Towards Assistive Robotics for Home Rehabilitation

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Abstract: In this paper, we want to point out the possibilities that arise from the latest advances in robotic exoskeleton design and control. We show that approaches of artificial intelligence research and robotics that integrate psychophysiological data analysis offer the possibility to assist disabled people in their everyday lives. Thus, continuous long term rehabilitation training and daily support can be provided in the future to help them to regain motor functions. We outline a possible scenario for fully embedded home rehabilitation and its components. The presented work further investigates two challenges of the application of such a system in more detail: (i) improvement of the interaction between the patient and the supporting interface and (ii) enhancement of reliability of predictions made about the patients intention. In the experimental part we demonstrate that the exoskeleton control can compensate for gravitational loads, imposed by the device itself. Further, we present results that show that movement onset prediction can be made based on different psychophysiological measures, and can be improved with respect to their reliability.

1 INTRODUCTION

Every year, more than 200.000 patients in Germany suffer from neurological impairments due to stroke (Platz and Roschka, 2009). They show major loss of motor abilities which severely impairs their ability to continue their lives both in private as in their professional domains. Apart from the dramatic impact on the individuals, a maior societal and financial impact on the economy has to be considered since too many of these individuals cannot be fully reintegrated into the professional world, or may have to abstain from a professional life altogether. When including other impairments of the motor system than those induced by stroke, an in-homogenous group of patients with different demands have to be treated. Hence, rehabilitation could be more efficient with rehabilitation systems that are able to cover a wide range of patients. Full recovery rate could further be increased by providing professional long term rehabilitation and support. Therefore, rehabilitation systems should allow to increase the number of treatment sessions that is so far limited due to the shortage of skilled therapists and costs. To summarize, there is a big need for rehabilitation tools that transfer rehabilitation and support in every day life.

In this paper we will outline a future fully embedded home rehabilitation and support system and pinpoint the technological developments needed to achieve our vision. This is a fully integrated, daily rehabilitation provided by a lightweight, comfortable-to-wear upper body exoskeleton that has enough force to move a plegic arm of a patient. By analysis of psychophysiological signals, like the electroencephalogram (EEG), the electromyogram (EMG) and gaze direction, an artificial intelligence-based control architecture is able to predict intentions of the user to support self-initiated movements.

The support of self-initiated movements has a positive effect on rehabilitation (Clark and Smith, 1999). The earlier a later supported movement is predicted the more will the patient have the impression that he himself is controlling his arm autonomously, although the exoskeleton is actually moving it. Early prediction of movements re-connects the movement planning phase of the brain with movement execution to re-establish the capability of the patient for freely and self-paced movements.

To cover the need for rehabilitation systems which are able to analyze and monitor the behavior of the subject while operating in a familiar environment, the patient should interact with a real or simulated everyday environment. All processing needed for the support system should fit into a smartphone sized onboard computing device.

In the long term vision, the patient should be able to live at home without the help of others, receiving rehabilitation sessions on demand and thus increasing the chances for full recovery. Additionally, such a system is in principle able to automatically protocol the success of rehabilitation. This can be done by analyzing psychophysiological data and action force, recorded by sensors that are integrated into the exoskeleton.

To implement such a rehabilitation system some challenges have to be dealt with, two of those are investigated here: (i) to develop a control mechanism that support the patient during interaction with the support system, i.e., by compensating for gravitational load of the exoskeleton, and (ii) to improve the reliability of prediction made with respect to the patients movement intention. Thus, the paper is structured as follows: after presenting relevant research (Sec. 2) in context of our technological approach for future home rehabilitation that is briefly described in Section 3, we present results of three studies conducted to deal with the before mentioned challenges (Sec. 4), closing with a conclusions and outlook (Sec. 5).

2 ROBOTIC REHABILITATION

Currently, there are already some robotic systems applied in rehabilitation. The conception of these systems is based on modern, evidence-based therapy approaches, such as repetitive task-orientated bilateral and distal training as well as assist-as-needed and mirror therapy (Hesse et al., 2009; Platz and Roschka, 2009). The main goal of these modern therapy approaches is to increase the neuroplasticity of the central nervous system (Volpe et al., 2000; Takahashi et al., 2008). Some examples from praxis show that the usage can be reported as successful and that a rehabilitation effect can be measured using these kinds of system (Volpe et al., 2000).

Depending on the characteristic and severety of symptom, different system designs are currently used. This means that in praxis a certain system is only used on a defined, usually small group of patients. For example, the swiss company Hocoma[1] provides three different rehabilitation systems (ArmeoPower, former ARMin (Mihelj et al., 2007), ArmeoSpring, ArmeoBoom) for upper limb rehabilitation which are based on task-oriented training scenarios in a virtual environment, which facilitates treatment of neurological diseases of different severity. Even though there are synergies between the rehabilitation systems (e.g., in the software platforms, the visual feedback or assessment tools) the physical systems are totally different, which means in order to address the whole range of possible patients, different physical systems are required.

Today, some approaches of exoskeleton-based assistance exist. The exoskeleton system HAL presented in (Otsuka et al., 2011) aims at expanding, intensifying and supporting physical capabilities of humans during activities of daily living. In context of an everyday task (meal assistance), the device is able to guide and support the user during reaching movements and thus facilitates the impaired subject to take his meal independently. The overall system has 4 electrically actuated degrees of freedom (3 shoulder, 1 elbow) and offers a grasp-assistance mechanism, which operates separated from the rest of the system. HAL moves the user's limb totally passive using a minimum jerk control approach. Like ARMin (Mihelj et al., 2007), HAL is fixed to a grounded support and thus is massively restricted in his operational range.

Besides exoskeleton devices also end-effector-based approaches can be found in modern therapy. A good example is the InMotion Arm Robot (former: MIT Manus (Hogan et al., 1992)) which assists patients by moving their totally passive arm or by supporting an active movement coming from the patient. This system simulates the classical hand-to-hand therapy of a therapist with a continuous determination of position and force applied to the arm of the patient. It is also equipped with a visual feedback which allows to address even complex tasks. A drawback is that the system is stationary and restricted to planar movements.

Independent of the physical system, the usage of virtual reality scenarios is one important approach of supporting patients within typical daily activities as discussed in (Guidali et al., 2011). In their work, an exoskeleton is combined with a virtual reality scenario. The integration of daily purposeful activities in rehabilitation sessions is thought to improve rehabilitation progress much more than artificial movements could, since trained motor behaviors and brain pathways are addressed.

Another example for the usage of virtual reality

[1] *http://www.hocoma.com/en/products/armeo/*

is the PITS system (Villiger et al., 2011). This assistance system is not applying physical therapy but allows the realization of known therapeutical principals and therapies, e.g., mirror therapy. The pathological weak or plegic arm can behave in a virtual reality. The therapeutic approach can differ depending on the state of the patient, i.e., whether he is already able to carry out own activity or not.

The integration of pyschophysiological measures and stimulation of motor activity are future approaches that can help to improve rehabilitation. In the Brain2Motion project[2] an exoskeleton shall be combined with a textile-based surface motor neuroprosthesis. This neuroprothesis shall apply functional electrical stimulation (FES). Besides, a non-invasive EEG-based Brain-Computer Interface (BCI) and an electrooculography (EOG) interface will be integrated as well to support the whole system. Other approaches integrate electromygraphic signals alone (Lenzi et al., 2012) or both, EMG and EEG in combination (Gancet et al., 2011).

To summarize, approaches reviewed here address one or more of the three main fields of expertise: BCI technologies, virtual reality, and exoskeleton. In some systems, it is shown that the integration of at least two of these fields into a support system can improve the support of the user. However, they are very specialized in function and design, mostly stationary and can only address certain pathologies according to the therapy approach the individual developer groups are following.

3 TECHNOLOGICAL APPROACH

To combine different approaches, the proposed rehabilitation system (see Fig. 1) should be composed of 1) an exoskeleton which adapts to the body characteristics of the user and supports or carries out intended movements 2) a virtual (or real) environment the user can move in and perform natural interactions, and 3) integrated psychophysiological data analysis for movement prediction of self-paced movements by an 4) embedded processing module. In the following, we give an overview of our technological approach and the main components of the system.

3.1 Exoskeleton

The exoskeleton system presented is a 7 degrees-of-freedom (DOF) haptic device, built *around* the human

[2] *http://hal.umh.es/brain2motion/description.html*

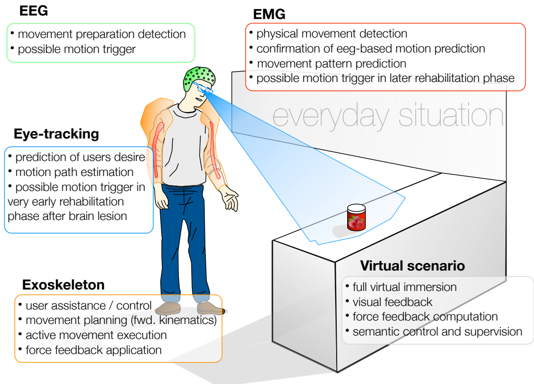

Figure 1: Future home rehabilitation supported by an exoskeleton, a virtual scenario and biosignal analysis.

body and worn by the user. It allows support of subjects with impaired motor skills during activities of daily life.

In the initial design phase, we identified the three main goals for designing the system, described in the following: 1) The exoskeleton has to be wearable by the user and not to be fixed to a special support mechanism, 2) it should have multiple contact points to the user's body, allowing for the reflection of complex force patterns to the user and thus enable precise guidance of movements. 3) It has to be inherently safe, which means that the subject always has to be able to overcome any force the exoskeleton imposes on the body of the operator during movement execution. The mechanical structure of an exoskeleton has to be highly adaptive to be able to cope with different human proportions (segment lengths & joint position). In addition to that, human joints are not joints in the sense of classical mechanical engineering. Often axes are not fixed in space, but drift along trajectories (especially in the shoulder and the elbow) to optimize the force of the muscle-tendon system. This has to be captured by the exoskeleton through permanent alignment of system axes to the corresponding human joints.

Based on multiple literature studies on human physiological and behavioral tests, a one arm exoskeleton haptic device was developed (see Fig. 2). The exoskeleton interacts via four points with the human, meassuring the forces by sensors integrated in the structure. Another important factor is the operational workspace of the system coupled to the user. Several experiments show that the exoskeleton does not prevent the execution of the most important arm movements with a coverage of about 60 % of the overall human arm workspace and up to 90 % of the natural manipulation workspace. The 7 active DOFs are driven by an electro-hydraulic actuation concept,

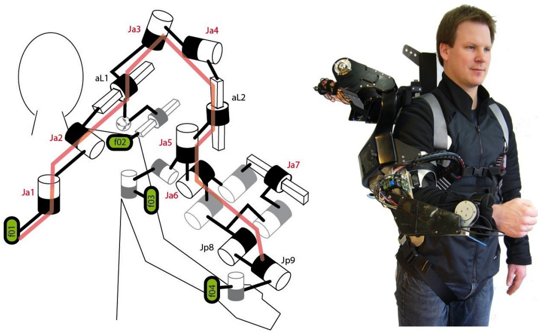

Figure 2: (left) The kinematics of the designed exoskeleton with 7 active degrees of freedom and two passive measured degrees. (right) The DFKI RIC exoskeleton worn by a user.

which encompasses a highly integrated low-pressure fluid servo-valve that can be directly mounted on a rotary vane actuator, resulting in a safe and dense actuation unit, operating at 30*bar* hydraulic supply pressure. The entire control of the actuation is carried out locally by a set of distributed μControllers, which run a combination of model-based feed-forward and classical feed-back control approaches, and communicate to a central control system via CANbus (Jordan et al., 2012). On top of this inner loop of n low-level torque controllers (n equal to the number of active DOF), the overall control system of the exoskeleton is organised in a multi-layer architecture, with a cascaded structure. The outer loop contains several elements (feed-forward as well as feedback), which determine the reference torque $\vec{\tau}_{ref}$ for the controllers in the inner loop. Within this context, a special *gravity compensation* block deals with minimizing the impact of the exoskeleton on the wearer by compensating for the weight of the device.

3.2 Home Rehabilitation

To start therapy, the usage of a virtual environment allows controlled interaction of the patient with objects in known scenarios. A controlled retrieval of certain simple and complex movements through a therapist, who is controlling the scenario and is designing the therapy for the subject, is easily possible. By this, one can make use of the positive and motivating effect of having a patient interacting in known scenarios that replicate possible activities in normal life, like preparing breakfast in the kitchen, while still controlling the patients activity by, e.g., setting a jar of jam in different positions in the interaction space (Fig. 1)). A virtual scenario can further easily be used to predict the intention of a patient. An intended behaviour of a patient can – in the simplest approach – be pre-defined by the semantic content of a fixated object in a virtual scenario. For example, if the subject is fixating a jar of jam in a shelf (Fig. 1) it is likely that the patient wants to grab it. If the jar of jam is already standing in front of him on the table, he might want to open it. If it is already open, he may likely want to get a spoon to scoop out some jam for his slice of bread etc.. Further, movement direction and even the target position can be determined and used to calculate movement direction to be executed by the exoskeleton. Thus, by making use of the semantic context, intended movement directions can be computed during the patient's interaction with a virtual environment.

In real environments, object recognition and context analysis would further be required, which puts greater demands onto the whole system and its artificial intelligence. However, by extending the system to be able to deal with real environments, a transfer of the rehabilitation system from its usage for therapy into daily support is possible.

3.3 Psychophysiological Data

To enhance human-machine interaction for the purpose of rehabilitation, it is not enough to equip robotic systems with sensors that allow to react on the human behavior, but to predict his behavior with the goal to adjust the support of the robotic device to the current and upcoming requirements of a patient.

In our approach, a movement is initiated by movement onset prediction based on EEG or EMG. In case some data is disturbed, as it is likely the case for EEG and EMG data recorded from stroke patients, movements can still be triggered by means of eye tracking. Hence, interruption of the motor-sensor loop due to different kinds of disorders can be compensated very flexible by the system to allow psychophysiologically adapted guidance of an exoskeleton. This allows the application of one rehabilitation device to a number of different disorders and even to patients with paretic limbs, while being situated in an every day environment.

For any kind of adaptation of the exoskeleton control by psychophysiological data, one has to assure that malfunction due to misclassification is avoided. This can be assured by combining and weighting predictions made on the basis of different types of data, e.g., to predict movements based on EEG data while using EMG signals to assure that the subject wants to move and did not just imagine a movement, or to predict movement by EEG data and use force sensors integrated in the exoskeleton to trigger the onset of the movement (Folgheraiter et al., 2012). When eye tracking is used to control for, e.g., movement direction, even a weak EEG or EMG signal can be used to

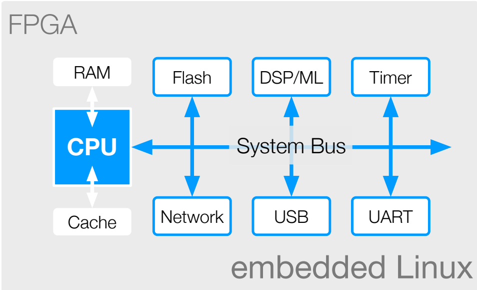

Figure 3: Design for system on chip for processing of psychophysiological data.

assure that the patient wants to use his gaze to trigger a movement, as shown for a BCI application (Zander et al., 2010). Hence, the combination of different kinds of psychophysiological data enables different kinds of control and adaptation of the exoskeleton with respect to the requirements of the patient and the state of rehabilitation to support correct function.

3.4 Embedded Processing

For a full integration of our approach into the daily life of a patient, not only the sensors but also the data analysis hardware has to be embedded into the rehabilitation system. Reconfigurable, application-specific hardware components can be a solution realized by using field-programmable gate arrays (FPGAs) which become increasingly popular for DSP techniques (Meyer-Bäse, 2007). So far only few approaches had applied embedded analysis for psychophysiological data (e.g., (Shyu et al., 2010)). A special embedded computational systems is currently developed that allows to combine a generic processor for software-specific tasks and application-specific parallel DSP architectures, as shown in Fig. 3.

4 Experimental Part

In the following, we present and discuss results of a study investigating the capability of the developed exoskeleton to compensate for gravitational loads. This is especially important in order to keep the device as transparent as possible to the user during training sessions and extend the application time of the device. Further, compensation of gravitational loads prevents user fatigue, by relieving the subject from additional load, and helps to successfully fulfill the rehabilitation task (Beer et al., 2008). A second study was conducted to develop a procedure that improves performance in the prediction of movement planning based on EEG single trial analysis (see Sec. 4.2). In future, EMG signals could alternatively or additionally to EEG signals be used to predict movement onset. Further, EMG signals can be used to confirm movement onset earlier than it can be done when using force sensors integrated into the exoskeleton as discussed in (Folgheraiter et al., 2012)). Hence, in a third study EMG onset activity during different types of movements that may occur during rehabilitation of arm movements are investigated with respect to the earliness and reliability of detection (see Sec. 4.3). For this paper, offline EEG and EMG analysis were both performed on a standard PC.

4.1 Exoskeleton Inverse Dynamics

As described, inside the exoskeleton control system a *gravitation compensation* block exists, which aims at minimizing the impact of the exoskeleton to the user, by compensating for the weight of the device. This was realized via a feed-forward controller based on the inverse dynamic model of the haptic device, which is updated at a frequency of $100Hz$. Briefly, inverse dynamics is establishing the following relationship:

$$\tau_{grav}(t) = f(\mathbf{q}_{act}(t), \mathbf{m}) \quad (1)$$

The function describing Eq. 1 defines, according to the actual pose of the exoskeleton in the joint space $\mathbf{q}_{act}$, the torque τ_{grav} for each active joint of the device, which is necessary to compensate for gravitational effects caused by the following mechanical structure (gravitation compensation). For this purpose, a mass model of the active exoskeleton system $\mathbf{m}$ was developed and integrated into the real-time control loop. The resulting reference values are communicated via CANbus to the distributed joint control system, which is directly located at the mechanical structure of the exoskeleton and running at a frequency of $2kHz$. Due to the fact that the compensation of gravitational loads is always active, the remaining control structure includes permanent knowledge about the dynamic behaviour of the system, which is advantageous (Kelly, 1997).

Experimental Setup To verify the capability of the exoskeleton system to compensate for gravitational loads caused by the device itself, 15 subjects with different anthropometric measurements were asked to wear the system and perform voluntary movements in space. Within the test, alternation between wide and small motions was encouraged in order to cover the full-body working range. This enabled us to record data during long transitional movements as well as short, precise movements. Furthermore subjects were asked to state how much the exoskeleton influenced them during operation, in order to get a subjective feed-back of the comfort of the device.

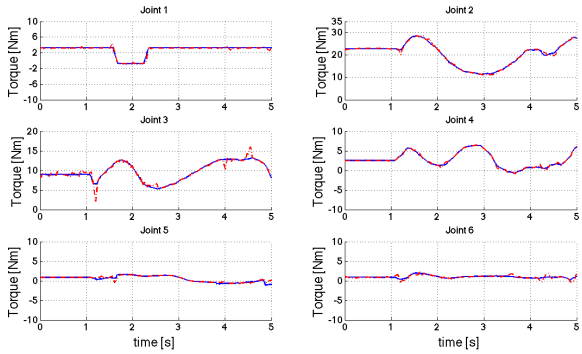

Figure 4: Movement associated joint torques for active degrees of freedom of the exoskeleton; (blue) reference torque; (red) actual torque.

Results Fig. 4 shows experimental results for the desired and actual joint torques of all actuated degrees-of-freedom during a voluntary movement of one subject in combination with the exoskeleton system. It is obvious that the torque control system of the device is able to track the desired reference torques very well. Small errors occur mainly when the user changes the direction of movement of a joint. These errors cannot be further reduced due to the fact that the control frequency of the torque controller is limited by the control frequency of the valves (11Hz). Presented results are representative for all tested subjects. Nonetheless, even with detectable small errors, all subjects reported that the exoskeleton appears transparent to them, especially during small movements.

4.2 Reliability of EEG-based Movement Predictions

Directed motor action requires planning by the brain. Several parts of the brain are involved in motor planning including the primary motor cortex. Its activity can be recorded with the help of EEG systems. Changes in EEG activity are expressed in the frequency range (Leeb et al., 2006) as well as in event-related potential (ERP) activity, especially in the Lateralized Readiness Potential (LRP) (Kornhuber and Deecke, 1965; Santucci and Balconi, 2009). By detecting those differences in brain activity, it is generally possible not only to predict the execution of movements but also which side (right or left body side) and which part of the body (arm or leg) will be moved (Leeb et al., 2006).

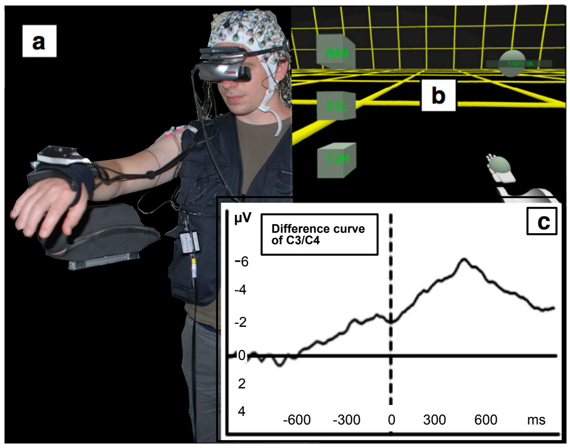

Figure 5: (a+b) Experimental setup (details see text). (c) Averaged difference curve between electrodes C3 and C4.

In a pilot study published in (Folgheraiter et al., 2011), we investigated whether ERP activity can be used to predict upcoming movements by applying supervised classification techniques. The prediction can be transferred into a continuous score to prepare an exoskeleton for movement onsets. The study presented here was performed in a similar setup. We investigated the reliability of movement prediction during complex arm movements. As extension of the first study, a multi-task condition was created to simulate a more realistic situation, where subjects' concentration is shared among different activities. The main goal of the study was to investigated the effect of the number of training windows (used to train a classifier) onto the stability of movement prediction.

Experimental setup Four male subjects (between 25 and 31 years, right-handed, and normal or corrected-to-normal vision) were situated in a virtual scenario (see Fig. 5). Subjects had to move their right arm from a rest position, supported by an armrest (see Fig. 5 a), to a target position visualized by a virtual target ball (see Fig. 5 b, upper right corner). After entering the target ball, the subjects returned to the rest position while the next target ball appeared. Participants had to stay in the rest position for at least 5 seconds before starting the next movement. The number of movements out of the rest position differed in each run from 116 to 159. While performing this task, subjects had to respond to three different seldom, important messages that were presented together with unimportant information in a ratio of 1:20 (Fig. 5 b, all types of information were projected in front of the target ball). To respond, subjects had to touch one particular response cube out of three possible ones that were displayed in the virtual environment (Fig. 5 b, left side). For each subject, 3 runs were conducted on the same day and merged for data analyses.

Data processing During the experiment, EEG was continuously recorded from 124 electrodes (extended 10-20 system, actiCap, Brain Products GmbH, Munich, Germany), referenced to FCz and amplified using four 32-channel DC amplifiers (Brain Products GmbH, Munich, Germany) and filtered with a low cutoff of 0.1 Hz and high cutoff of 1000 Hz. Signals were digitized with a sampling rate of 5000 Hz. Impedance was kept below 5 kΩ.

To train the classifier and evaluate experimental results, a movement marker was added to the EEG stream whenever the subjects moved their arm 5 cm away from the rest position. According to this marker, windows of 1000 ms length were cut out. 13 different training windows for the “movement preparation” class were analyzed, i.e. $[-1600, -600]$, $[-1550, -550]$, ..., $[-1000, 0]$. For the “resting state” class, training windows of an equal length were cut out every 1000 ms, if no other marker was stored in the data stream 1000 ms before or 2000 ms after that window.

In the test case, windows were cut out every 50 ms independent of the class label. Each window was standardized channel-wise (subtraction of mean and division by standard deviation). A decimation was applied with a finite impulse response (FIR) filter to reduce the sampling rate of the data from 5000 to 20 Hz. Next, a FFT band-pass filter with a passband of 0.1 to 4 Hz was applied and the last 4 values of each channel were used as features. Finally, normalized features were classified by a support vector machine (SVM) with a linear kernel. In each training run, SVM parameters were optimized with an internal 5-fold cross validation using a pattern search algorithm (Nocedal and Wright, 1999). To calculate a performance measure the labeling of the continuous instances (i.e., windows in the test case) was required. Since the onset of the LRP cannot exactly be determined for single trials, we defined an uncertain area (from -600 to -350 ms) which was left out for metric calculation. Also, predictions made based on windows ending at -150 to 0 ms were excluded due to the fact that the actual movement onset had happened before the movement marker was stored. The balanced accuracy (Brodersen et al., 2010), i.e., the mean of true positive and true negative rate, was used as performance measure.

To investigate the effect of the number of training windows an iterative procedure was applied. In each iteration, the training window with best performance on the training data was calculated and used for the next iteration. This led to an increased number of training windows in each iteration until all training windows were used. Parts of test data performances were analyzed for individual subjects by repeated measures ANOVA with *number of training windows* as a within-subjects factor.

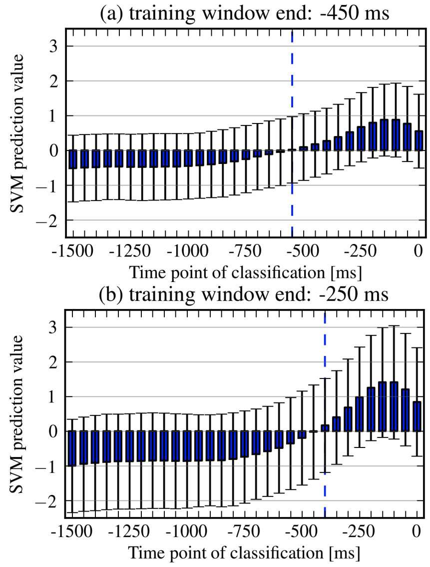

Figure 6: Mean (bars) with SD (error bars, $n = 8600$) of SVM prediction values for consecutive classified instances. The dashed line illustrates the time point when the mean prediction value exceeds zero.

Results Fig. 6 illustrates the trade-off between training on an early window (-450 ms, Fig. 6 a) compared to training on a later window (-250 ms, Fig. 6 b): a classifier based on the later window learned a later prediction (compare crossing of zero), but yield higher prediction scores.

When combining training windows, Fig. 7 a) shows that adding a second window during training significantly increased performance for each subject. Using more than two training windows showed no significantly higher performance. The performance does even decrease significantly when combining more than nine windows (Fig. 7 b). Our results are consistent with (Blankertz et al., 2006) who stated to train a classifier on two training windows to obtain a somewhat time shift invariant classifier for online application. Highest improvement of performance could be shown for subject 4 which obtained clearly lowest performance with a single training window. However, by adding training windows, the total amount of training data is also increased. Hence, we ensured that the found effect is not just a result of an enlarged amount of training data by comparing different training set sizes (150 vs. $160, \ldots, 350$ examples). Results showed no training set size effect ($p = n.s.$ for all pair-

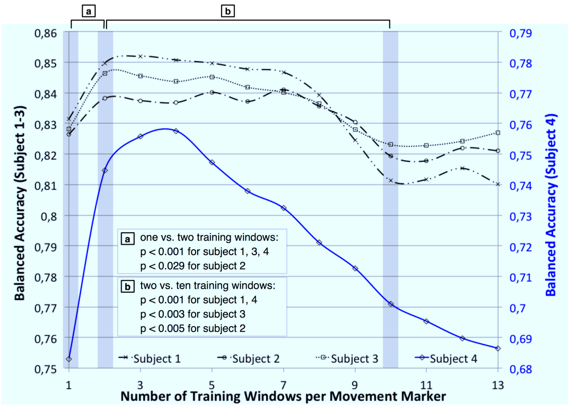

Figure 7: Movement prediction performance of a 5×2-fold cross validation for a greedy addition of training windows. Statistical comparison for each subject of a) one and two training windows, b) two and ten training windows.

wise comparisons). The decrease in performance can be explained by the increase in variation due to the high number of different training times. Although all of the 13 training windows under investigation can be counted as "movement preparation" instances (Fig. 5 c), likely not the same discriminative information is contained. Evaluation constraints (depending on the application, e.g., the time when a movement at least has to be detected) may have an impact on final performance as well.

4.3 EMG-based Movement Prediction

For rehabilitation, EMG is typically used to actively control devices by *detecting* movement onset or classifying the kind of movement, e.g., type of hand movement (Arvetti et al., 2007). However, EMG can also be used to *predict* movement onset since some time is required to transfer the electrical signal measured at the muscle into a contraction of the muscle, also known as electromechanical delay. Thus, we investigated whether EMG can be used to *predict* movement onset. In our proposed rehabilitation system (see Fig. 1) EMG could further be used to *detect* movement onset earlier in time than the force sensors that are integrated in the exoskeleton to trigger lockout (Folgheraiter et al., 2012). Hence, by means of reliable EMG onset detection the force required for interaction could possibly further be reduced. Results of a study investigating reliable *prediction* and *detection* of movement onsets by means of EMG analysis are presented and discussed in the following.

Experimental setup Eight male subjects (right-handed, and normal or corrected-to-normal vision) participated. Arm movement was executed immediately or with a delay based on a cue, or self-determined. Each of the different movements were performed slowly (movement duration of at least 1000 ms), in normal speed and fast (individual movement duration of at most 120 to 275 ms). For each of the nine conditions 120 movements had to be performed with two short breaks after 40 and 80 trials. EMG was recorded bipolar with 8 channels positioned at muscles M. brachioradialis, M. biceps brachii, M. triceps brachii, M. deltoideus using a bipolar amplifier (Brain Products GmbH, Munich, Germany) with a sampling rate of 5000 Hz (low cutoff of 0.1 Hz and high cutoff of 1000 Hz). The physical movement onset was recorded with a motion tracking system (ProReflex1000, Qualisys AB, Gothenburg, Sweden) sampled at 500 Hz using an infrared sensitive marker placed on the hand of the subject. The signal was synchronized with the EEG data and allowed a position estimation of 0.15 mm.

Data processing The output of all four EMG channels as well as the mean of all four channels was used as input for the movement onset detection. For evaluation of movement *prediction*, a classified movement onset was counted as true positive (TP) in case it was detected 500 to 0 ms before the physical movement (Fig. 8 a). For evaluation of movement *detection*, all classified movement onsets 500 ms before and up to 500 ms after the physical movement onset were counted as TPs (Fig. 8 b). Movements that could not be detected within the given time were counted as false negative (FN). Movements that were detected outside of the given time were counted as false positive (FP) (see Fig. 8). As performance metric, the balanced accuracy was used. To detect the movement onset, EMG was preprocessed to enhance the signal-to-noise ratio by calculating the variance (VAR) and an adaptive threshold (Equ. 2) was applied to distinguish the two classes "movement onset" and "no movement" (Tabie and Kirchner, 2013):

$$threshold(t) = \bar{x}_N(t) + p * \sigma_N(t), \quad p \in \mathbb{N} \qquad (2)$$

where t is the current time point, $\bar{x}_N(t)$ and $\sigma_N(t)$ are the mean and standard deviation of a window of length N ending at time point t and p is a sensitivity factor. A grid search approach was used to optimize all parameters for classification: EMG electrode (EMG1, EMG2, EMG3, EMG4, mean of EMG1-EMG4), window length for VAR (20, 50, 100 ms), p (0 to 19), window length N (1, 2, 3, 4 s) and the required interval of data points exceeding the threshold (0, 4, 10, 20, 40 ms).

Results Best performance was obtained with EMG2 (M. biceps brachii), a window length of

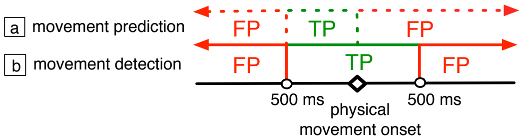

Figure 8: False positives (FP) and true positives (TP) in EMG based movement prediction (a) and detection (b).

20 ms for VAR, $p = 5$, $N = 2$ s, and a 20 ms interval during which data points had to exceed the threshold. EMG onset could be *detected* with a high mean performance (BA = 0.88). Movement *prediction* showed only a slightly but significant lower mean performance of BA = 0.81 [mean difference = 0.075, SE = 0.007; F$(1,213) = 129.73$, $p = 0.001$]. To quantify how early a prediction of upcoming movements was possible, we further calculated the mean time difference between physical movement onset and our prediction which was 95.26 ms (SE = 27.76). Results clearly show that movement onset can be predicted based on EMG data, i.e., before the physical movement onset.

5 CONCLUSION AND OUTLOOK

We presented results of an experiment, which investigated the performance of our control approach of a multi-contact-point and wearable exoskeleton with respect to the interaction between human and exoskeleton. It could be shown that the exoskeleton behaves transparent to the user and thus can act as a guidance and support system for human arm movement without impeding the person wearing it. The presented exoskeleton so far only supports one arm. In the design decisions for a full upper body rehabilitation that covers a wide range of patients, it is useful to consider both arms and the torso. Hence, the kinematics of a new exoskeleton has to take into account both shoulders and the spine. We are currently designing a new upper-body system which focuses on full-force feedback and a comfortable way to wear the system.

Results of studies presented in Sec. 4.2 and 4.3 showed that upcoming movements can be predicted by EMG and EEG analysis with a similar high performance. Reliability of EEG-based prediction can be enhanced by appropriate combination of training data. This should help when analyzing data containing less information, e.g., in case of neuronal impairment. Currently we are planning studies that allow to record EMG and EEG data during supported movements on different groups of patients to further investigate possible improvements during data processing and classification and by combining psychophysiological measures, e.g., EMG and EEG data. The integration of gaze control into real and virtual scenarios using eye tracking based on technical devices (eye tracker) is the next step, that will allow interaction within the virtual scenario even in case of massive neuronal and muscular impairment.

By adapting the support to the requirements of the patients, not only in respect to the severity of neuronal and muscular impairment but also in respect to the progress of rehabilitation, support can be minimized by time based on the progress in rehabilitation. Automatically recorded and analyzed psychophysiological and interaction data of the patient can be a good indicator for progress in rehabilitation. This and the parallel analysis and integration of different psychophysiological data raises high requirements on the effectiveness of computational devices regarding calculation capacity and time as well as power consumption. Hence, to accomplish rehabilitation that is fully integrated into the people's everyday life and adapts to the patient's state requires further research and development in software and hardware design.

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