \times C_x \times T \times 1)$	0
	Conv3D (2, 2, 1) $\times$ 16	$(4 \times 3 \times T \times 16)$	80
	Batch normalization	$(4 \times 3 \times T \times 16)$	64
	ELU	$(4 \times 3 \times T \times 16)$	0
	Dropout (.25)	$(4 \times 3 \times T \times 16)$	0
2	Conv3D (2, 2, 27) $\times$ 8	$(4 \times 3 \times T \times 8)$	13832
	Batch normalization	$(4 \times 3 \times T \times 8)$	32
	ELU	$(4 \times 3 \times T \times 8)$	0
	Max pooling 3D (2, 3, 4)	$(3 \times 1 \times 62 \times 8)$	0
	Dropout (.25)	$(3 \times 1 \times 62 \times 8)$	0
3	Conv3D (2, 1, 3) $\times$ N	$(2 \times 1 \times 62 \times N)$	196
	Batch normalization	$(2 \times 1 \times 62 \times N)$	16
	ELU	$(2 \times 1 \times 62 \times N)$	0
	Max pooling 3D (2, 1, 4)	$(1 \times 1 \times 15 \times N)$	0
	Dropout (.25)	$(1 \times 1 \times 15 \times N)$	0
	Global Average Pooling 3D	(N)	0
4	Activation (Softmax)	(N)	0

C_x = channels (mediolateral direction), C_y = channels (anteroposterior direction), T = time samples, N = number of classes.

disadvantage of performing the training procedure through all steps. Nevertheless, this method was selected because the ConvNet has a relatively small number of training examples, and early stopping did not always result in the best possible accuracy. In this regard, the relationship between training set size and performance was also derived to verify that the training set size was appropriate in relation to the dataset size [25]. Furthermore, the performance of the ConvNet was evaluated with a modified version of the dataset in which the labels for each class were randomly scrambled, in order to determine the level of classification by chance. Additionally, the ConvNet was also evaluated in the case where the spatial distribution of the electrodes was randomly shifted, in order to test the importance of the spatial relationship between input channels. The results from these analyses (selection of step size and training set size, and prediction accuracy after random scrambling of labels and spatial distribution) are included in the supplementary material.

Support vector machine SVMs are popular supervised learning models used for classification. SVMs transform a non-linearly separable problem into a linearly separable problem by projecting data into a new feature space through the use of kernel functions, in order to find the optimal decision hyperplane in this feature space. This method was initially proposed to solve two-class problems, although strategies were later developed to extend this technique to multi-class classification problems [26]. For this study, SVMs were implemented for reproducibility purposes, as they would allow a direct comparison with prior studies using the same data [16, 17]. In this regard, a Radial Basis Function (RBF) were used as kernel. Based on a heuristic search, the cost hyperparameter of the SVM was set to 0.001 and the gamma hyperparameter of the kernel was set to 0.0002. Furthermore, a one-against-one strategy was used to implement the multi-class SVM prediction strategy. This method constructed *k(k-1)/2* classifiers, where k is the number of classes of the problem. Each classifier used the training data from two classes chosen out of k classes. After the training process was over, a voting strategy was used to determine to which class each pattern belongs to. The open source library tool for classification and regression problems (LIBSVM) was used to build the SVMs [27].

Data analysis and statistics

An individual prediction strategy was trained for each subject (i.e., one ConvNet and 6 SVMs to address the 4-class classification problem), and the same data partitioning for training, validation and testing was used for the ConvNet and the SVMs to ensure comparability. A 5-fold cross-validation procedure was performed to ensure the generalizability of the results. The overall classification accuracy and per-class precision and recall were quantified for each subject, as the mean values of the 5-fold cross-validation. Furthermore, confusion matrices were computed to evaluate classification bias. Only test results were shown.

A paired t-test was used to assess differences in overall classification accuracy between classifiers (ConvNet vs. SVM). A repeated measures analysis of variance was used to assess differences in precision and recall, with Classifier (levels: ConvNet, SVM), Speed (levels: Fast, Slow) and Force (levels: 20% MVC, 60% MVC) as factors. Main effects and two-way interactions were analysed. The Shapiro-Wilk test was performed in order to assess the assumption of normality, which held for all indexes. Significant interactions were evaluated using a Tukey post hoc test when required. Performance indexes are reported as $mean \pm standard$ deviation unless stated otherwise. P values smaller than 0.05 were regarded as statistically significant.

Results

Performance indexes for healthy subjects

The overall classification accuracy for the ConvNet model (78.6±7.9%) was significantly higher compared to the SVM ($64.4 \pm 6.9\%$; $t_{15} = 6.524$, $p < 0.001$). Precision and recall values for all healthy volunteers are shown in Fig. 3. The precision of the ConvNet model ($79.8 \pm 7.9\%$) was higher compared to the SVM ($65.8 \pm 6.7\%$; $F_{1,15} = 41.320$, $p < 0.001$). Additionally, there was a significant interaction between Speed and Force ($F_{1,15} = 16.318$, $p = 0.001$). Post hoc analysis revealed that precision to predict slow movements at 20% MVC ($78.5 \pm 8.1\%$) was significantly higher compared to slow movements at 60% MVC ($67.9 \pm 9.8\%$; $p = 0.004$) and fast movements at 20% MVC ($70.3 \pm 9.2\%$; $p = 0.027$). With regards to recall, it was significantly higher for the ConvNet model ($78.6 \pm 7.8\%$) compared to the SVM ($64.4 \pm 6.9\%$; $F_{1,15} = 42.563$, $p < 0.001$). No further significant main effects or interactions were found.

Performance indexes for stroke patients

No significant differences were found in the overall classification accuracy for the ConvNet model ($57.0 \pm 19.6\%$) compared to the SVM ($39.9 \pm 7.1\%$; $t_4 = 2.551$, $p = 0.062$). Precision and recall values for stroke patients are shown in Fig. 4. No significant main effects or interactions were found in terms of precision. With regards to recall, there were significant interactions between Classifier and Speed ($F_{1,4} = 28.289$, $p = 0.006$) and also between Classifier and Force ($F_{1,4} = 107.302$, $p < 0.001$). Post hoc tests on the Classifier × Speed interaction showed that the recall for the prediction of slow movements using the SVM ($26 \pm 9.6\%$) was significantly lower compared to the remaining three combinations (p values ranging from 0.007 to 0.022). Moreover, post hoc tests on the Classifier × Force interaction showed that the recall for the prediction of movements at 60% MVC using the ConvNet ($63.5 \pm 17.5\%$) was significantly higher compared to the remaining three combinations (p values ranging from 0.001 to 0.008). Finally, the recall for the prediction of movements at 60% MVC using the SVM ($32.2 \pm 7.6\%$) was significantly lower compared to the remaining three combinations (p values ranging from 0.001 to 0.004).

Discussion

The aim of this study was to determine the prediction accuracy of movement kinetics that can be achieved from single-trial EEG signals recorded from healthy volunteers and stroke patients. In this regard, a ConvNet was proposed as prediction strategy. Furthermore, a SVM classifier was also implemented for reproducibility purposes, as this was the prediction strategy used in previous reports using the same data. EEG data were minimally pre-processed, in order to mimic online classification scenarios. Overall accuracy for the 4-class classification problem using ConvNets was close to 80% for healthy volunteers, representing a substantial improvement over previously reported accuracy using the same data. The prediction accuracy improvement for stroke patients was lower, with average values around 60%.

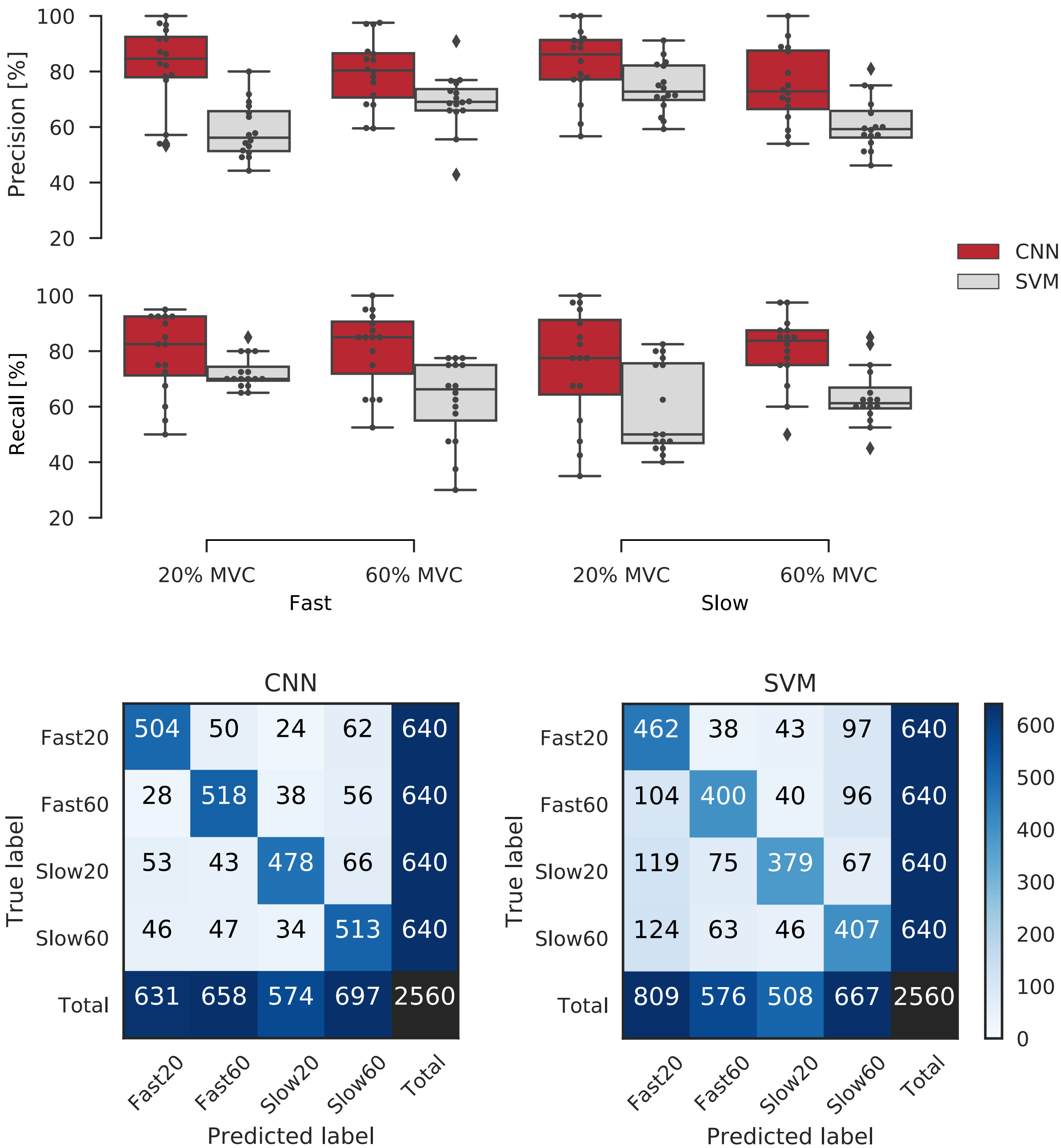

Figure 3: Classification results over test data. Top: precision and recall for healthy volunteers (n = 16). Boxes represent the median and the 25$^{\mathrm{th}}$ and 75$^{\mathrm{th}}$ percentiles, whiskers represent 5$^{\mathrm{th}}$ and 95$^{\mathrm{th}}$ percentiles, diamonds represent values outside of the 5$^{\mathrm{th}}$ - 95$^{\mathrm{th}}$ percentile range and the individual dots represent the average precision/recall for each individual subject, calculated from the 5-fold cross-validation. Bottom: confusion matrix for all available trials. *Slow20*, 3 s to reach 20% MVC; *Slow60*, 3 s to reach 60% MVC; *Fast20*, 0.5 s to reach 20% MVC and *Fast60*, 0.5 s to reach 60% MVC.

Neurophysiological aspects of movement prediction

Building efficient movement decoding models from brain signals is crucial for many biomedical applications, particularly in the BCI field that require precision in online

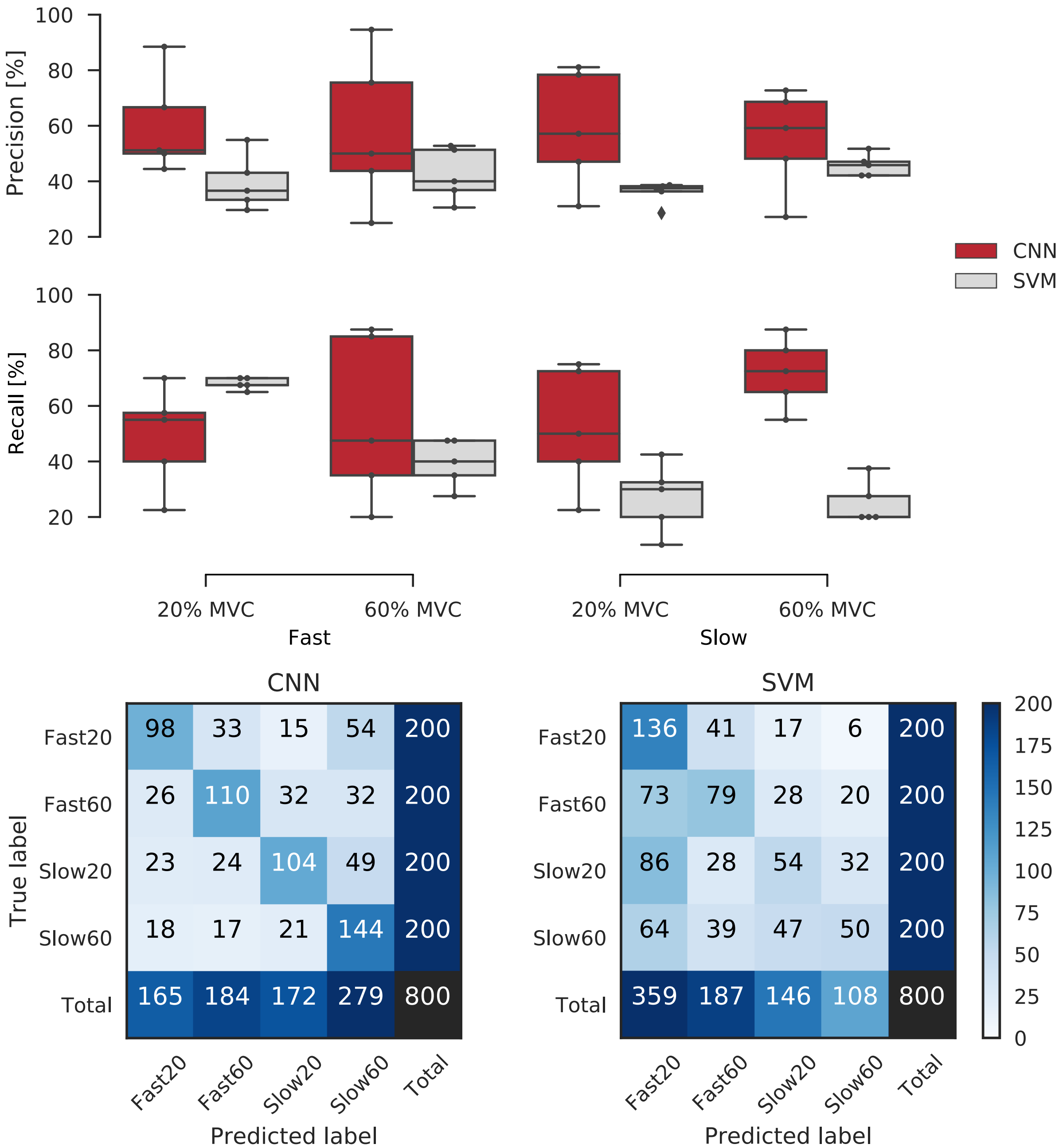

Figure 4: Classification results over test data. Top: precision and recall for stroke patients (n = 5). Boxes represent the median and the 25th and 75th percentiles, whiskers represent 5th and 95th percentiles, diamonds represent values outside of the 5th - 95th percentile range and the individual dots represent the average precision/recall for each individual subject, calculated from the 5-fold cross-validation. Bottom: confusion matrix for all trials. *Slow20*, 3 s to reach 20% MVC; *Slow60*, 3 s to reach 60% MVC; *Fast20*, 0.5 s to reach 20% MVC and *Fast60*, 0.5 s to reach 60% MVC.

control of assistive devices. Moreover, decoding specific movement features, such as speed, force and/or direction, provides additional degrees of freedom, resulting in more accurate and natural motor commands at the expense of increasing the complexity of the decoding problem [28, 15, 13, 14]. Early attempts to decode movement from brain signals during movement execution or imagination were focused on classifying between limb movements [29, 30, 31]. Classification accuracy for these studies is close to 80% for 2 classes [29, 30], and close to 56% for 4 classes [31]. Other studies have tried to decode movement of specific body parts from a single limb, such as wrist [32], or individual finger movements [10], obtaining similar results (accuracy $\approx$ 80% for 2 classes).

On the other hand, prediction of movement, i.e., decoding movement not during, but before its execution, is a much more difficult task. Considering the brain as a predictive neural system, expectation can be seen as a representation of prediction that serve to sensory or motor areas as preparatory processing prior to an event, particularly in short time scales [33]. Movement intention is the first interesting command to decode from EEG before a movement is executed, as trigger for other more complex motor instructions. It is well known that information about movement intention is encoded in the MRCPs, around 1.5 s prior to movement onset [6]. The timing of the prediction is a relevant feature to study, since it has been shown that a sensory stimulus delivered synchronously with the peak negativity of the MRCP maximizes neural plasticity [34]. Furthermore, kinetic information encoded in the movement intention could be particularly useful; for example, by decoding these movement parameters it would be possible to introduce task variability in the rehabilitation training, which has been shown to maximize the motor learning [35].

In general terms, and although it has been shown that pre-movement EEG contains valuable information about motion kinetics, classification rates were still relatively low in healthy volunteers, particularly for multi-class classification problems. Whereas detection of voluntary movement from single trial EEG was achieved using a matched filter approach, obtaining relatively good performance in a 2-class classification (sensitivity $\approx$ 82.5% for healthy subjects) [36], recent studies directed towards the extraction of additional information from movement intention beyond simple detection, such as the prediction of the body part that is about to perform the movement [19], or the classification between different types of movement used in daily life, such as palmar, lateral and pinch grasps [11], resulted in classification accuracies not better than chance levels for the 4-class classification attempts.

In particular, previous work with the same dataset used in this study obtained mean accuracy values of approximately 32-40% for the 4-class classification [17], which is on par with the chance level for that type of problem [37]. These result might be partially explained by the fact that the aim of the study was to obtain a fast prediction scheme using few electrodes and a simple classifier that did not require extensive calibration. As such, only one channel was used as input, and the signals were band filtered using low cut-off frequencies values. However, it was recently suggested that information from the entire EEG spectrum is needed to discriminate between task-related parameters from single-trial movement intention [18].

In this work, it was possible to significantly improve the movement prediction accuracy using twenty available channels without band filtering or additional pre-processing, such as artifact removal or epoch selection. Accuracy levels reach values close to 80% in healthy volunteers, representing an improvement of almost 40% compared to previous results. Therefore, it could be hypothesized that the decoding of complex movement requires more information (in terms of number of channels or features) in order to achieve a classification accuracy comparable with that obtained for simpler movements, such ankle or wrist flexion/extension (binary classification problems) [38, 32, 39, 16]. Furthermore, precision and recall were also evaluated for each class, with slow movements at low force levels showing a slightly higher classification precision without any differences in terms of recall. This difference can be explained by a small negative classification bias for the aforementioned class from the SVM, as can be observed in the confusion matrices in Fig. 3. No such interactions between force and speed were observed in the previous study with this dataset [17], although speed tasks resulted in higher accuracy values in the prediction of ankle dorsiflexion tasks [16].

The decoding of brain signals becomes even more complex when the EEG is recorded from volunteers that suffered neurological damage [40]. Indeed, it has been shown that a disruption in cortex integrity changes brain activation patterns and responses in patients with motor impairments [41, 42]. One of the first studies involving BCI and patients attempted to use imagination of foot movement to recover hand function by orthotic devices in one tetraplegic patient [8]. This was followed by other studies, in which binary classification was usually tested, either between both hands, hands and feet, or simply against a resting state, resulting in accuracy levels between 60% and 70% for 2-class classification [8, 43, 44, 45]. Further studies attempting movement detection from EEG signals of stroke patients generally resulted in a lower classification accuracy compared to healthy volunteers (accuracy $\approx$ 55% for binary classification) [36].

However, little research has been performed on movement prediction in patients. In particular, Jochumsen et al. attempted to predict movement kinetics from stroke patients, but the results were barely above chance levels (around 30%) [17]. Our results using the same data showed an average classification accuracy around 60% for 4-class classification. A large variation was generally observed in performance between subjects (fig. 4), which might be attributed to the differences in the type and degree of lesion and differences in electrode density compared to healthy volunteers. In any case, it is worth noting that a moderate classification accuracy does not impede positive rehabilitation [46, 44, 47].

Methodological aspects of movement prediction

Deep learning methods were originally developed in the computer vision field [48], but recently started to gain popularity in EEG analysis, with the aim of improving classification performance over traditional approaches, such as linear discriminant analysis, k-nearest neighbours or SVMs [21]. ConvNets are a type of feed-forward deep learning networks that are useful when data have a known topological structure [20, 25]. As a representation learning method, one of the advantages of ConvNets is that feature extraction and classification is intrinsically optimized. Typically, ConvNets consist of a combination of convolutional and pooling layers. The convolutional layer applies mathematical convolution operations through a number of kernels that perform a local weighted sum along the input and return each one in a feature map. Then, the same weights are shared across the input and have only local connections, thereby reducing the amount of network parameters. The pooling layer performs a reduction of the input by applying a function to nearby units, e.g. the maximum value among neighbours, where the units are the pixels of an image or the temporal samples of a biosignal.

The ConvNet implemented in this study is based on a recently proposed architecture that demonstrated good performance employing a small number of parameters in the classification of EEG signals recorded using different paradigms [22]. In this model, the first layer works as a spatial filter, in which the outcome consists of a number of feature maps representing different combinations of channels that minimize the error at the output. In accordance with the input structures used in image processing, the EEG input to a ConvNet is usually reshaped into a 2D distribution, by arranging channels along the rows and time samples in the columns [49, 50] or by transforming the input into a new space [7], e.g., to a time-frequency domain through Fourier transform and averaging along the channels [51, 52]. In both options, the spatial relationship between neighbouring electrodes is lost. The ConvNet implemented in this study considered the localization of the electrodes in order to keep the spatial relationship between them. Furthermore, EEG signals are commonly pre-processed by using temporal and spatial filters, and epochs containing artifacts or with amplitudes above a certain threshold are rejected in order to improve the signal-to-noise ratio [6]. These processes are often performed offline, are subjective and time-consuming and may result in the loss of useful information to decode movement. Taking this into consideration, only minimal pre-processing (baseline correction and notch filtering) was performed in this study prior to the classification stage, and no epochs were removed in order to emulate online classification scenarios.

The present study neither attempted to find *the* optimal strategy for movement prediction nor advance the knowledge on machine learning strategies for single-trial EEG classification. Instead, the main goal of this work was to determine the achievable levels of prediction accuracy from single-trial EEG using state-of-the-art machine learning techniques, and compare the results obtained with recent reports from the literature, using SVMs as classification strategy and feature selection based on temporal and spatial parameters [17]. The prediction results of the ConvNet were better than the SVM for all tasks and all performance indexes in healthy volunteers by an average of 15 percentage points. This is even more relevant considering that the SVMs implemented in this study (using twenty available channels) already improved the classification accuracy by 20 to 30 percentage points compared to the previous study with the same dataset (using only a single channel, C3, plus an eight-channel Laplacian filter) [17]. For comparison purposes, a systematic investigation regarding movement prediction performed with combinations of spatial filtering (principal component analysis, independent component analysis, common spatial patterns analysis, and surface Laplacian derivation), temporal filtering (power spectral density estimation and discrete wavelet transform), pattern classification (linear and quadratic Mahalanobis distance classifier, Bayesian classifier, multi-layer perceptron neural network, probabilistic neural network, and support vector machine) and multivariate feature selection strategy using a genetic algorithm, achieved a maximum accuracy of 75% for binary classification [53]. In contrast, the ConvNet shows better results with minimal pre-processing and optimal combination of feature extraction and classification in a multi-class classification scenario.

Limitations

Several constraints need to be considered: attempts to use a single ConvNet to predict movements from all subjects resulted in low performance indexes during pilot tests. This is not an issue in most real-life applications where the decoding is used to control a device for a single subject (and thus an individual ConvNet is trained for each subject), but nevertheless highlights the difficulty in describing a general behaviour of the EEG signal in terms of decoding force and speed. Another issue is related to the understanding and visualization of the specific features that allow a good classification, since it is not always straightforward to extract and interpret physiological information from the network. Furthermore, even if high accuracy was achieved offline, it is crucial to perform real-time tests with adequate feedback. With regards to the dataset from stroke patients, there was a trend for better performance indexes with the ConvNets, but these results should be interpreted with caution given the small sample size.

Conclusion

The results from this study suggest that movement kinetics can be accurately predicted from single-trial EEG using convolutional neural networks. However, additional considerations are required to transfer these protocols from laboratory to clinic. Future work will be directed towards closing the loop to test the strategy with a real application, for which an accurate detection of the movement onset is necessary and an idle state should be considered [54]. Finally, once the definitive scheme has been defined, efficient hardware implementations should be tested in chips or field-programmable gate arrays [20].

References

[1] Nordin A D, Rymer W Z, Biewener A A, Schwartz A B, Chen D and Horak F B 2017 Biomechanics and neural control of movement, 20 years later: what have we learned and what has changed? *Journal of NeuroEngineering and Rehabilitation* **14** 91

[2] Brunner C, Birbaumer N, Blankertz B, Guger C, Kübler A, Mattia D, Millán J d R, Miralles F, Nijholt A, Opisso E, Ramsey N, Salomon P and Müller-Putz G R 2015 BNCI Horizon 2020: towards a roadmap for the BCI community *Brain-Computer Interfaces* **2** 1–10

[3] Wolpaw J R, Birbaumer N, McFarland D J, Pfurtscheller G and Vaughan T M 2002 Braincomputer interfaces for communication and control *Clinical Neurophysiology* **113** 767–791

[4] Machado S, Araújo F, Paes F, Velasques B, Cunha M, Budde H, Basile L F, Anghinah R, Arias-Carrión O, Cagy M, Piedade R, de Graaf T A, Sack A T and Ribeiro P 2010 EEG-based brain-computer interfaces: an overview of basic concepts and clinical applications in neurorehabilitation. *Reviews in the neurosciences* **21** 451–68

[5] Brunia C 1999 Neural aspects of anticipatory behavior *Acta Psychologica* **101** 213–242

[6] Shakeel A, Navid M S, Anwar M N, Mazhar S, Jochumsen M and Niazi I K 2015 A review of techniques for detection of movement intention using movement-related cortical potentials *Computational and Mathematical Methods in Medicine* **2015** 346217 346217

[7] Uktveris T and Jusas V 2017 Convolutional Neural Networks for Four-Class Motor Imagery Data Classification *Intelligent Distributed Computing XI. IDC 2017* vol 737 (Springer, Cham) pp 185–197

[8] Pfurtscheller G, Guger C, Müller G, Krausz G and Neuper C 2000 Brain oscillations control hand orthosis in a tetraplegic *Neuroscience Letters* **292** 211–214

[9] Rohm M, Schneiders M, Müller C, Kreilinger A, Kaiser V, Müller-Putz G R and Rupp R 2013 Hybrid brain-computer interfaces and hybrid neuroprostheses for restoration of upper limb functions in individuals with high-level spinal cord injury *Artificial Intelligence in Medicine* **59** 133–142

[10] Liao K, Xiao R, Gonzalez J and Ding L 2014 Decoding Individual Finger Movements from One Hand Using Human EEG Signals *PLoS ONE* **9** e85192

[11] Jochumsen M, Niazi I K, Dremstrup K and Kamavuako E N 2015 Detecting and classifying three different hand movement types through electroencephalography recordings for neurorehabilitation *Medical & Biological Engineering & Computing* **54** 1491–1501

[12] Jerbi K, Vidal J R, Mattout J, Maby E, Lecaignard F, Ossandon T, Hamamé C M, Dalal S S, Bouet R, Lachaux J P, Leahy R M, Baillet S, Garnero L, Delpuech C and Bertrand O 2011 Inferring hand movement kinematics from MEG, EEG and intracranial EEG: From brain-machine interfaces to motor rehabilitation *Irbm* **32** 8–18

[13] Bradberry T J, Gentili R J and Contreras-Vidal J L 2010 Reconstructing Three-Dimensional Hand Movements from Noninvasive Electroencephalographic Signals *Journal of Neuroscience* **30** 3432–3437

[14] Lv J, Li Y and Gu Z 2010 Decoding hand movement velocity from electroencephalogram signals during a drawing task *BioMedical Engineering OnLine* **9** 64

[15] Kim J H, Bießmann F and Lee S W 2015 Decoding three-dimensional trajectory of executed and imagined arm movements from electroencephalogram signals *IEEE Transactions on Neural Systems and Rehabilitation Engineering* **23** 867–876

[16] Jochumsen M, Niazi I K, Mrachacz-Kersting N, Farina D and Dremstrup K 2013 Detection and classification of movement-related cortical potentials associated with task force and speed *Journal of Neural Engineering* **10** 056015

[17] Jochumsen M, Khan Niazi I, Taylor D, Farina D and Dremstrup K 2015 Detecting and classifying movement-related cortical potentials associated with hand movements in healthy subjects and stroke patients from single-electrode, single-trial EEG *Journal of Neural Engineering* **12** 056013

[18] Jochumsen M, Rovsing C, Rovsing H, Niazi I K, Dremstrup K and Kamavuako E N 2017

Classification of Hand Grasp Kinetics and Types Using Movement-Related Cortical Potentials and EEG Rhythms *Computational Intelligence and Neuroscience* **2017** 1–8

[19] Morash V, Bai O, Furlani S, Lin P and Hallett M 2008 Classifying EEG signals preceding right hand, left hand, tongue, and right foot movements and motor imageries *Clinical Neurophysiology* **119** 2570–2578

[20] LeCun Y, Bengio Y and Hinton G 2015 Deep learning *Nature* **521** 436–444

[21] Lotte F, Congedo M, Lécuyer A, Lamarche F and Arnaldi B 2007 A review of classification algorithms for EEG-based braincomputer interfaces *Journal of Neural Engineering* **4** 1–24

[22] Lawhern V J, Solon A J, Waytowich N R, Gordon S M, Hung C P and Lance B J 2016 Eegnet: A compact convolutional network for eeg-based brain-computer interfaces ArXiv: 1611.08024 [cs.LG]

[23] Chollet F and others 2015 Keras Github repository https://github.com/fchollet/keras

[24] Abadi M, Barham P, Chen J, Chen Z, Davis A, Dean J, Devin M, Ghemawat S, Irving G, Isard M, Kudlur M, Levenberg J, Monga R, Moore S, Murray D G, Steiner B, Tucker P, Vasudevan V, Warden P, Wicke M, Yu Y and Zheng X 2016 TensorFlow: A system for large-scale machine learning *12th USENIX Symposium on Operating Systems Design and Implementation (OSDI '16)* 265–284 1605.08695

[25] Goodfellow I, Bengio Y and Courville A 2016 *Deep Learning* (MIT Press) available in http://www.deeplearningbook.org

[26] Niu X X and Suen C Y 2012 A novel hybrid CNNSVM classifier for recognizing handwritten digits *Pattern Recognition* **45** 1318–1325

[27] Chang C C and Lin C J 2011 LIBSVM: A Library for Support Vector Machines *ACM Transactions on Intelligent Systems and Technology* **2** 27:1–27:27

[28] Agashe H A and Contreras-Vidal J L 2011 Reconstructing hand kinematics during reach to grasp movements from electroencephalographic signals *33rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (IEEE) pp 5444–5447 ISBN 978-1-4577-1589-1 ISSN 1557170X

[29] Pfurtscheller G, Neuper C, Schlögl A and Lugger K 1998 Separability of EEG signals recorded during right and left motor imagery using adaptive autoregressive parameters *IEEE Transactions on Rehabilitation Engineering* **6** 316–325

[30] Yorn-Tov E and Inbar G 2001 Selection of relevant features for classification of movements from single movement-related potentials using a genetic algorithm *2001 Conference Proceedings of the 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (IEEE) pp 1364–1366 ISBN 0-7803-7211-5

[31] Pfurtscheller G, Brunner C, Schlögl A and Lopes da Silva F 2006 Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks *NeuroImage* **31** 153–159

[32] Gu Y, Dremstrup K and Farina D 2009 Single-trial discrimination of type and speed of wrist movements from EEG recordings *Clinical Neurophysiology* **120** 1596–1600

[33] Bubic 2010 Prediction, cognition and the brain *Frontiers in Human Neuroscience* **4** 1–15

[34] Mrachacz-Kersting N, Kristensen S R, Niazi I K and Farina D 2012 Precise temporal association between cortical potentials evoked by motor imagination and afference induces cortical plasticity *The Journal of Physiology* **590** 1669–1682

[35] Krakauer J W 2006 Motor learning: its relevance to stroke recovery and neurorehabilitation. *Current Opinion in Neurology* **19** 84–90

[36] Niazi I K, Jiang N, Tiberghien O, Nielsen J F, Dremstrup K and Farina D 2011 Detection of Movement Intention from Single-Trial Movement-Related Cortical Potentials *Journal of Neural Engineering* **8** 066009

[37] Müller-Putz G R and Pfurtscheller G 2008 Control of an electrical prosthesis with an SSVEP-based BCI *IEEE Transactions on Biomedical Engineering* **55** 361–364

[38] Shibasaki H and Hallett M 2006 What is the Bereitschaftspotential? *Clinical Neurophysiology* **117** 2341–2356

[39] Gu Y, Do Nascimento O F, Lucas M F and Farina D 2009 Identification of task parameters from movement-related cortical potentials *Medical and Biological Engineering and Computing* **47** 1257–1264

[40] Birbaumer N 2006 Breaking the silence: Brain?computer interfaces (BCI) for communication and motor control *Psychophysiology* **43** 517–532

[41] Nam C S, Woo J and Bahn S 2012 Severe motor disability affects functional cortical integration in the context of brain-computer interface (BCI) use *Ergonomics* **55** 581–591

[42] Park W, Kwon G H, Kim Y H, Lee J H and Kim L 2016 EEG response varies with lesion location in patients with chronic stroke *Journal of NeuroEngineering and Rehabilitation* **13** 21

[43] Ang K K, Guan C, Chua K S G, Ang B T, Kuah C W K, Wang C, Phua K S, Chin Z Y and Zhang H 2011 A large clinical study on the ability of stroke patients to use an EEG-based motor imagery brain-computer interface *Clinical EEG and Neuroscience* **42** 253–258

[44] Pichiorri F, Morone G, Petti M, Toppi J, Pisotta I, Molinari M, Paolucci S, Inghilleri M, Astolfi L, Cincotti F and Mattia D 2015 Brain-computer interface boosts motor imagery practice during stroke recovery *Annals of Neurology* **77** 851–865

[45] Arvaneh M, Guan C, Ang K K, Ward T E, Chua K S, Kuah C W K, Ephraim Joseph G J, Phua K S and Wang C 2017 Facilitating motor imagery-based braincomputer interface for stroke patients using passive movement *Neural Computing and Applications* **28** 3259–3272

[46] Ang K K, Chua K S G, Phua K S, Wang C, Chin Z Y, Kuah C W K, Low W and Guan C 2014 A Randomized Controlled Trial of EEG-Based Motor Imagery Brain-Computer Interface Robotic Rehabilitation for Stroke *Clinical EEG and Neuroscience* **46** 310–320

[47] Ramos-Murguialday A, Broetz D, Rea M, Läer L, Yilmaz Ö, Brasil F L, Liberati G, Curado M R, Garcia-Cossio E, Vyziotis A, Cho W, Agostini M, Soares E, Soekadar S, Caria A, Cohen L G and Birbaumer N 2013 Brain-machine interface in chronic stroke rehabilitation: A controlled study *Annals of Neurology* **74** 100–108

[48] Krizhevsky A, Sutskever I and Hinton G E 2012 ImageNet Classification with Deep Convolutional Neural Networks *Advances in Neural Information Processing Systems 25* ed Pereira F, Burges C J C, Bottou L and Weinberger K Q (Curran Associates, Inc.) pp 1097–1105

[49] Tang Z, Li C and Sun S 2017 Single-trial EEG classification of motor imagery using deep convolutional neural networks *Optik - International Journal for Light and Electron Optics* **130** 11–18

[50] Schirrmeister R T, Springenberg J T, Fiederer L D J, Glasstetter M, Eggensperger K, Tangermann M, Hutter F, Burgard W and Ball T 2017 Deep learning with convolutional neural networks for EEG decoding and visualization *Human Brain Mapping* **38** 5391–5420

[51] Soare C v 2016 Brain Computer Interface using Machine Learning *13th International Conference on Human Computer Interaction, RoCHI* ed Iftene A and Vanderdonckt J (Iasi, Romania: Matrix Rom) pp 65–68

[52] Lu Y, Jiang H and Liu W 2017 Classification of EEG Signal by STFT-CNN Framework: Identification of Right-/left-hand Motor Imagination in BCI Systems *The 7th International Conference on Computer Engineering and Networks* (Shanghai, China)

[53] Bai O, Lin P, Vorbach S, Li J, Furlani S and Hallett M 2007 Exploration of computational methods for classification of movement intention during human voluntary movement from single trial EEG *Clinical Neurophysiology* **118** 2637–2655 nIHMS150003

[54] Lew E, Chavarriaga R, Silvoni S and Millán J d R 2012 Detection of self-paced reaching movement intention from EEG signals *Frontiers in Neuroengineering* **5** 00013

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Additional information

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