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# MOREGRASP: RESTORATION OF UPPER LIMB FUNCTION IN INDIVIDUALS WITH HIGH SPINAL CORD INJURY BY MULTIMODAL NEUROPROSTHESES FOR INTERACTION IN DAILY ACTIVITIES

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ABSTRACT:

The aim of the MoreGrasp project is to develop a non-invasive, multimodal user interface including a brain-computer interface (BCI) for intuitive control of a grasp neuroprosthesis to support individuals with high spinal cord injury (SCI) in everyday activities. We describe the current state of the project, including the EEG system, preliminary results of natural movements decoding in people with SCI, the new electrode concept for the grasp neuroprosthesis, the shared control architecture behind the system and the implementation of a user-centered design.

## INTRODUCTION

In Europe, there are 11,000 new cases of SCIs per year with a total population of 330,000 [1]. More than half of the individuals with SCI are tetraplegic, meaning that they not only suffer from paralysis of the lower but also of the upper extremities. The bilateral loss of hand function with its associated dependency on caregivers result in a tremendous decrease of quality of life and represent a major barrier for inclusion in professional and social life. Besides the burden for each affected individual, the consequences of a high SCI also have a substantial impact on the healthcare system.

Motor neuroprosthesis, systems based on functional electrical stimulation (FES), can be used to restore lost functions in particular of the grasp function. Basic grasp patterns such as the palmar or lateral grasp can be re-established by positioning FES electrodes on dedicated positions on the forearm of an end user [2]. For the control of such systems mainly the contralateral shoulder can be used, if there are enough residual voluntary movements present. This only works if the shoulder function is not restricted at all. If the shoulder control cannot be used, a BCI offers an alternative to implement a simple grasp control by the detection of imagination of movements [3, 4, 5, 6]. Most of the studies in the field are single case studies that show the feasibility of coupling BCI with FES. However, up to now no BCI-controlled neuroprosthesis has showed its successful use in the everyday life of potential end users. To overcome this situation, the European collaborative project MoreGrasp aims at the following objectives:

(O1) development of novel multimodal user interfaces based on noninvasive BCIs, which detect intentions of various hand movements from EEG using gel-less electrodes and wireless amplifiers.

(O2) development of a sophisticated noninvasive multichannel motor and sensory grasp neuroprosthesis including the integration of orientation, position and force sensors and implementation of haptic feedback as well as a closed-loop control concept for semi-autonomous operation.

(O3) implementation of the concept of personalization and user-centered design.

(O4) setup of a web-based service infrastructure by a registration and matchmaking platform for the assessment of priorities of individuals with disabilities; screening of potential users' functional, neurological and personal status with a specific evaluation toolkit; documentation of the BCI and FES performance and evaluation of the training of end users with a training toolkit.

(O5) evaluation of the novel technology with a long-term clinical study with end users in real need of a grasp neuroprosthesis to demonstrate its reliability, usefulness and impact on the end users' quality of life.

## MATERALS AND METHODS

*EEG Amplifier:* From the EEG recording technology point of view, the MoreGrasp project final objective is to develop easy-to-use, wearable, ergonomic and comfortable systems that can be used over an extended

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period of time in everyday conditions. One of the main ways to increase user friendliness is to abandon gel-based electrodes. To achieve this goal, MoreGrasp is developing three EEG systems. The first two systems use water–based electrodes and will be integrated in the evaluation toolkit (32-channel amplifier) for screening and in the mobile toolkit (16-channel one) for training. Fig. 1 shows both amplifiers. They record EEG with a sampling rate of 256 Hz, 24-bit, RMS noise under 1µV, input range ±100 mV and [0,40] Hz bandwidth. The dimensions of the 16-channel amplifier are 78x72x32 mm and weighs 125g. The 32-channel version is a little bit larger (107x72x32 mm) with a weight of 164g. They are designed to be carried on the cap, or attached to the upper arm or the wheelchair. They have Bluetooth connectivity and include an inertial measurement unit (IMU) to measure motions during operation, one digital input, one photodiode input and, in the case of the 32-channel system, 2 extra ExGs inputs.
The third system will be used to evaluate the control of the final system using dry electrodes. It is still under development and will integrate as few sensors as possible placed in those locations that optimize the control of the MoreGrasp system. This cap will have the amplifier integrated within a small and light support structure. With the current prototypes, a setup and time-to-signal well under four minutes for 12 sensors is possible. Signal-to noise-ratio is not as good as water-based systems, but preliminary tests have shown that the brain processes required for MoreGrasp can be measured (motor-related cortical potentials (MRCPs), error potentials and sensorimotor rhythms). Fig. 2 shows MRCPs and ERD/S measured with the dry technology.

Figure 1: 32- and 16-channel MoreGrasp amplifiers (left). 16-channel system with the sensors and amplifier on a commercial cap (right).

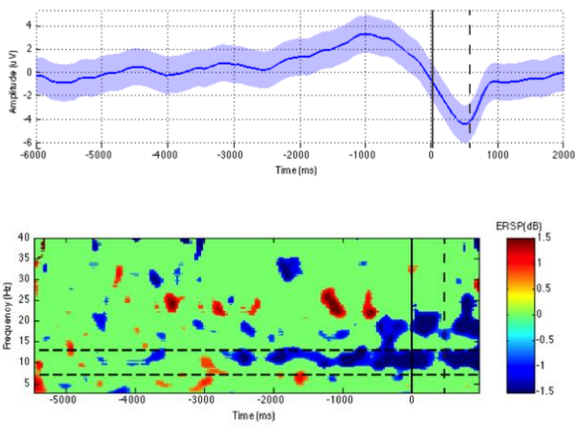


Figure 2: MRCPs measurements (top) and ERD/S (bottom) during self-paced grasping of able-bodied subjects. Results show the average EEG patterns of 10 subjects (100 trials each), measured in CP1 location. The dashed vertical line shows the EMG onset.

*Decoding of natural movements with EEG:*

**CLASSIFICATION OF SINGLE JOINT MOVEMENTS:** Based on EEG signals from 0.3 to 3 Hz, we found 6 different upper-limb movements to be discriminable with a classification accuracy of 37% in a group of 15 able-bodied subjects. The classifier sources originated mainly from premotor and primary motor areas.

**CLASSIFICATION OF DIFFERENT GRASP TYPES:** We conducted an EEG study in 15 able-bodied subjects to find out whether palmar, pinch and lateral grasps can be discriminated from each other and from a no-movement condition. Our results show that time-domain features located in the low frequency range provide sufficient information for classification (binary classification of 74% grasp vs. grasp).

**CLASSIFICATION RESULTS IN SCI PATIENTS:** Based on the previous results on able-bodied subjects [7], we conducted preliminary studies in a clinical environment with individuals with SCI (see Tab. 1). EEG was obtained from 61 channels covering frontal, central, parietal and temporal areas using active gel-based electrodes (g.tec medical engineering GmbH, Austria). The reference electrode was placed on the right mastoid, ground on AFz. We used an 8th order Chebyshev bandpass filter from 0.01 Hz to 200 Hz and sampled with 512 Hz. Power line interference was suppressed with a notch filter at 50 Hz. We downsampled the data to 32 Hz, removed artifacts based on statistical methods, and bandpass filtered the data with an 4th order zero-lag Butterworth filter from 0.3 to 3 Hz.

Table 1: Neurological and functional characteristics of the participants with SCI. EU = end user, NLI = neurological level of injury, AIS = American Spinal Injury Association (ASIA) impairment scale.

| EU | NLI | AIS | Status of upper extremity motor function |
|---|---|---|---|
| P1 | C3 | D | rudimentary grasps |
| P2 | C5 | B | Little finger and hand function right hand |
| P3 | C4 | B | No finger function in (dominant) hand |
| P4 | C4 | C | Little index finger and thumb movements |
| P5 | C3 | D | Right: finger function, but no sensory perception<br>Left: no motor function |

**GRASPS VERSUS PRONATION/SUPINATION (PARADIGM WITH ICON CUES):** In this experiment, data of the 5 participants (P1-P5) were recorded while they attempted to perform two different grasp patterns and a rotation of the forearm. Recording was done using a cue-guided paradigm. At second 0 a cross appeared on the screen together with an auditory beep to get the participants'

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attention. At second 2 a cue indicating the type of movement was shown. This cue consisted in a hand icon in different postures, according to the movement type. The cue was on the screen for 4 seconds. As soon as the cue appeared, the participant was asked to attempt to perform the movement according to these instructions: starting from a neutral, slightly opened hand position, perform a grasp and return to the starting position. For arm rotation, participants were asked to perform a pronation followed by wrist supination.

**GRASP PATTERNS VERSUS HAND OPENING (PARADIGM WITH OBJECT CUES):** In this experiment, instead of the hand icons explicitly representing the movement types, objects were used as cues. Participants P3 to P5 were asked to perform/attempt the appropriate grasping action for the designated cue. The objects presented and respective instructions were:

1. **Glass** - attempt to perform palmar grasp and release
2. **Spoon** - attempt to perform lateral grasp and release
3. **Glove** - attempt to open your hand with spread fingers like putting on the glove
4. **Bush** - diverse object, just look at it and rest (not used for classification)

The EEG data from both experiments were then classified with a shrinkage regularized linear discriminant analysis (LDA) classifier using the time-lags 0, 100 and 200 ms of the EEG as input. As both experiments comprised 3 classes, we applied a 1-vs-1 classification strategy. The results were then validated with a 10-fold cross-validation.

Fig. 3 shows the classification accuracies of the icon paradigm. The maximum average classification accuracy was 53 % at 2.6 s after trial start. The classification accuracies of the object paradigm can be seen in Fig. 4. The maximum average classification accuracy was 57 % at 2.6 s after trial start. Fig. 5 and Fig. 6 show the MRCPs.

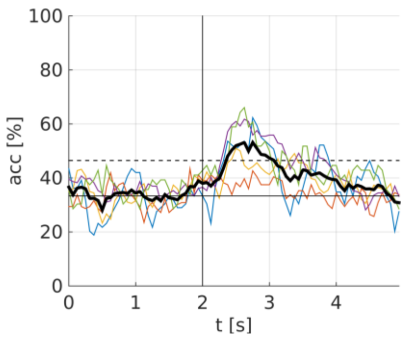


Figure 3: Classification accuracies of 5 EUs with SCI for grasps and pronation/supination (icon paradigm). The dashed line is the significance level.

*New electrode concept for the grasp neuroprosthesis:* Apparent disadvantages of todays grasp neuroprostheses based on a set of single surface electrodes include difficulties with daily reproduction of the desired movements and large variations in finger and thumb movements during wrist rotations due to electrode-skin shifts.

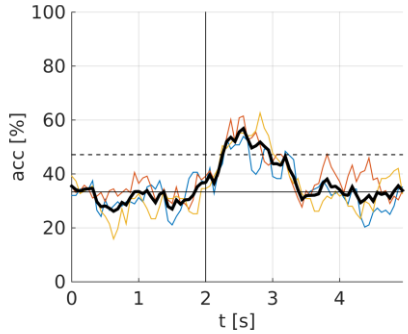


Figure 4: Classification accuracies of 3 EUs with SCI for grasps and hand open (object paradigm). The dashed line represents the significance level.

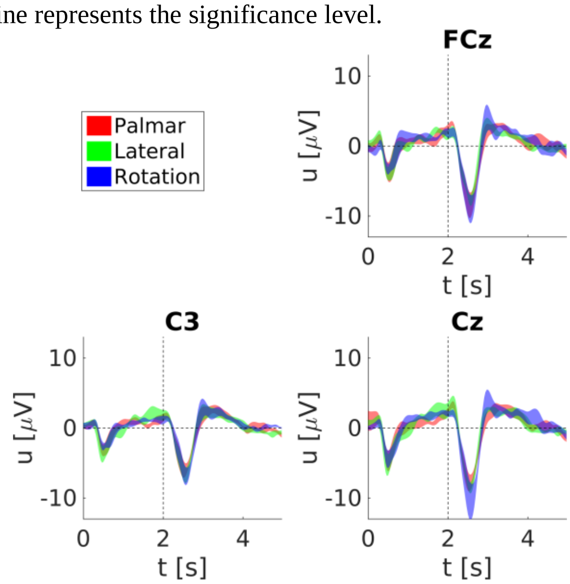


Figure 5: MRCPs evolving in the icon paradigm.

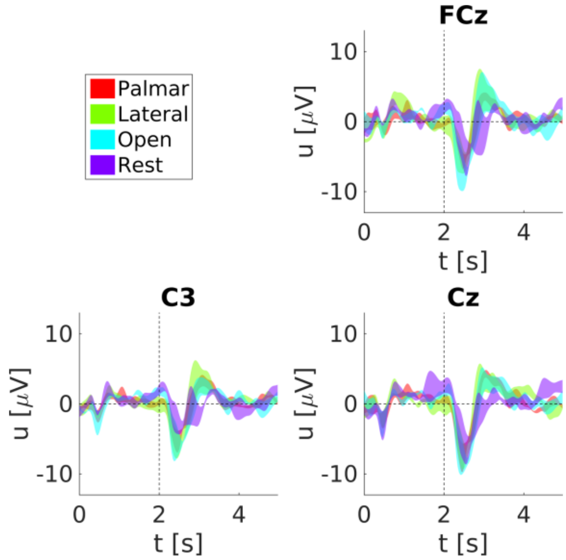


Figure 6: MRCPs evolving in the object paradigm.

In MoreGrasp, an electrode array has been developed, which consists of up to 64 electrodes integrated into a forearm sleeve (Fig. 7), which is personalized to the anatomy of each individual end user. The first prototype

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consists of a sleeve made from medical-grade silicon, in which an electrode array made from conductive silicon material is embedded. In the final version, the silicon array electrodes will be integrated into a textile sleeve to improve handling and comfort in particular in respect to sweating. The electrodes of the array can be electronically merged to larger electrode clusters according to context-specific demands such as varying wrist rotation angles. For measurement of the wrist angle a set of position and orientation sensors (IMUs) have been integrated in the electrode sleeve to allow for automatic adjustment of stimulation schemes (selection of electrodes, amplitudes) according to the sensor data.
With this approach, we have shown in two able-bodied subjects that dynamic electrode and skin shifts during operation can be compensated and a stable grasp pattern can be achieved.
Another important issue for users is to have feedback from the neuroprosthesis to perform fine motor tasks. Foil force sensors attached to everyday objects will allow for measurement of grip forces. Data of grip forces will be transmitted by a Low Energy (LE)-Bluetooth module to a central control unit, where a semi-autonomous grasp control can be implemented. By assignment of unique identifiers to different Bluetooth modules an automated selection of an object-dependent grasp pattern is possible. If the user moves her or his hand near the object of interest, the neuroprosthesis will automatically switch to the grasp pattern predefined for this object. By using additional FES electrodes in parts of the body with preserved sensation, e.g., the upper arm or the upper torso, electrotactile feedback about the applied grip forces will be provided to the end user.

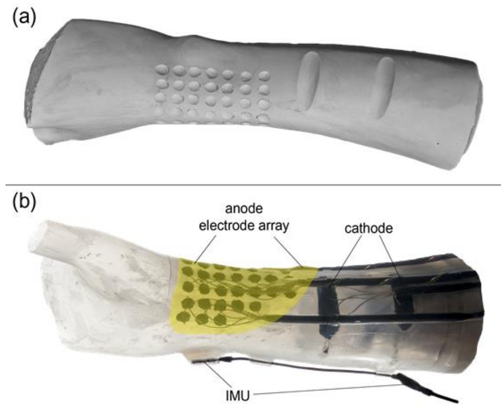


Figure 7: First prototype of a multi-electrode forearm electrode sleeve. (a) individual gypsum model of the forearm with electrode cavities, (b) prototype of personalized arm sleeve made from non-conductive medical silicon with integrated conductive silicon electrodes and cables, and Inertial Measurement Units (IMUs) for measurement of the wrist and elbow position and calculation of the wrist rotation angle.

*Shared control principles:* Successful FES-supported grasping requires continuous, real-time control, but existing neuroprostheses are driven by low-bandwidth, constrained input channels such as an EEG-based BCI or a shoulder position sensor. Efficient interfaces are required that maximize the control of these channels with minimum effort. Environmental sensing can be used to gather broader context about reaching and grasping tasks, and has the potential to empower users to conduct everyday tasks through the limited control channels available. Therefore, we developed a shared control architecture for the MoreGrasp project. The aim is to maximize grasping performance with minimum user effort by supporting human control processes with environmental sensing. The development of our shared control architecture was driven by the following principles: the system should be able to reason under the uncertainty of noisy and ambiguous input; to gracefully handle sensor failure; and to respond safely to emergency situations.
The proposed shared control architecture has a set of loosely coupled, configurable elements as illustrated in Fig. 8 (top panel). A sensor encoder unit estimates the probabilities of binary events such as “is the hand close enough to an object to grasp?”, “is the user activating the shoulder joystick?”, and “is the BCI indicating an intended wrist rotation?” from sensor feature vectors. A Bayesian network with binary nodes estimates the intention of the user in terms of discrete FES stimulation outcomes, and the certainty of that estimate. User feedback from this unit indicates prediction of user intentions. An action-state-machine monitors the probability of actions, and switches between activity states (e.g. “begin open grasp fully now”) when probability thresholds are crossed. Outputs affecting the estimation of intention (e.g. “the user is unlikely to release grasp 5 ms after opening it”) are fed back to the Bayesian network. User feedback from this unit indicates prediction of future actions. A continuous dynamics module generates the signals to open/close, rotate or reconfigure the hand smoothly when the action-state-machine indicates a change of state, separating the synthesis of continuous values from underlying discrete states. Direct feedback from the sleeve inertial sensing will be used for closed-loop control in this module. The “emergency stop” estimator feeds directly in here to override all pattern generation and return safely and quickly to a neutral state. The electrode pattern generator generates appropriate FES patterns across the electrode array to satisfy the continuous dynamics required.
The system is fully probabilistic between the sensor input vectors and the action-state-machine, which makes it practical to support sensors with widely-varying reliability and also to provide meaningful feedback about inferred user intentions. It is feasible to reason about the intention decoding process because of our simplifying assumptions that (i) intention can be mapped onto a set of (unknown) latent binary variables, (ii) that actions can be seen as transitions in a finite-state machine (iii) continuous closed-loop physical output can be generated from discrete internal transitions. The factorization of the decoding/control process allows different elements of behavior to be

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implemented by altering the Bayesian Network, without interfering with the optimization of electrode patterns or the continuous-time dynamics. Each of the pipeline elements can be developed with a significant degree of independence; for example, the electrode pattern generator can be optimized automatically without changing the sensor interpretation model. This framework is also flexible enough to support interaction spread over time. For example, a grasp may be "cued" by the BCI in advance and only executed when the probability of being close enough to an object is sufficiently high. Alternatively, the BCI could immediately issue commands, but be "locked out" by holding the shoulder joystick high to suppress control. Estimates of both local reliability (per-command) and general reliability (e.g. tiredness detection) from the BCI can be encoded as rules in the Bayesian network to support control across the full spectrum of signal quality. User feedback via electrotactile (primary) and audio/visual (secondary) channels includes the system's estimate of what the user is trying to do (intention); the certainty of that intention (reliability); and the prediction of the future action sequence that is going to occur imminently (predicted action). Simple feedback, like "countdown" style displays on LED strips or via electrotactile, can be used alongside display modes that show the uncertainty or "tension" within the inference engine.

*Appraisal, Monitoring and Training Services:* As has been described already, the MoreGrasp system comprises a range of complex devices and subsystems that must work in harmony to accomplish the desired task: restoring autonomy in grasp function. To benefit from it, users need to learn the skills to use it.

The consortium emphasizes adoption going beyond proof of concept, and designing a set of services to walk the user from finding out about MoreGrasp, through appraisal, training, customization of the neuroprosthesis, to a practical use.

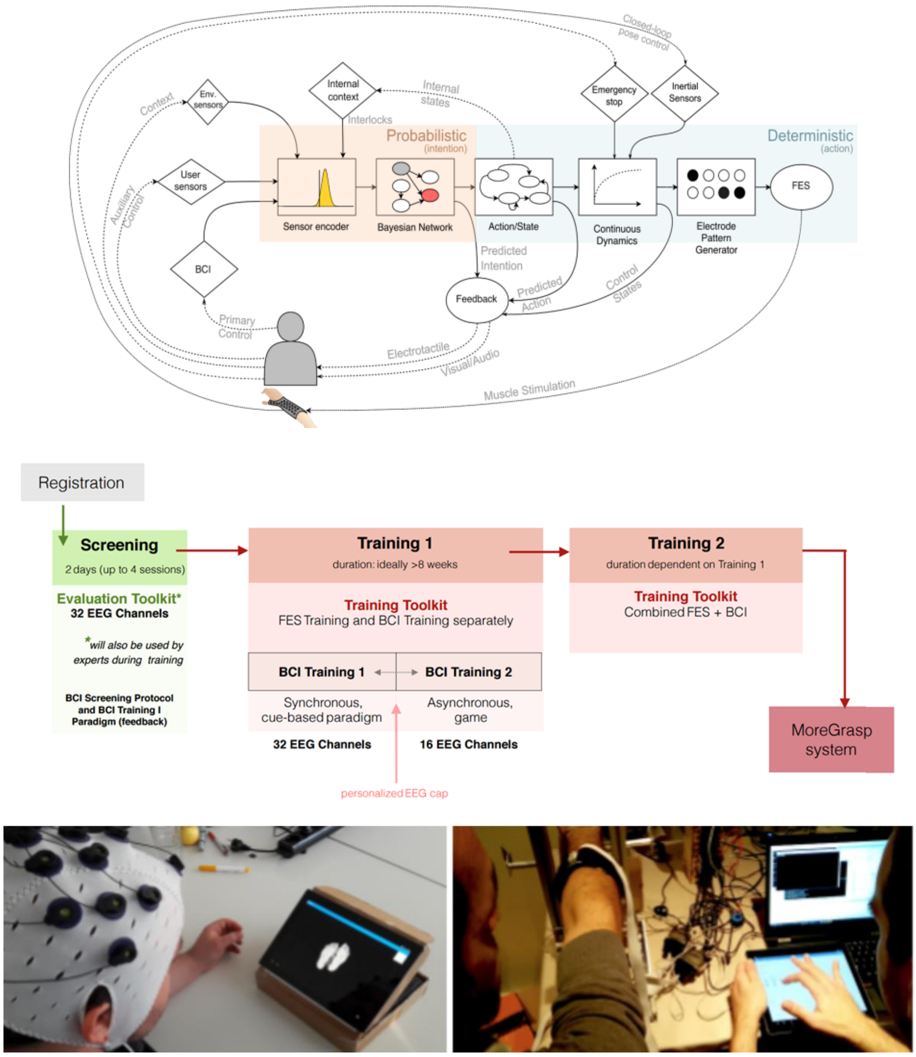

Figure 8: Shared control structure, showing the internal processing pipeline and the user in the loop. A probabilistic intention decoder is connected to a deterministic action synthesizer (top panel). MoreGrasp screening and training schemes leading to the final MoreGrasp system, including FES and BCI and respective stages of use of MET and MTT (middle panel). MET during BCI screening (lower panel, right) and MET during FES screening (lower panel, left).

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**WEB SERVICES FOR DATA COLLECTION AND MONITORING:** In the MoreGrasp approach, a potential user with SCI registers, if necessary with the help of a caregiver or relative, on the MoreGrasp registration platform (online since 03.2016). A decision maker is notified to schedule a screening visit with the potential user. He/she uses a matchmaking platform to overview the status of all registered users, filtering by medical pre-injury conditions to assign new users to a screening.

To assess if the potential user can benefit from MoreGrasp, two different screenings need to be performed: a clinical evaluation including a FES screening and a BCI screening. In both cases, an expert brings the hardware to the potential user and, with the aid of a Mobile Evaluation Toolkit, gathers the needed data, which are then used for the decision of study inclusion. A user passing the screening receives an ID and enters a training program. During the months of FES and BCI training the personalized MoreGrasp system is manufactured and is finally delivered to the end user. The systems used during screening and training collect data and seamlessly deliver it to a cloud service for analysis and personalization. These steps are represented in Fig. 8 (middle panel).

**THE MOREGRASP MOBILE TOOLKIT:** The MoreGrasp system consists of two subsystems: control and presentation. The control subsystem is a self-contained system with a computational unit connected to the EEG and FES systems. It includes algorithms for control, feedback, and data collection modes. A presentation subsystem was developed with interfaces for experts and caregivers to configure the control subsystem for data collection during screening and training. Both subsystems communicate over a private secure network with a proprietary protocol, optimized for streaming. There are two versions of the system with two distinct functions: evaluation (Fig. 8, lower panel) and training.

The mobile evaluation toolkit (MET) is used for evaluation (screening) mainly by experts, who visit a potential end user to acquire data about the user's condition, residual abilities and the possibility for inclusion in the MoreGrasp training programme. Two separate screening steps are carried out: Clinical/FES screening and BCI screening. The clinical screening assesses the clinical and neurophysiological condition of the potential end user as well as the degree of denervated muscles, which cannot be activated by FES. BCI screening assesses the ability of the PU to produce distinct brain patterns by the imagination of movements as a prerequisite for BCI control.

The mobile training toolkit (MTT) is used to tap the residual abilities of the user and turn them into the ability to operate a neuroprosthesis. The MTT is mainly operated by caregivers and relatives. It includes periodic training sessions for FES and BCI. The FES training aims to gradually strengthen the muscles of the end user for grasping. During the BCI training the user is expected to learn how to modulate his/her brain signals to operate the BCI.

## CONCLUSION

In its current state the MoreGrasp project has created substantial basic knowledge together with various hard- and software components for a noninvasive, intuitive BCI-controlled motor and sensory grasp neuroprosthesis and the associated services for registration, evaluation and training of end users. In the next few months, a clinical proof-of-concept study will be conducted to obtain information about its impact on everyday life in end users with high SCI and to quantify their perceived changes in quality of life.

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