**S9. Description of orthoses' usability test of inserted articles.**

| Author (s) | Characteristics of participants | | | | Description of usability test | Benefits |
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| | Sample size | Diagnosis | Diagnosis time (symptoms initial) | Age (yo) | | |
| **Delijorge et al., 2020** | - HS: 18;<br>- ALS patients: 8 | HS and ALS | 2-3 years | - Mean age of HS: 32.7 yo;<br>- ALS patients: 59.6 yo. | - The participants were instructed to calibrate the BMI and perform a short validation. In this test, subjects selected freely any option of the interface and were notified if the system detected the desired action correctly. The purpose of the free selections was to obtain information about the detection times and demonstrate to the users that the BMI is effectively responding to their intentions. Participants repeated at least three times the free targets selection before continuing with the experiment.<br>- In the next and last stage, subjects were indicated to focus attention on the specified target option until the BMI recognized a P300 response for one of the flashing elements. All online attempts were similar to the calibration runs. The interface presented a fixation cross to indicate the beginning of a test run, followed by the presentation of the target option and preparation time. Then, the random flashing started, and the BMI tried to recognize an evoked response. If the system detected in <30s the correct option, the hand-orthosis performed the selected movement; otherwise, nothing happened. Finally, there were 5s of resting time before starting another attempt. | P300-based BMI with a robotic hand-orthosis has been tested in ALS patients being able to manipulate each finger of a hand mentally or perform a sequence of movements of one or more fingers.<br>The P300 paradigm used an unlimited number of possible movements providing a range of options for different needs. |

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| **Ren et al., 2019** | 8 | HS | Not applied | 22 - 25yo | - The subjects were asked to move their arms in the air arbitrarily for one minute and repeated 3 times.<br>- Sensors were positioned on BB and another 6 cm below the middle of the lateral and medial epicondyle.<br>- The data recorded during this process is defined as a session.<br>- Each subject had 8 sessions. | The results of offline experiments showed that the MS-LSTM model has better accuracy than other DL models and traditional regression models. In the real-time experiment, they compared IMU control with MSLSTM mode control, and the results showed that the proposed method reduces about 50% of the mean average error of joint angles between the human arm and robot arm, and reduces approximately 70% of the average delay time to allow users to feel better human-robot coordination. |
| **Ha, Kim and Jo, 2018** | - | - | - | - | Two grasping motions offered hand position information on the 78-dimensional data format composed of each finger joint and the palm-center coordinate as the thumb does not have metacarpals, leap motion sensor publishes the same position about proximal phalanx and metacarpal. | DNN-based orthosis using pressure and position data can estimate and control the soft glove without an analytical model. |
| **Wang et al., 2018** | 1 | HS | - | - | Patient seated with their right arm coupled with the robot at the end-effector, and made 2-DOF movements in the horizontal plane assisted by the shoulder and elbow joints, at the same time, the patient can do wrist pronation/supination with the help of the wrist module. | A sEMG-driven orthosis has been developed based on a time delay ANN model to estimate torque through RMS error of 0.068N, showing that the obtained model was capable of estimating the joint torque. |

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| **Zeng et al., 2018** | 12 females and 13 males) | HS | - | Not specified | - HG, 4 FF, IFE, TIR, TO, KP. Subjects performed 10 trials for each gesture. Especially, every training of gesture TIR consisted of 3 times of thumb internal rotation.<br>- 8 muscles of both hands have been assessed: BRA, FCU, FCR, EDC, FDS, APB, FDI, and ADM. | - High accuracy;<br>- Device carried out well in gesture classification and actuator control. |
| **Khan A, Khan F, Han, 2016** | More than 1. However, it was specified. | - | - | - | A task was given to a subject who was asked to start from the initial position "p", go towards point "q", pick an object from there and then place it on the position "r" and return back to position "p". | ELM estimated the learning human motion pattern and predicted the future movement based on the inputs obtained from force sensors, joints' current position, and current moving speed. |
| **Agarwal, Fernandez and Deshpande, 2015** | 1 | HS | Not applied | 29yo | It has been carried out one trial for each kind of control:<br>- Learned force-field control: a subject's torque-angle relationship was learned using the developed neural network and the trained subject-specific network was then used for force-field control of the index finger with the desired target trajectory in the joint angle space. The subject was asked to keep the finger passive while the torque data was collected for training the NN. Once, the model was learned, the subject was asked to follow the motion, while the controller was assisting the subject with the applied force field.<br>- Adaptive-assistance-based control: the performance of the controller in terms of adapting to the requirement of the subject and thereby, resulting in improved joint angle trajectory tracking performance was assessed. | The learned force-field control was able to maintain the desired relation between the joint displacements for coordinated motion. Also, the adaptive assistance-based control was able to quickly adapt to the changing requirements of a subject and track the desired joint angle trajectory with small RMS errors. |
| **Huang et al., 2015** | - | - | - | - | Force intensity was recorded during movements of each finger hand. However, tasks were not described. | RLNN might be applied to control the exoskeleton in different force intensities. |

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| **Khan et al., 2015** | 3 | HS | Not applied | 26 - 34yo | - Each subject was asked to pick up a cup and place it on the desk five times.<br>- Sensors were located on BB and TB.<br>- Firstly, this task has been performed without MCS and load cells to get the actual trajectory for comparison. | Convergence of the closed-loop system was analyzed by the Lyapunov function and implemented on a unilateral exoskeleton for E/F motion demonstrating successful estimation of DMI and smooth tracking. |
| **Ramirez, Alfaro and Chairez, 2015** | 7 | - | - | - | The data was recorded during therapeutic exercises while the participants moved each finger. In addition, the information about sets and repetitions has not been shown. | ANN classifier has been implemented over the sEMG in order to control hand orthosis. |
| **Kavya et al., 2015** | 30 individuals (15 of each gender) | HS | - | 18 - 28 yo | - Sensors were placed on FCR and BB.<br>- sEMG signals were achieved while subjects were performing hand and forearm movements in supinated and pronated positions. | Features resulted in the highest classification accuracies to control the orthotic arm |
| **Chen and Lau, 2015** | Not performed | Not performed | Not performed | Not performed | Not performed | - High accuracy;<br>- Fast computation speed;<br>- The 5-DOF planar robot was developed and tested from MATLAB, verifying the effectiveness and efficiency of the proposed method. This type of robot manipulator is more dexterous and flexible than traditional non-redundant ones.<br>- The motion planning or the inverse kinematic problems of the redundant robot arms become rather |

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| | | | | | | challenging. In this way, a novel heuristic approach combining hierarchical clustering and KNN is proposed to solve this problem. |
| **Loconsole et al., 2014** | 1 | HS | Not applied | 29yo | - sEMG data were recorded during reaching tasks.<br>- 5 pairs of sensors are located on PM, DA, DP, BB, and TB.<br>- The ECG for the crosstalk suppression in the sEMG signals affected by the ECG signal. The training set acquisition procedure was divided into two phases: 1. a first phase in which the subject was relaxed. During this phase the ECG and the sEMG signal of the PM affected by the electrocardiography crosstalk was acquired in order to model the filter for the disturbance suppression; 2. a second phase in which the sEMG signals of the subject were acquired according to the following protocol. The subject was asked to perform 15 repetitions of isometric contractions for each of the four orthogonal directions on the plane (upward, downward, forward, and backward). The repetition of the isometric contractions was interspersed with 10 seconds of muscular rest and was not time or force (maximum) bounded. | - The EMG-based online control of the exoskeleton is promising and demonstrates the possibility to use this approach in supporting patient movements during therapy.<br>- This system is able to adapt itself to each different user. |

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| **Tang et al., 2014** | 6 | HS | Not applied | 25±3yo | - 4 pairs of sensors located on BB, BRA, TB, and anconeus.<br>- There were four experiments: (1) the subject held a 1-kg load wearing the exoskeleton, but with no actuation, and performed the elbow F/E movement; (2) the subject held a 1-kg load by hand without wearing the exoskeleton; (3) the subject held a 1-kg load wearing the exoskeleton, but with no actuation; (4) the subject held a 1-kg load wearing the exoskeleton under direct proportional myoelectric control. | The proportional myoelectric control method was proposed to control the exoskeleton according to the user's motion intention in real-time. The elbow angle was estimated based on the sEMG signals in the proposed method. A BPN was applied to construct the sEMG-angle model to make the exoskeleton adaptable to every subject. |
| **Seki et al., 2011** | 1 | Essential tremor | - | 60yo | The subject carried out F of the elbow while holding a bottle filled with water (500g) to simulate the movement of drinking water 10 times. | An EMG-controlled robotic device using NN to improve performance through reduction of tremors. They have implemented a tremor noise canceling filter which detects attenuation ratio by the correlation between the last EMG database wave. |
| **Zhang and Nakamura, 2006** | - | - | - | - | The human requests on the dishes are detected by analyzing the change of the EOG of the subject. If the subject wants to eat the food in one of the dishes, the MAO will assist the upper limb to move to the dish first to take the food, then to return to the mouth to eat them, and finally to move back to the initial position. The subject will continuously eat the food in dishes A, B, and C one by one. The process for performing meal assistance tasks will totally last about 120s. | ANN-based hybrid human-in-the-loop control for the MAO is capable of assisting upper limb movement while eating. |

Abbreviations: ADM = Abductor Digiti Minimi; ALS: Amyotrophic Lateral Sclerosis; APB = Abductor Pollicis Brevis; ANN: Artificial Neural Network; BB = Biceps Brachii; BMI: Brain-Machine Interface; BRA = brachioradialis; BPN = Back-Propagation Neural Network; DA = Deltoideus Anterior; DL = Deep Learning; DP = Deltoideus Posterior; DMI = Desired Motion Intention; DNN = Deep Neural Network; DOF:Degree Of Freedom; E = Extension; ECG =

Electrocardiographic; EDC = extensor digitorum communis; ELM = extreme learning machine; EOG = Electrooculogram; F = Flexion; FCR = flexor carpi radialis; FCU = flexor carpi ulnaris; FDI = first dorsal interosseous; FDS = flexor digitorum superficialis; FF = Fingers flexion; HG = Hand grasp; HS = Healthy Subject; IFE = index finger extension; IMU = Inertial Measurement Unit; KP = Key pinch; KNN = K-Nearest Neighbor Regression; PM = Pectoralis Major; MAO: Meal Assistance Orthosis; MCS = Muscle Circumference Sensor; MS-LSTM = Multi-Stream - Long Short-Term Memory; N = No; NN = Neural Network; RLNN = Reinforcement Learning Neural Network; RMS = Root Mean Square; sEMG = Surface Electromyography; TB = Triceps Brachialis; TIR = Thumb internal rotation; TO = Thumb opposition; yo = years-old; - = Not informed.