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Adaptive multimodal biosignal control for exoskeleton supported stroke rehabilitation

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***Abstract*—A relevant issue of neuro-interfacing wearable robots in rehabilitation is the necessity to have training data, since the collection of sufficient data from patients within a reasonable recording time is not always possible. However, the use of historic data (e.g., session-to-session transfer, subject-to-subject transfer) can often lead to a reduction in classification performance which is affected by the selection of the historic data (i.e., which historic data was chosen for transfer). In this paper, we analyze two approaches to handle this reduction. First, we used incremental algorithms that can be adapted to the current session when trainable components (the spatial filter and the classifier) are transferred between different sessions. Second, we increased the number of sessions to learn more generalized models. To evaluate the approaches, we used electroencephalographic data that was recorded as training data for demonstrating our neuro-interfacing wearable robot in the application of upper-body sensorimotor rehabilitation. The data was collected from the same healthy subject on 14 different days (14 sessions). Our results showed that the use of a mixture of training sessions improved the classification performance. Further, we could show that the adaptive approaches contributed to less variability in performance that allows the system to be more robust. Hence, one can efficiently use both approaches (i.e., adapting and generalizing the models) depending on how much training data is available. Finally, the analyzed approaches are very promising to increase system applicability in upper-body sensorimotor robotic rehabilitation.**

I. Introduction

For a broad acceptance and dissemination of neuro-interfacing wearable robots not only several technological improvements and innovations are still needed on both sides, i.e., the wearable robot as well as the interface, but also long term tests of reliability and effectiveness under possibly natural conditions. Having this said, it must be stressed that studies under rather uncontrolled natural conditions are very hard to be conducted successfully since usually not products and not even prototypes but rather demonstrators of scientific work with immature technology are available within research projects. Beside this, it is difficult to obtain reliable results from studies under uncontrolled conditions. For these reasons we propose to combine controlled studies and application-driven demonstrations as much as possible. This helps to obtain reliable and interpretable results on the one hand and to infer on the principle operability of a neuro-interfacing wearable robot, which is a system with a great complexity that sharply increases the fault potential, on the other hand.

Looking from the application perspective it can be stated that besides applications in the field of gaming and entertainment (see [1] for review), neuro-interfacing wearable robots for the assistance and rehabilitation focusing on the human motor system (see [2] for an overview on orthoses, exoskeleton systems and control strategies) have become of increasing interest. Especially the number of stroke cases which can be treated by neuro-interfacing wearable robots [3] will increase in many western countries due to the demographic changes [4]. For rehabilitation and assistance, systems should be comfortable to wear, behave transparently and intuitively support daily as well as common work activities [5]–[7]. The neuro-interface should reestablish the link between brain and motor system after disruption caused by illness such as stroke [3], [8] or by accidents [9]. This interface should implicitly identify relevant brain states to trigger or adapt the supportive function of the wearable robot to e.g., enable intense training of impaired limb function [10] for neurological recovery [11]. It may use multimodal data, e.g., combine brain data with behavioral data or muscle activity, but it does mainly relay on a stable and reliable interpretation of brain activity [12].

Current neuro-interfaces based on surface electroencephalography (EEG) usually rely on supervised machine learning techniques [13] to learn neural correlates of the brain states [14] that need to be distinguished in an application [15]. One challenge here is the individuality of the neural correlates, differing substantially between subjects, but also between different recording days (sessions) of the same subject [16]. This means, on each day the neuro-interface is used, training data has to be acquired to account for the individual changes of the day. To overcome the problem of training data acquisition, which impairs the overall usability of the system, online learning approaches can be used to adapt the trainable components to the new session. It has been shown in the past, that this approach is promising (e.g., [17]–[19]). Another approach to avoid training data acquisition is the use of historic data. Here, the idea is to generalize the learned models across subjects or sessions and thus to lower the drop in performance compared to a model only trained on a single subject or session

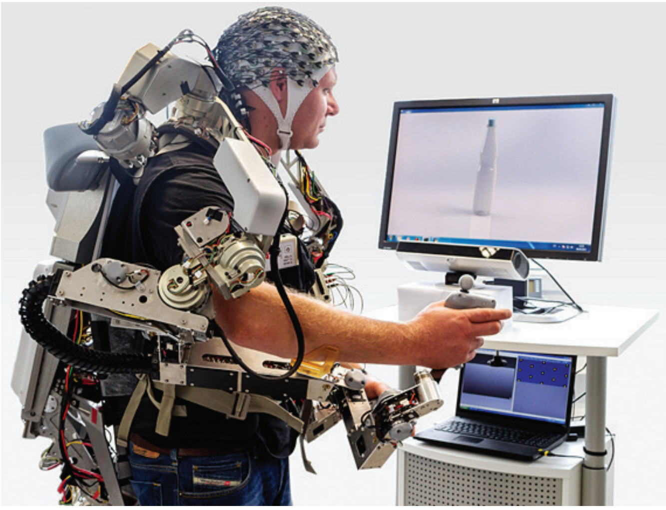

Fig. 1. The active upper body exoskeleton CAPIO, developed in-house for telemanipulation is shown within a demonstration of multimodal signal analysis for exoskeleton supported rehabilitation. The support by the exoskeleton of either the right or the left arm is triggered by activity from the EEG and EMG as well as eye-tracking data. Physiological data analysis was running on the FPGA-based system ZynqBrain developed in-house.

[20], [21].

In this work we investigate by means of a case study the reliability of right and left arm movement prediction based on single-trial analysis of the EEG. We show prediction results over 14 recording sessions, investigate the effect of the amount of training data and test our approach of online adaptation by feedback generated from the electromyogram (EMG) recorded from the subjects arm muscles. The data was recorded as training data for a complex demonstration scenario for exoskeleton supported rehabilitation making use of multimodal, i.e., EEG, EMG and eye movement data analysis (see Fig. 1). This demo was shown 19 times for different guests of our institute, open days and under other highly uncontrolled conditions using 14 times the same subject who's data was used for the case study. While we never recorded the data from the online tests since physiological data analysis runs online on a field programmable gate array (FPGA)-based system without enough resources to save the data at this stage of development, training data was conducted before each demonstration within a controlled environment enabling systematic analysis of the data.

The paper is structured as follows: data acquisition, experimental setup, and data analysis are described under Section II, followed by a section on results and discussions (Section III) and a concluding section (Section IV).

II. Methods

A. Data Acquisition

In this study one healthy subject (male, age: 36) participated in 14 measuring sessions. The EEG was continuously recorded by using a 64-channel actiCAP system (BrainProducts GmbH, Munich, Germany) and amplified by two BrainAmp DC amplifiers (BrainProducts GmbH, Munich, Germany). The electrodes were placed according to the 10-20 system with reference at FCz. Impedance was kept below $5\,\mathrm{k}\Omega$. Further, bipolar EMG was recorded from the left and right biceps using a ExG MR bipolar amplifier (BrainProducts GmbH, Munich, Germany). All signals were recorded with a sampling frequency of $5000\,\mathrm{Hz}$ since this was the output sampling frequency of the amplifiers. The subject gave written and informed consent to participate and all experiments were conducted in accordance with the declaration of Helsinki. Each session consisted of two sets in which at least 40 movements of each arm were performed.

B. Experimental Setup

The experiments were conducted in a shielding cabin, which allows measurements without the influence of electromagnetic interference. The subject sat in a comfortable chair in front of a table with a computer screen. The scenario used was implemented with the software Presentation (Neurobehavioral Systems, Inc.). Subjects were instructed to focus on a green circle with a black fixation cross on a gray background to minimize eye movement artifacts in the EEG data. As input device a custom-made board with two switches (for the left and right hand) and a light barrier approximately $40\,\mathrm{cm}$ above the switches were used. In each set the subject had to lift each hand at least 40 times and return to the switch. Movement onset and type (left or right) was freely chosen by the subject. In-between two consecutive movements a minimal resting time of $3\,\mathrm{s}$ had to be fulfilled. Early movements were reported to the subject by changing the circle's color to red for $100\,\mathrm{ms}$ and were not counted. The resting time ensured that enough data for the *no movement* condition could be acquired. All events from the switches and light barrier were labeled in the EEG and EMG for later performance analysis.

C. EMG Processing

Raw EMGs were preprocessed with a variance based filter approach. Within a window of $0.2\,\mathrm{s}$ length the variance was computed and assigned to the last sample in the window. This was done consecutively for each sample. For onset detection an adaptive threshold was used. The threshold was also calculated in a sliding window manner. The mean of the last $1\,\mathrm{s}$ plus p times the standard deviation of the same window length was used as threshold, where p is a sensitivity factor which was chosen to be 6. After finding an onset in one of the EMG channels, the signal had to be lower than the threshold for at least $1\,\mathrm{s}$ before a new onset can be found. This was done since in the movement phase there is obviously high activity in the EMGs and this shall not always lead to a new onset detection.

D. EEG Processing

Movement preparation is reflected in the EEG by several patterns: event related (de)-synchronization (ERD/ERS) [22] and movement related cortical potentials (MRCPs) [23]. The aim of our EEG processing was to detect MRCPs, mainly the late readiness potential, which is an increase in negative activity at central electrodes contralateral to the side of movement

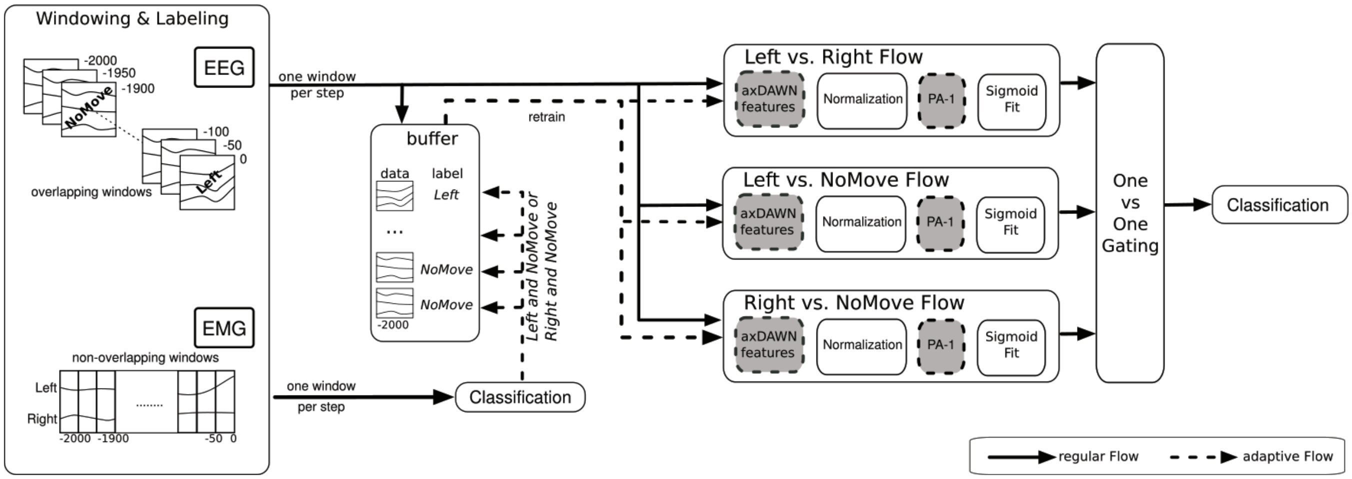

Fig. 2. Illustration of the processing of EEG and EMG data after pre-training, i.e., during application. Every 0.05 s the current data was classified. If a movement was recognized by the EMG processing, e.g., a left movement, the buffered EEG data was labeled accordingly and the aXDAWN and PA-1 classifier were adapted.

starting approximately 0.5 s before movement onset [23], [24]. To detect the MRCPs and reduce the computational load for further processing, the data was decimated to 20 Hz and low-pass filtered (cutoff 4 Hz) with a finite impulse response filter. This radical filtering also reduces muscular artifacts in the data which manifest mainly in higher frequency ranges.

For supervised machine learning and later performance evaluation, the data was segmented into windows and labeled based on the events of the switches. The data between 2.2 s before each switch event and the switch event was considered. For each movement, two windows with a length of 0.2 s ending at 0 and -0.15 s with respect to the movement onset were cut and labeled according to the movement type (*Left* or *Right*). For the third class (*NoMove*), windows of the same length ending at -1.7, -1.5, -1.3 and -1.1 s were used.

Classification was performed with a passive aggressive perceptron (PA-1) [25]. A one-vs-one approach was applied to differentiate between *NoMove*, *Left* and *Right* with this binary classifier type. That means three binary classification problems had to be solved: *Left* vs. *Right*, *NoMove* vs. *Left*, and *NoMove* vs. *Right*. The output scores of the classifiers were combined by first calculating probability estimates using Platt's sigmoid fit [26], [27] and then summing up the probabilities for each class. Finally, the class with highest probability was returned. In the demonstration scenario, a movement of the exoskeleton was triggered, whenever the returned class indicated a movement that was confirmed by EMG analysis within the next 500 ms and the subject focused on the bottle (revealed by eye-tracking, see Figure 1).

The processing within each of the binary classification problems was similar and is thus described only once: For dimensionality reduction and increase of the signal-to-noise ratio, a spatial filter was trained. Here we used a variant of the xDAWN algorithm [28] that can be trained incrementally [19]. The number of retained pseudo-channels was set to four. The values of the pseudo-channels formed a feature vector of dimension 16 (4 pseudo-channels $\times$ 4 time points). Each feature dimension was normalized to have zero mean and a standard deviation of one. The normalized feature vectors were the input of the PA-1 classifier. The cost parameter of the PA-1 was optimized using a grid search where internally a 5-fold cross-validation was performed on the training data and the best value of $[10^{-6}, 10^{-5}, ..., 10^{0}]$ was selected. Further, all training examples of the movement classes were used twice during training to account for the imbalance in comparison to the *NoMove* class.

Figure 2 illustrates the EEG processing (starting from the segmented windows) and the usage of EMG as trigger of adaptation during application (details, see Section II-E1).

E. Analyses

For all analyses we used an inter-session evaluation scheme. That means the EEG processing was evaluated on data of a session that was not included in the training data. As performance measure the balanced accuracy (BA) was computed, that is the arithmetic mean of the rates of correctly classified instances of each class. This metric is insensitive to different class ratios [29], i.e., insensitive to the overrepresented number of *NoMove* instances. Since a single detection of *Left* or *Right* in the application might trigger the exoskeleton to support the movement, a single detection within the interval $[-0.6, -0.05]$ s counted as classified movement. The remaining range (-2 to 0.65 s), i.e., the *NoMove* class, was evaluated for each sliding window. For all analyses the software pySPACE was used [30].

1) Adaptation of the Trained Models: During testing, the sliding windows were classified based on each modality separately (see Fig. 2). Before the EEG data was passed to the three processing chains for binary classification (Left vs. Right, Left vs. NoMove, Right vs. NoMove), it was stored in a buffer for getting supervised labels later in time. As soon as a movement

TABLE I
CLASSIFICATION PERFORMANCE (% BALANCED ACCURACY) FOR ALL TRAIN-TEST-SESSION COMBINATIONS. VALUES REPRESENT AVERAGES OVER THE TWO RECORDING SETS.

train / test	1	2	3	4	5	6	7	8	9	10	11	12	13	14	Min	Avg	Max
1		77.86	60.16	86.41	83.39	87.18	83.74	81.99	83.13	84.33	83.33	85.91	86.49	86.78	60.16	82.36	87.18
2	67.28		81.13	81.72	59.44	68.28	77.95	83.83	81.88	84.51	80.15	72.02	85.39	86.26	59.44	77.68	86.26
3	50.21	75.69		64.09	42.07	57.25	61.79	61.31	54.48	61.50	51.48	51.16	61.12	64.11	42.07	58.18	75.69
4	74.29	79.50	68.42		69.83	78.09	75.21	76.45	75.48	75.83	75.23	77.35	77.90	79.65	68.42	75.63	79.65
5	87.90	83.91	61.64	88.98		88.03	81.13	84.96	86.17	87.54	88.93	83.49	88.88	91.16	61.64	84.83	91.16
6	86.74	72.17	57.69	79.88	81.41		73.06	76.18	78.12	74.92	78.58	80.33	80.74	77.05	57.69	76.68	86.74
7	80.60	84.80	71.06	79.52	76.77	78.77		79.19	90.03	79.29	87.66	80.29	85.78	85.66	71.06	81.49	90.03
8	83.07	87.64	77.14	86.16	84.21	84.34	84.61		87.70	91.19	87.13	82.18	87.97	90.70	77.14	85.70	91.19
9	81.81	88.18	72.78	85.03	82.98	83.75	83.16	90.16		86.60	87.23	84.75	89.06	89.55	72.78	85.00	90.16
10	80.86	89.14	81.96	82.26	65.99	79.42	78.32	83.37	85.91		83.72	79.06	85.21	84.49	65.99	81.52	89.14
11	86.32	82.86	66.52	86.25	84.21	87.95	87.53	84.63	91.45	84.15		86.91	89.18	88.29	66.52	85.10	91.45
12	78.94	70.61	65.65	84.80	78.27	72.77	77.82	78.75	78.78	79.57	77.43		81.23	88.67	65.65	77.95	88.67
13	85.24	95.21	81.08	92.93	76.93	86.17	86.99	91.07	88.68	90.49	87.76	89.65		91.46	76.93	87.97	95.21
14	90.86	88.21	78.92	84.83	89.89	82.47	87.58	91.43	74.24	83.05	85.05	93.02	89.67		74.24	86.09	93.02
Avg	79.55	82.75	71.09	83.30	75.03	79.57	79.91	81.79	81.24	81.77	81.05	80.47	83.74	84.91			

was detected based on EMG, labels were sent to the buffer. The idea was to label the windows similar as during training (see Section II-D): Due to the electromechanical delay [31], we expect the EMG onset before the switch release. Previous analyses in a similar experimental setup revealed a mean difference of $0.08\,\mathrm{s}$ between EMG onset and switch release. Hence EEG windows ending at $-0.05\,\mathrm{s}$ and $0.1\,\mathrm{s}$ with respect to the EMG onset were labeled as movement (corresponding on average to time points $-0.15\,\mathrm{s}$ and $0.0\,\mathrm{s}$ with respect to the switch release). Further EEG windows ending at -1.6, -1.4, -1.2 and $-1\,\mathrm{s}$ with respect to the EMG onset were labeled as *NoMove*. When all data and labels for one movement cycle were present in the buffer, they were processed again and updates of all aXDAWN and PA-1 were performed.

Our adaptivity approach relies on supervised labels that were obtained based on a different signal source. The correctness of these labels is crucial to perform the model adaptation. Hence, we also computed the performance of EMG classification. For that, evaluation settings were the same as those for EEG classification, except that for EMG a detected movement in the interval $[-0.25, 0]\,\mathrm{s}$ with respect to the switch release was counted as correctly classified movement.

2) Number of Sessions for Generalized Models: To investigate how the models generalize across different sessions we increased the number of training sessions successively. We computed results for one, two, three, four and five training sessions, since from the application perspective the number of used sessions should be small. We even reduced the training size to one set of a session since it is not easy to obtain enough training data from patients in real-world applications. However, it can be expected that more sessions increase generalization performance. For this reason, we also computed results for 13 training sessions to serve as a baseline. Note that for 0.5, 1, 2 and 13 training sessions, all possible combinations were computed and results were averaged. For the remaining numbers of training sessions we limited the computed combinations to 100 randomly chosen combinations to obtain a feasible amount of computation time.

3) Statistics: For statistical evaluation, the data was analyzed by a two-way repeated measures ANOVA with *training size* and *method* as within-subjects factors. The factor *training size* contains 7 levels: 0.5, 1, 2, 3, 4, 5, 13 sessions and the factor *method* contains 4 levels: aSF-CL, SF-aCL, aSF-aCL, and SF-CL (baseline) where aSF stands for adapted spatial filter and aCL stands for adapted classifier. When necessary, the Greenhouse-Geisser correction was applied and the corrected p-value is reported. For multiple comparisons, the Bonferroni correction was applied. 28 data pairs (sample size of 28: 2 evaluations $\times$ 14 test sessions) were used for the statistical analysis.

III. RESULTS AND DISCUSSION

As mentioned earlier, we evaluated the classification performance based on EMG, which was used to obtain supervised labels for model adaptation. We obtained a high BA of on average $97.35\,\%$ ($\pm$ $3.14\,\%$) across all sessions.

Table I shows the classification performance (balanced accuracy, BA) based on EEG for all train-test-session combinations as well as minimum, maximum and average performance across training sessions. There was a huge variance in classification performance of up to $30\,\%$ BA for several testing sessions. This variance resulted from the used training session and could be reduced by the two approaches: a) adaptation of the pre-trained models to the testing session and b) increase of the number of training sessions.

Figure 4 summarizes our results and Figure 3 depicts a detailed comparison of the adaptive approaches when one session was used for training. The statistical evaluation reveals that the classification performance was influenced by both factors (training size and method). First, the classification performance was increased with the amount of training instances [main effect of training size: $F(6, 162) = 125.76, p < 0.001$]. Here, we observed no significant increases after four training sessions over all methods [comparisons of all session pairs: $p < 0.02$, except for 4 vs. 13 and 5 vs. 13 sessions: $p = n.s.$]. In other words, a saturation of performance increase was

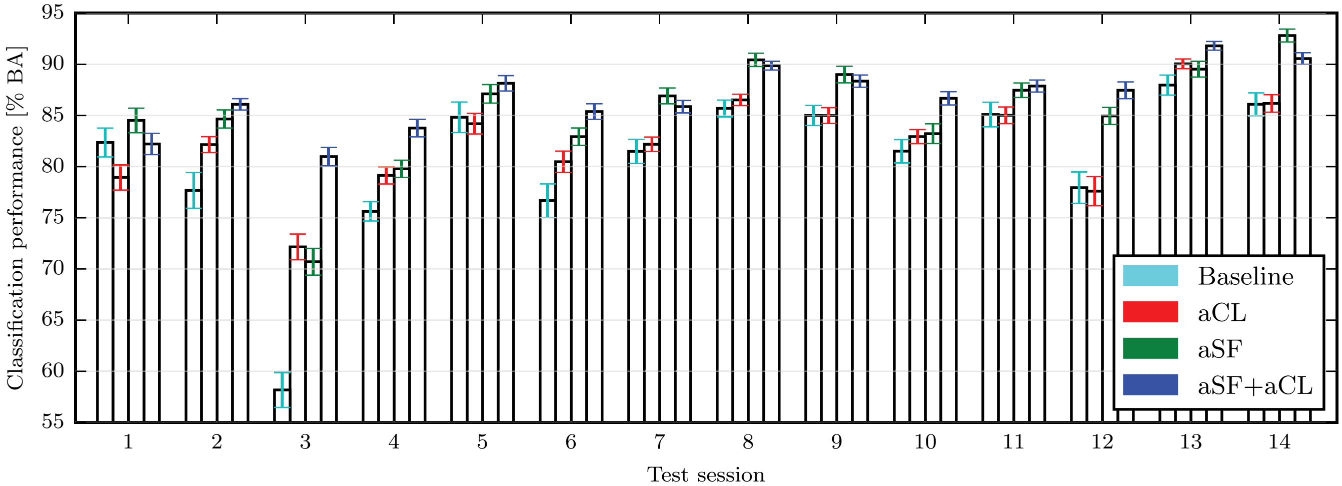

Fig. 3. Mean classification performance (% balanced accuracy) and standard error of the mean (SEM) across all training combinations of one session for each test session. Baseline – static algorithms, aSF – adaptive spatial filter, aCL – adaptive classifier, aSF+aCL – adaptive spatial filter and classifier.

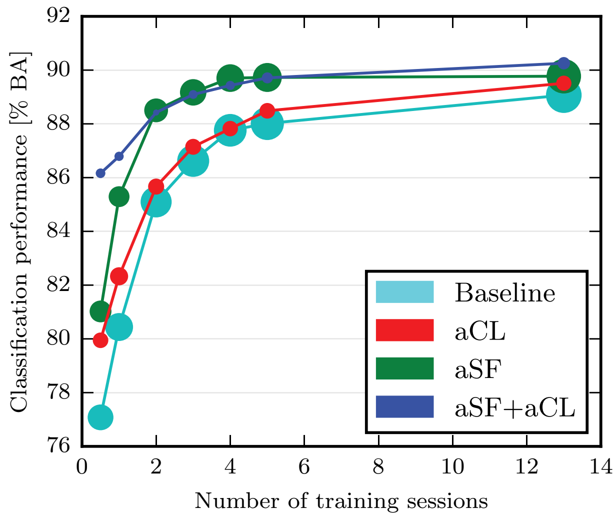

Fig. 4. Mean classification performance (% balanced accuracy) for different amounts of training data and methods: Baseline – static algorithms, aSF – adaptive spatial filter, aCL – adaptive classifier, aSF+aCL – adaptive spatial filter and classifier. The marker size is proportional to the variance of the mean, i.e., standard error of mean (SEM). For example, a large marker corresponds to a large SEM.

achieved after three sessions, which in total contained 240 left and 240 right movements.

Second, the methods (adapted or not adapted spatial filter and classifier) had also an impact on the classification performance [$F(3, 81) = 7.59, p < 0.001$]. The combined approach (aSF+aCL) and the adaptive spatial filter (aSF) achieved significantly better performance compared to the case of using only the adaptive classifier (aCL) or no use of any adaptive approach (baseline) over all sessions [$p < 0.001$].

Third, both factors interacted with each other [$F(18, 486) = 30.19, p < 0.001$]. The effect of training size was greater when using the adaptive classifier compared to all other methods [combinations of all sessions pairs: $p < 0.001$ for aCL; 4 vs. 5, 4 vs. 13, and 5 vs. 13 sessions: $p = n.s.$ for aSF+aCL; 2 vs. 3, 4 vs. 5, 4 vs. 13, and 5 vs. 13 sessions: $p = n.s.$ for aSF; 4 vs. 5, 4 vs. 13, and 5 vs. 13 sessions: $p = n.s.$ for baseline]. A possible reason is that the variance of the performance mean obtained by aCL is very small compared to aSF or baseline. Hence, the large variance of aSF was substantially reduced when aSF has been applied together with aCL (aSF+aCL).

In particular, when only few training data was available (see Fig. 4: 0.5 session, i.e., 40 left and right movements), the combined approach (aSF+aCL) was superior compared to the cases of adapting only one of both (aSF or aCL) [aSF+aCL vs. aCL: $p < 0.001$, aSF+aCL vs. aSF: $p < 0.001$, aSF+aCL vs. baseline: $p < 0.001$].

However, this effect was attenuated when the training size was increased (see Fig. 4: 1 session, i.e., 80 left and right movements). Both the adaptive spatial filter (aSF) and the combined approach (aSF+aCL) achieved better performance compared to the case of adapting only the classifier or no adaptive approach [baseline vs. aSF or aSF+aCL: $p < 0.001$, aCL vs. aSF or aSF+aCL: $p < 0.001$].

For one session of training data, Figure 3 shows a session-based comparison of the adaptive methods. Especially, we observed a substantial performance increase by the combined approach for the sessions which had a low performance baseline (e.g., session 3, 4 and 6). Further, the variance was reduced for most sessions in comparison to the baseline. Not surprisingly, the baseline did not significantly differ from the adaptive approaches, when the training size was further increased [combinations of all method pairs: $p = n.s.$, see Fig. 4: 13 session].

In summary, the combined approach (aSF+aCL) achieved significantly better performance than the other approaches including the baseline, when few training data was available.

IV. CONCLUSION

In this study, we could show that the analyzed approaches (adapting and generalizing models) can increase the systems performance and make the system more robust in the setting of session-to-session transfer. Further, our results indicate that one can choose between the two approaches depending on how much training data is available. When only a small amount of historic data is available, the adaptive algorithms can be applied to increase the classification performance. In contrast, when already sufficient amount of training data has been collected, the whole amount of data can be used to generalize the models. In this case, not surprisingly, the adaptation of the models has no further impact on the systems performance. Hence, historic data can be efficiently used depending on real-world daily rehabilitation situations.

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