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Multimodal adaptive interfaces for 3D robot-mediated upper limb neuro-rehabilitation: An overview of bio-cooperative systems

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HIGHLIGHTS

- Novel classification of bio-cooperative robotic systems.
- A multimodal 3D robotic platform for upper limb rehabilitation of post stroke patients.
- Mechatronic module for guaranteeing arm-weight support during therapy.

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ABSTRACT

Robot-mediated neuro-rehabilitation has been proved to be an effective therapeutic approach for upper limb motor recovery after stroke, though its actual potential when compared to other conventional approaches has still to be fully demonstrated. Most of the proposed solutions use a planar workspace. One key aspect for influencing motor recovery mechanisms, such as neuroplasticity and the level of motivation and involvement of the patient in the exercise, is the design of patient-tailored protocols and on-line adaptation of the assistance provided by the robotic agent to the patient performance. Also, when abilities for performing activities of daily living shall be targeted, exercises in 3D workspace are highly preferable. This paper wants to provide a complete overview on bio-cooperative systems on neuro-rehabilitation, with a special focus on 3D multimodal adaptive interfaces, by partly in-depth reviewing the literature and partly proposing an illustrative case of how to build such a bio-cooperative based on the authors' current research. It consists of an operational robotic platform for 3D upper limb robot-aided rehabilitation, directly derived from the MAAT system previously developed by the same research group. The system features on-line adaptation of therapy characteristics to specific patient needs and to the measured level of performance, by including the patient in the control loop. The system is composed of a 7-DoF robot arm, an adaptive interaction control system, a motorized arm-weight support system and a module for on-line evaluation of patient performance. Such module records patient biomechanical data through an unobtrusive, wearable sensory system, evaluates patient biomechanical state and updates robot control parameters for modifying level of assistance and task complexity in the 3D workspace. In addition, a multimodal interface provides information needed to control the motorized arm-weight support by means of a dedicated cable–pulley system.

1. Introduction

Rehabilitation robotics is one of the most active research fields in the neuro-rehabilitation panorama. There are several research groups actively working in this field, for the development of new robotic devices, as well as for the application of already existing robots to new challenging scenarios of robot-aided rehabilitation. It has been extensively demonstrated that robotic devices for upper limb treatment may enhance motor recovery and neuro-plasticity due to their ability to supply highly-intensive, repeatable, accurate and patient-tailored movement therapy, while guaranteeing patient safety and unloading therapist workload with respect to traditional methods [1–11]. Additionally, robotic technologies offer the huge advantage of providing the clinicians with

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quantitative and objective measurements about patient's recovery through the sensors embedded into the robots [12,13].

Despite these encouraging findings, however, most of the robotic machines for upper-limb rehabilitation rely on an "if-then" functioning mode, which permits to execute only predefined unidirectional action on human subjects, from the robot to the patient, without actively including the patient in the control loop and participating in the therapy definition [14,15]. Such an approach tends to force the patient to follow predetermined trajectories that usually do not take into account subject features, spontaneous intentions and voluntary efforts [16,17].

Bio-cooperative systems represent the new generation of robotic platforms that promote a bidirectional interaction between the robot and the patient based on multimodal interfaces also arousing interest in the European Commission, who has financed European projects on this topic, such as MIMICS [14] and Echord-MAAT (2009–2013) [15] in the FP7 and AIDE (2015–2018) in Horizon 2020 programme.

Information coming from different sources allows the users to close the loop by providing a continuous feedback on their global status, i.e. their condition, described through user properties, actions, intentions and environmental factors and provided by biomechanical, physiological and psychological measures. The inclusion of physiological and psychological measurements of the patient's state into the control loop, in addition to biomechanical measurements, makes the system "Bio-Cooperative" [14].

Such an approach, trying to adapt dynamically and in real-time robotic assistance to patient's needs, based on continuous multimodal measures of the user's state, is expected to foster patient engagement in robotic therapy more than in previously reported studies in the field [18–23].

The multi-sensory information describing the patient's condition can also be employed to quantitatively assess patient recovery during the therapy.

Moreover, bio-cooperative systems have recently been expanded to include non-invasive Brain Computer Interfaces (BCIs) based on electroencephalography (EEG) and non-cortical interfaces (Electrooculography (EOG) Electromyography (EMG) and eye-tracking) for detecting user movement intentions, and virtual reality environment as well as haptic perception for augmenting sensory feedback for the patient [23].

Robotic technologies for stroke rehabilitation have focused for a long time on simple motor tasks (also called analytical tasks) such as reaching actions, typically restricted to planar workspace, i.e., vertical planes and lateral planes [20], taking into account motor learning principles and biomechanics. In addition, focusing more on separate joints (e.g. proximal or else distal joints alone), rather than distal and proximal together, may have contributed to limit transfer of motor gains to Activities of Daily Living (ADL) [23–25]. Only recently attention has progressed towards more functional tasks, thus developing robotic training oriented to functional upper limb tasks, such as reaching to pick up a drink [26–28]. There is strong evidence that real therapy is effective in improving independence of people with sensory-motor impairment in ADL [6,9,10,25,29–32].

Typical ADL tasks involving upper limb, such as eating, drinking, dressing, and grooming, are normally performed in the 3D space. Furthermore, execution of arm movements within a reasonable workspace during ADL tasks may allow patients to improve functional abilities. In this context robotic devices become assistive robots since they provide help to patients performing daily life activities in 3D space.

In this paper an overview on bio-cooperative systems with multimodal adaptive interfaces for 3D upper-limb neuro-rehabilitation is presented, and an illustrative case of how to build such systems is provided, based on the authors' current research. It is directly derived from the Echord/MAAT system previously developed by the same research group [15,33–35]. It features on-line adaptation of therapy characteristics to specific patient needs and to the measured level of performance, by including the patient in the control loop. The system is conceived to also enable functional tasks of daily living.

The paper is structured as follows. In Section 2 a review of the bio-cooperative systems is reported, by proposing a general scheme of the system and then in-depth analyzing each subsystem. Section 3 presents the platform developed by the authors as a case study of bio-cooperative system for 3D upper limb robotic treatment with special focus on: (i) the adaptive robot control based on real-time monitoring of biomechanical user performance; (ii) a mechatronic module purposely conceived for providing adaptive support to the patient's arm during motor exercises. Discussion and conclusions are finally reported in Sections 4 and 5, respectively.

2. Overview on bio-cooperative control strategies for promoting patient engagement in therapy

A general scheme showing the functioning of a bio-cooperative system is proposed in this section (Fig. 1). It aims at providing a clear picture of all the possible bio-cooperative systems currently available in the literature, which can be obtained from the scheme in Fig. 1 by just eliminating some modules. In particular, with respect to the scheme already presented in [14], it is conceived to also include non-invasive cortical and non-cortical interfaces and context and environmental factors that are soliciting interest in the recent years. Each module will be widely discussed in the following.

As shown in Fig. 1, a central role is given to the patient who is closed in the control loop thanks to a multimodal interface that collects and processes data coming from different sources. The multimodal interface mainly consists of: biomechanical, physiological and psychological measurements for extracting a complete picture of the patient's state during therapy; non-invasive cortical (i.e. EEG) and non-cortical interfaces (EMG, EOG, eye tracking, etc.) for identifying the user's motion intention.

Data fusion and processing algorithms are developed working on the multimodal signals recorded by the acquisition system. Information about patient status and intention are used to update the sensory feedback to the patient (including visual, e.g. virtual reality, audio, and haptic feedback) and the bio-cooperative control in a patient-tailored manner, always guaranteeing safety in human–robot interaction.

2.1. Bio-cooperative control system

One possible categorization of current control algorithms for rehabilitation machines is the following:

- Assistive controller. This is the most widely developed control paradigm [16]. Assistive controllers help participants move their weakened limbs in desired patterns during grasping, or reaching, a strategy similar to "active assist" exercises performed by rehabilitation therapists.
- Challenge-based control. The term "challenge-based" refers to controllers that are in some ways the opposite of assistive controllers because they make movement tasks more difficult or challenging. Examples include controllers that provide resistance to the participant's limb movements during exercise, require specific patterns of force generation, or increase the size of movement errors ("error amplification" strategies) [21].
- Haptic simulation. It refers to the practice of ADL movements in a virtual environment. Haptic simulation offers flexibility, convenience, and safety as advantages compared to practice in a physical environment [26,27].

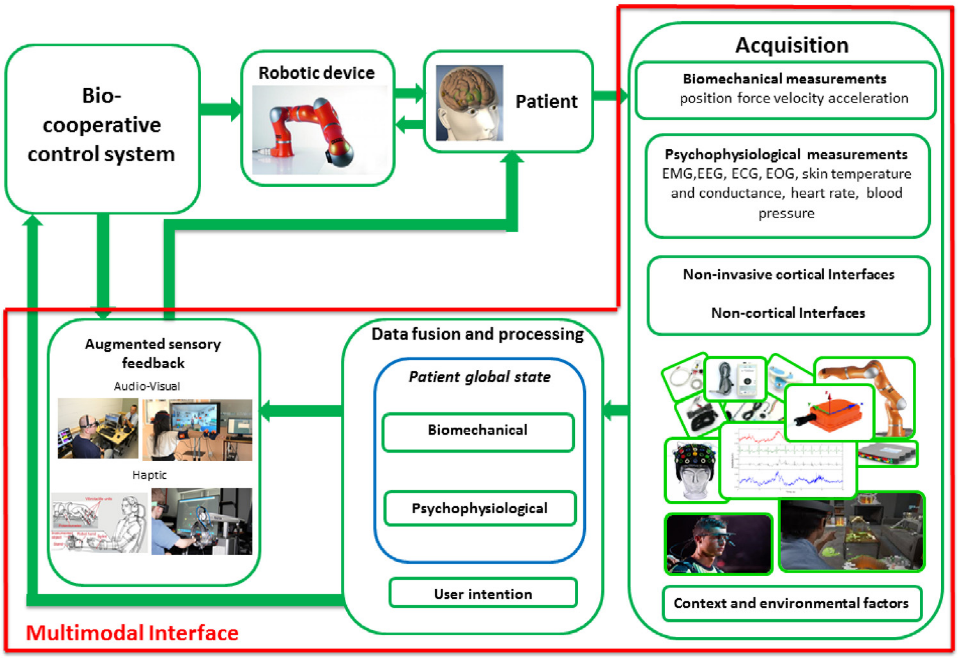

Fig. 1. Computational schema of the proposed bio-cooperative system for upper limb robotic rehabilitation.

- Non-contact coaching. There are some works on robotic devices that do not enter into physical contact with the participant, but playing the role of non-contact coaches that decide and direct the therapy program and motivate participants. For such devices, it has been hypothesized that physically embodying the automated coaching mechanism has special merit for motivating participants [36].

Bio-cooperative control can be regarded as a combination of assistive control and haptic simulation.

Assistive, or assist-as-needed control provides the patient with the minimal robotic assistance for completing the task execution, thus enabling user consistent effort and active involvement [37–39].

Assistive control strategies can be grouped into four conceptual categories: impedance-based, counterbalance-based, EMG-based and performance-based adaptive assistance. The impedance-based controllers are simple position controllers based on a proportional action [16,40–42]. The desired reference trajectory is generated by a minimum jerk trajectory [43,44] or, in some cases, an averaged pre-recorded path from healthy subjects. Actually, several studies have shown that giving the patient the possibility to choose its own trajectory can result in muscle tone reduction and improvements in ADL [18,45,46]. Algorithms based on radial basis function (RBF) approach have also been developed for estimating the patient's arm model and update it throughout the training [47–50]. Bayesian learning techniques are another attempt to establish the needed amount of assistance for completing rehabilitation tasks [51], as well as works carried out by Pérez-Rodriguez et al. [38,52], in which the learned model of patient skills is exploited to predict deviations from a reference path by applying corrective forces before they occur. Machine learning techniques, such as POMDP (Partially Observed Markov Decision Process), SVM (Support Vector Machines), KNN (K-Nearest Neighbor) and RBF are nowadays employed for adaptively classifying, choosing and setting difficulty of movement task depending on patient impairment level [34,39,53,54].

In bio-cooperative control, multimodal information from the patient is used to adapt the level of robot assistance to the patient specific status [45,55]. In [56] biomechanical and psychophysiological measurements are used for including human in the loop. In 2010 Guerrero et al. presented a human-centered approach method resorting to psychophysiological feedback [57] to customize therapy on patient requirements and state, without compromising its health and augmenting stress level.

EMG-based control can be adopted for subjects who are able to generate muscle activation instead of force or movement. A threshold approach is proposed in [58–61], while a continuous EMG control method is presented in [32], where the assistive force is proportional to the measured electromyography signal.

Recently, a research group from University of Tübingen has developed a conceptual framework in which bio-signals from brain and body are merged together in order to control robotic devices [62,63]. In [64,65] a novel Brain/Neural-Computer Interaction (BNCI) system that integrates EEG and EOG has been developed. Such physiological non-invasive signals are employed as a trigger for initiating and stopping movement therapy intending to provide an online modification/adaptation of robot-aided rehabilitation exercises by continuously monitoring patient's intention.

Finally, BCI-gaze-driven control proposes a method aimed to integrate in a multimodal platform, eye-tracking information and BCI technologies for control robotic devices to deliver rehabilitation [66].

However, past clinical studies with InMotion robot grounded on performance-based control [18], showed that adapting therapy to specific patient's motor characteristics led to better improvements with respect to conventional therapy, although they are very small. Moreover, it has recently been showed that upper-limb 3D training provided by an exoskeleton with a patient-cooperative control can enhance motor function improvement more than conventional therapy [46]. Therefore, it is expected that the more the knowledge about the patient's condition is complete the more the bio-cooperative control can meet user's needs during robotic therapy.

The proposed bio-cooperative control in Section 3 aims to provide an example of adaptive control strategy tailored on patients' status. Biomechanical and physiological measures (based on EMG) are used to describe the patient's status; however, the approach can be easily extended to include a greater number of measurements of patient condition.

2.2. Acquisition block

The acquisition block collects all the signals that can be extracted from the patient during the robotic treatment, thus allowing the analysis of user needs throughout the therapy sessions.

2.2.1. Biomechanical measurements

Biomechanical data, such as position, velocity, acceleration and force, have been widely employed to establish robust and adaptive robotic control laws [18,67–69]. They can be obtained through sensors embedded into the robot, or else sensors on the subject (e.g. wearable sensors magneto-inertial sensors), or else sensors in the environment (e.g. RGB cameras and optoelectronic systems).

Across the last ten years, the bio-cooperative approach in rehabilitation robotics has been defined as a human-centered scenario where psychophysiological measurements are jointly extracted with the biomechanical ones provided by the robotic device and used to develop adaptive control strategies [14].

2.2.2. Psychophysiological measurements

Psychophysiological measurements can be extracted from a number of biological signals (see Fig. 1), e.g. EMG, EEG, EOG, heart and respiration rate, skin conductance and temperature, blood pressure.

2.2.3. Context and environmental factors

In addition, the capability of automatically detecting people and understanding their behaviors is a crux in functionality of intelligent virtual reality systems.

Analyzing the rehabilitation scene at different levels of abstraction requires a discrete number of processing steps starting from patient and robot behaviors. For instance, RGB cameras and gaze detection systems can be employed to select specific actions or monitor user interaction with the robot and the environment. Human specific behaviors and intentions are often triggered by gaze focalization. Gaze estimation acquires a crucial importance into detection of contextual factors. In the various object localization and eye-tracking tools available nowadays [70,71], Microsoft Kinect sensor represents an affordable as well as economic solution. Visual (RGB) and depth data provided by Kinect camera can be exploited in order to perform a visual tracking of active objects on rehabilitation scenario within the 3-D workspace where the objects can be reached and located [66].

2.3. Data fusion and processing

Once data coming from different sources have been collected, data fusion and processing procedures are necessary [72] to depict the patient's global state and update accordingly the sensory feedback (including the virtual reality as well as audio and haptic feedback) and the bio-cooperative control.

Kinematic and dynamic outcomes are collected to define the patient's biomechanical performance through a discrete number of both kinematic and dynamic indicators. Psychophysiological state is a crux to detect the user's cognitive load and physiological response to the rehabilitation treatment. Furthermore, physiological and context and environmental measures can be used to detect user intention through typical techniques of non-invasive cortical and non-cortical human–machine interfaces, especially in the case of patients with severe impairments.

2.3.1. Biomechanical state

Patients' biomechanical state can be estimated through kinematic and dynamic indicators [12,33]. They can provide kinematic measures of movement duration, accuracy and smoothness, or else dynamic measures of forces and work expended during therapy [12].

Bio-cooperative controller receives biomechanical feedback able to adapt robot gains and stiffness to specific patient's conditions [33].

2.3.2. Psychophysiological state

The user's psychophysiological state is estimated by continuously identifying patient cognitive load during the task execution.

In rehabilitation robotics the first examples of online detection of patient mental state can be found in [72–75]. They employed physiological measurements, such as heart rate, respiration rate, skin conductance and blood pressure [75,76], to depict the psychological state of the patient as cognitive load during the therapy. A linear adaptive classifier was developed to estimate in real time patient "high cognitive load" or "low cognitive load" [72].

Recently in [34] an overview of different classification methods to estimate patients physiological state, based on machine learning models and algorithms [77] has been proposed. Extracting features can help robot to learn the way to automatically update its behavior depending on specific user requirements.

2.3.3. User intention

Detection of user's intention may represent a further contribute to the bio-cooperative control loop in order to actively engage the patient into the therapy.

Non-cortical interfaces exploit either biomechanical parameters, such as force, velocity, position, time thresholds for triggering therapy, or electromyography (EMG) and eye-tracking signals [18,32,63–66]. Robot assistance is provided when the signal detecting patient motion intention overcomes a predefined threshold of the trigger-cue. Preliminary tests conducted on healthy subjects with the ARMIn III [78] exoskeleton have shown the technical feasibility of this approach and its potential clinical relevance, although data fusion algorithms needs to be improved [79].

On the other hand, non-invasive cortical interfaces, such as BCI [80], may infer the user's intent through neural data acquired from the brain i.e. EEG, exploiting them as input control for robotic assistive devices [81–83].

EEG-based BCIs [65,66,84] are often employed directly with motor imagery; in such a case the EEG signal can act as a trigger for initiating and stopping movement therapy. However, once the movement is triggered, the resulting movement may be always the same, invariant of the amount of effort the patients put in to imagine the movement. To overcome this drawback, a Linear Discriminant Analysis (LDA) algorithm for classifying specific EEG signals as "move" or "rest" has been carried out in [65]. Differently from previous study this binary classification has not been used as the output to the robot controller, but the LDA's extracted posterior probabilities, have been directly exploited as the continuous-valued outputs to control the robotic device.

The coupled use of BCI with EOG, EMG and eye-tracking signals is also fostered for strengthening system capability to detect patients' intentions.

2.4. Augmented sensory feedback: visual and haptic

Providing the patient with sensory feedback during the robotic treatment contributes to further enhance engagement and motivation by returning the patient with a perception of the executed task. It may be visual, audio, haptic and their

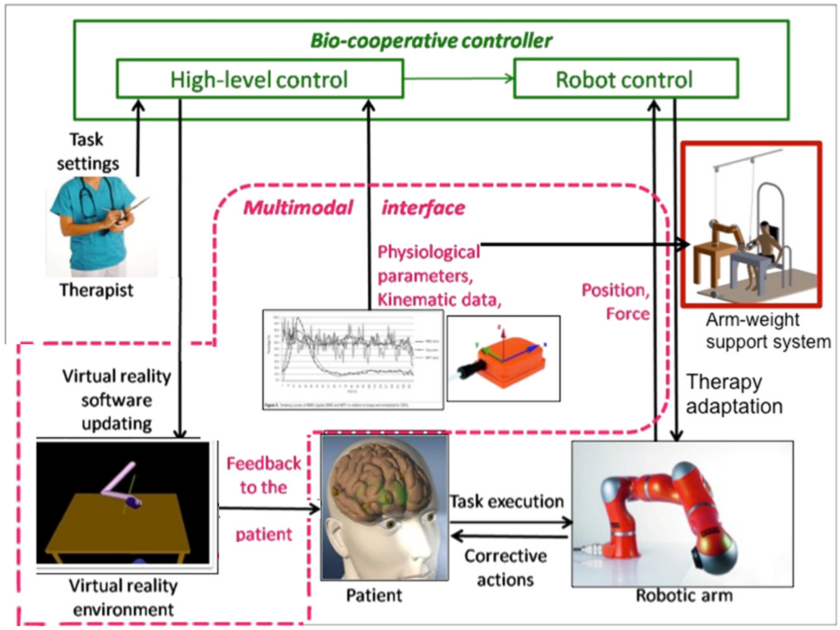

Fig. 2. Overview of the overall MAAT system with the integrated module for arm-weight support.

combination [85,86]. It has been showed that using virtual reality (VR) and computer games techniques in post stroke upper limb rehabilitation may enhance neuroplasticity [87–90]. VR offers the advantage of keeping the patient immersed into the task to execute. Acoustic feedback can also be coupled with VR resulting in a more challenging patient sensorimotor engagement thus operating as "augmented feedback" [91].

Further manners to enhance patient sensorial state are represented by merging together with VR, haptic and vibrotactile feedback. In particular, haptic is a kinesthetic or tactile feedback that the user "feels" while performing the exercise [92]. It provides the user with the perception of the task and help her/him to accomplish it in a more efficient way. Haptic feedback also includes vibrotactile cues provided onto the skin to guide the user's arm into the desired target configuration shown on a graphical interface or virtual environment [93].

3. The proposed bio-cooperative robotic platform

In this section a bio-cooperative system developed by the authors for 3D upper limb rehabilitation is presented. It was partly developed within the Echord/MAAT project [15,33–35,94], and is composed of a 7-DoF robot arm (Kuka LWR-III [95]), a motorized arm-weight support system, an adaptive interaction control system, and a module for on-line evaluation of patient performance in order to adaptively and dynamically change robot behavior (see Fig. 2). It represents an illustrative case of bio-cooperative system originating from the general scheme in Fig. 1, also coping with the very delicate requirement of introducing an adaptive arm-weight support for 3D rehabilitation with end-effector machine. So, the motorized arm-weight support can be regarded as the main innovative element of our bio-cooperative system [33], aimed to overcome patients' difficulty to self-sustaining their own arm during the motor exercises.

The multimodal interface is composed of the following sources of information, providing a picture of the patient's condition: robot sensors for hand pose and force, magneto-inertial sensors for reconstructing the user's joint motion, EMG electrodes for recording muscular activity. The module for on-line evaluation of patient performance records patient biomechanical data through an unobtrusive, wearable sensory system, evaluates patient biomechanical state and updates robot control parameters for modifying the level of assistance and task complexity in the 3D workspace.

Moreover, for further promoting patient motivation and engagement, a virtual reality is developed in which the selected task is reproduced and updated according to the patient's biomechanical data.

The system is conceived as an end-effector machine that, interacting with the patient only at the end-effector, can provide assistance in analytical tasks, such as point-to-point in 2D and 3D space, as well as in functional tasks of daily living (ADLs). However, because of the interaction limited to just one point, an additional mechatronic arm-weight support has been developed. It has the fundamental purpose of providing an adaptive level of support, by compensating the gravity force depending on the subject arm configuration in the space.

3.1. Patient-tailored adaptive robot control system

The main goal of the controller is to assist the patient (who is connected to the end-effector of the robot) when he/she is not able to accomplish the task autonomously, with a level of assistance that is tuned on the patient global state. The robot is highly compliant when patient is able to follow the planned path, while adaptively change its behavior when he/she moves away from reference trajectory. To this purpose an impedance control in the Cartesian space has been implemented. Task duration and robot stiffness are the control parameters updated according to the patient biomechanical state, as explained in Section 3.2.

The robot control law is expressed as follows [15,33].

$$\vec{\tau}_{cmd} = J^T\left(\vec{q}\right)\left[K\left(\vec{x}_p - \vec{x}\right) + \vec{FT}\right] + D\left(d\right) + \vec{f}_{dyn}\left(\vec{q}, \dot{\vec{q}}, \ddot{\vec{q}}\right)$$

J^T is the transposed Jacobian matrix, K is the Cartesian stiffness matrix, $\vec{x}_p$ and $\vec{x}$ are the desired and actual Cartesian position vectors, $D(d)$ is the damping term, $\vec{FT}$ is an additional superposed Cartesian force, $\vec{q}$ is the joint vector, $\vec{f}_{dyn}$ is the dynamic model. Furthermore, in order to foster patient involvement and favoring voluntary efforts, a *dead band* around the reference trajectory is created [18,21] where no assistance is provided. For 2D and 3D point-to-point movements a minimum-jerk trajectory is planned as reference trajectory; on the other hand, for ADL tasks, pre-recorded trajectories from healthy subjects are used.

3.2. Module for biomechanical and physiological assessment of patient performance

Patients biomechanical measures are recorded by means of robot position and force sensors, and an accelerometer positioned on the patient's arm. Physiological measures are provided by EMG electrodes; a data fusion and processing algorithm allows evaluating the patient status through kinematic, dynamic and EMG indicators. Afterwards, control parameters are updated by means of purposely developed modulation functions, exploiting the computed indicators.

Kinematic indicators take into account patient behavior in the Cartesian and in the joint space. Encoders embedded into the robot are used to compute patient trajectories in the Cartesian space; on the other hand, an inverse kinematics algorithm (presented in detail in [96]) based on the patient augmented Jacobian has been developed for reconstructing the patient's joint motion. It resorts to the measures provided by the robot position sensors and the accelerometer located on the subject's arm.

The computed kinematic indicators are the following:

- Aiming angle (α) [12], i.e. the angle between the target direction and the direction of travel from the starting point up to peak speed. It allows evaluating motion direction and accuracy.
- Mean Arrest Period Ratio (MAPR) [97,98], defined as the proportion of task duration where movement speed exceeds the 10% of peak speed. It is used to quantify motion smoothness.
- Inter-joint coordination ($q_{corr_{i,j}}$): it expresses the correlation index between two upper limb joint angles q_i and q_j [33].

The dynamic indicators are extracted from information about the interaction force provided by the robot torque sensors. The computed indicators are the following [12]:

- *Useful-Mean-Force (UMF)* which represents the amount of mean force exerted along the target direction;
- *Useful-Peak-Force (UPF)* that expresses the peak force along the target direction;
- *Total-Work (TW)* which is the total work expended during motion;
- *Useful-Work (UW)* that expresses amount of total expended work along target direction.

Finally, EMG indicators are extracted from electromyography signals coming from two couple of antagonist muscles (pectoral–deltoid and biceps–triceps muscles) in order to assess muscular force, power and fatigue expended during robotic therapy.

In detail they are expressed as:

- *Root Mean Square (RMS), i.e.* the quadratic mean of signal amplitude [99];
- *Power Spectrum (PS)*, that is power spectral signal density [100];
- *Co-Contraction Index (CCI)*, i.e. a quantitative measure of the simultaneous activation of antagonist muscles across a joint [101];
- *Median Frequency (MF)*, i.e. the median of frequency distribution of the signal [100,101].

Performance indicators are normalized with respect to their maximum and adjusted in order to increase with motor recovery. Hence, they are used for a twofold purpose: (a) to assess patient behavior during therapy and evaluate his/her level of recovery; (b) to tailor the therapy on the patient's state by updating control parameters t (i.e. task duration) and K (i.e. robot stiffness).

The aforementioned performance indicators are adjusted through properly defined weighted-sum modulation functions, expressed as follows by Eqs. (1)–(2).

$$C_t = \sum_{j=1}^{J} w_j PI_j \quad (1)$$

$$C_K = \sum_{i=1}^{I} w_i PI_i \quad (2)$$

PI_j is the jth performance indicator ($j = 0, 1, 2, .., J$) used for the adaptation of the time allotted for task execution; PI_i is the ith performance indicator ($i = 0, 1, 2, .., I$) used for the adaptation of robot stiffness and $w_{i,j}$ is the weight chosen for the selected indicators.

The different weights are chosen with a trial-and-error approach. For instance the aiming angle is employed only in C_K, since it quantifies accuracy and direction of the fulfilled movement; on the other hand, MAPR is used only in C_t, as it accounts for movement smoothness (describing the percentage of stops during task execution). All the other indicators are employed in both functions.

The modulation functions continuously vary between 0 and 1; a threshold strategy is employed to convert them into discrete performance levels related to predefined value of t and K. To this purpose, based on a trial-and-error approach, three performance levels are selected (1, 2 and 3) corresponding to three intervals of C_K and C_t [33] (i.e. [0, 0.5), [0.5, 0.70) and [0.70,1)). The robot control automatically associates them to predefined values of robot stiffness and task duration. Preliminary results of the proposed control can be found in [102].

3.3. Design and development of a mechatronic module for arm weight support

Patients who undergo robotic therapy with end-effector machine may require an arm-weight support to compensate for gravity and fulfill the motion exercises. Patient difficulty to self-sustain arm during robotic treatment is mainly due to neuromuscular damages caused by stroke [103] which produces upper limb muscular weakness, making really challenging for the patient to execute the required tasks.

Providing subjects with arm weight-support has been shown to reduce the abnormal coupling of shoulder abductors and elbow flexors often observed in stroke survivors who are affected by severe motor impairments [10,104–108].

Robotic devices which supply arm weight-support, have been demonstrated to facilitate arm movements during reaching tasks by reducing the required level of muscle activity, particularly for muscles involved in arm-sustenance against the effect of gravity [109,110].

These studies, as well as the collaboration with the clinicians have encouraged the development of a novel mechatronic module for online adaptation of arm-weight support. It is an extension of the bio-cooperative system developed within the Echord/MAAT project, and plays a key role in the application of the system to clinical trials on post stroke patients.

The new platform is shown in Fig. 3. It integrates the bio-cooperative system developed in Echord/MAAT project with the arm-weight support, and is specifically studied to enable multimodal measures during the execution of functional tasks of daily living with the assistance of the end-effector machine.

The arm weight support has to sustain patient's arm during 3D task execution by adapting the level of support to the limb configuration. To this purpose, arm weight (i.e. the load), arm

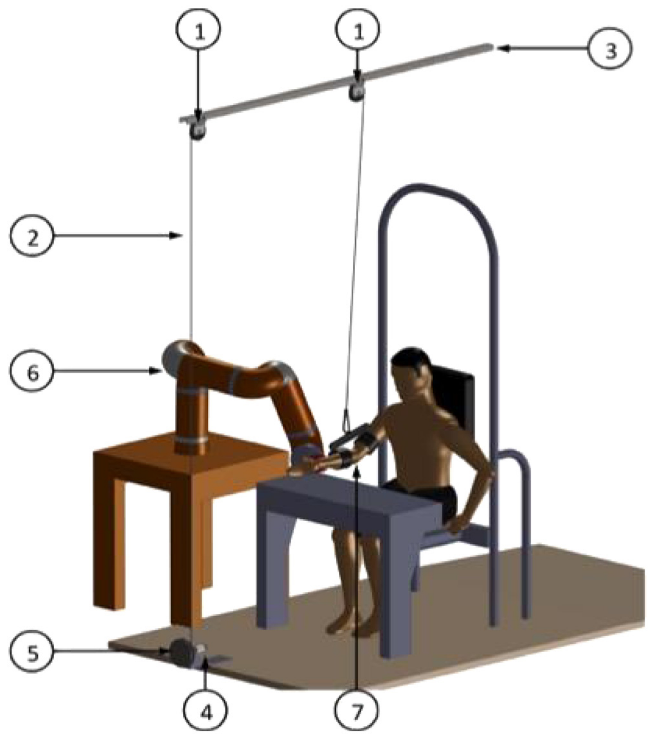

Fig. 3. Mechatronic module for arm weight support: (1) pulleys; (2) steel wire; (3) steel bar; (4) actuation system; (5) aluminum drum; (6) 7-DoF Kuka LWR; (7) forearm-belt support.

moment of inertia, approximate task velocity and required range of motion (ROM) were estimated.

In particular the following values were taken: load equal to 5 kg [111], arm moment of inertia is taken equal to 0.0245 kg m^2 [111], arm velocity is set as 0.5 m/s [33], arm ROM along z-axis is 0.5 m [33]; a safety factor 2 is used for overestimating these values.

As transmission system, a cable–pulley system is chosen driven by a DC motor secured on one extremity of the cable. A specific orthosis for arm/forearm support is fixed at the other cable extremity.

The cable–pulley system in Fig. 3 is composed of: (1) two pulleys (BNL acetal 25 mm pulley, 18 mm pitch diameter, 102 mm external diameter, 9 mm bore) with ball bearings and bore reduction bush; (2) 4 mm steel wire rope black nylon coated to 5 mm, with winding radius equal to 70 mm; (3) steel bar equipped with holes to allow choosing pulley's location, fastened on room ceiling; (4) an actuation system composed of: EC-max 40 brushless Maxon Motor, planetary gearhead Maxon GP 42-C 74:1, Maxon HEDL-5540 encoder and Maxon EPOS2 50/5 control unit; (5) aluminum drum, for enveloping steel rope, (diameter: 140 mm) is built-in with motor shaft; (6) 7-DoF Kuka LWR; (7) forearm-belt support, which enables to set correct fitting depending on patient's requirements.

The selected actuation group is able to provide the maximum continuous torque (load acceleration torque and continuous torque for maintaining arm) for sustaining the upper limb, which has been estimated as 4.1 N m. Moreover, the actuation group and the cable–pulley system can be adjusted according to the patient anthropomorphic characteristics and sitting position.

In order to provide the patient with online adaptive arm support during the 3D tasks and ADLs, a position control is being developed that can command the motor to reel in or else unroll the cable according to the patient's limb configuration. This is obtained by the already validated inverse kinematics algorithm in [96] which relies on sensor information provided by the robot and the accelerometer on the limb. The controlled rotational movement of the motor shaft coupled with drum is expected to induce translational movements to the cable capable of lifting and lowering the patient arm as required by the task.

4. Discussion

In this paper an overview on bio-cooperative robotic systems in the rehabilitation scenario has been provided; moreover, the case study of a bio-cooperative system for upper-limb motor therapy developed by the authors has been presented.

The key-issue of the bio-cooperative systems is to close the patient in the control loop in two ways: (a) by feeding back to the robot multimodal information about the patient's global status (through biomechanical, physiological, psychological information); (b) by returning to the patient the perception of the task being executed (through visual, auditory or haptic feedback). Hence, a multimodal human–robot interface includes all the modules responsible for acquisition, processing and feedback of such a huge number of signals.

The interest in bio-cooperative systems is growing in the recent years [33,45,73]. Although some clinical trials have been shown small potential benefits in terms of patient recovery [41,42,46, 112] a number of open issues regarding the use of bio-cooperative systems in rehabilitation robotics are still open. For instance the use of multimodal interfaces requires to gather different signals from several sources, thus notably increasing system complexity. This may cause a not negligible computational burden as well as the use of obtrusive equipment for the users. Obtrusiveness is a very delicate issue that can contribute to cause user's stress or unsatisfaction during the therapy. To this purpose, there is the attempt to realize bio-cooperative systems with unobtrusive equipment [33].

Bio-cooperative control goes beyond the "if-then" functioning mode based on a predefined trajectory and pave the way to the development of robot-aided therapies delivering functional tasks of daily living.

Robot control often resorts to the assist-as-needed approach in order to assist the patient to accomplish the required tasks by providing a patient-tailored assistance [18,21].

Several studies have shown that giving the patients the possibility to choose their own trajectory can result in muscle tone reduction and functional improvements in activities of daily living [18,45,46]. However, further clinical trials are required for demonstrating and assessing the real effectiveness of the assist-as-needed approach over traditional robotic therapy. On the other hand, EMG-based control has been widely adopted to extend therapy to ADLs [58,59,76,80]. However, it gives a significant movement freedom, with the consequent drawback that it may enhance pathological movements related to stroke conditions rather than allow regaining motor and functional skills. Notwithstanding, EMG-based control seems to improve muscle coordination as well as reduce spasticity in stroke patients [113,114].

The inclusion of psychophysiological measurements into the control strategy (as done in the bio-cooperative control) has been shown to improve patient engagement and provide further information on the patient's state (i.e. the cognitive load caused by the task execution). However, studies in [63–66] have pointed out that psychophysiological outcomes alone are not reliable as a primary data source for state estimation; they need to be coupled with task performance.

Furthermore, it still remains to verify the real effectiveness of including psychophysiological measurements in bio-cooperative approach compared to the added intrinsic complexity of the system. In fact augmenting critically complexity of device and environmental settings may constitute a not-negligible issue.

In addition to biomechanical and psychophysiological measures, more recent bio-cooperative systems also propose to use non-invasive, non-cortical and cortical interfaces to further enhance patient involvement in the robotic therapy by detecting user movement intention. The main advantage of detecting user intention is to extend the use of the robotic machines also to severe impaired patients who are often not able to directly move the robot. Several techniques are proposed to this purpose, based on Brain Machine Interface (BMI) and eye-tracking in virtual reality [85–89].

Due to large amount of information, originating from different sources, data fusion issues may arise; for this reason complex computing algorithms need to be implemented. Machine learning techniques have tried to overcome these significant problems, developing particular data fusion and processing algorithms [34,35,54]; they may help exploit biosignals in order to establish reliable real-time adaptive control system. Hybrid BNCI [115,116], fusing biosignals from different sources, aims to gain better performance in robotic system's control.

In [64] it is shown that the coupled use of EEG and EOG can improve control performance of a hand exoskeleton. On the other hand, coupling EMG with ECG [117], due to EMG susceptibility to fatigue, suggests to ameliorate control system performance. Future research is essential to show whether these novel approaches can indeed improve control of assistive devices in daily life contexts. Despite these encouraging findings, low-cost, non-invasive and easy installable BCI should be developed to enable their adoption in the clinical practice. Therefore, in order to move the BCI status from "promising" to "effective tool", several issues need to be coped with:

- The best way to integrate BCIs with actual rehabilitation methods, to establish a powerful and accurate rehabilitative scenario.
- Heterogeneity in post-damage expression that inevitably complicates the decoding of brain signals responsible for neuroplasticity recovery; this may lead to complicate extraction of suitable control inputs.
- So far no BCI systems exist which are able to provide a high accuracy level in robotic control. This aspect becomes crucial since control systems need accurate signals in order to accomplish robotic tasks; otherwise brain signals are not easy to detect clearly. In addition, at present is not clear how accurate a BCI system should be for providing a robust robotic control. These points represent the third fundamental issue to be solved.
- Another limitation related to BCI use in robotic upper limb rehabilitation, is the difficulty to real-time detect motion intention and correspondingly adapt the therapy [64,118]: patients' intentions are currently used only to initiate and stop the movement therapy.

Notwithstanding these issues, BCI technique may be used in rehabilitation robotics to provide multimodal movement-related physiological data, which can be exploited to generate reliable and robust "biomarkers" of motor and functional recovery in patients with neural damages [83].

Finally, providing the patient with sensory feedback during task execution is expected to enhance patient motivation. To this regard, virtual reality environment often coupled with acoustic and/or haptic feedback have demonstrated their meaningful impact on assistive and rehabilitation robotics [88] as multimodal enhanced feedback. Their positive effects result in:

- the reduction of the workload during motor task learning;
- facilitating learning of spatial and temporal aspects of the movements, thanks to visual and auditory feedback.

However, it is worth noticing that, despite these promising findings, the augmented feedback still present limitations. For instance, many devices that are required to operate a VR system, with sensory feedback, or to track user behavior, generally requires obtrusive hardware that are a source of distraction and inconvenience [119]. Real-time synchronization of signals dedicated to reconstruct VR may be delayed due to the large number of required devices. This lead to a bad real-time environmental reconstruction, thus increasing the task difficulty.

Future challenges regarding augmented feedback suggest to examine whether visual, auditory, and haptic feedback can induce similar effects on patients, whereby measuring brain activation in different feedback conditions [120].

For sure, task complexity, feedback design, feedback variables and modalities can be manipulated in order to optimally challenge the learner, thus contributing to speedup motor learning [121].

The paper also reports a bio-cooperative system developed by the authors as a case study. It exploits patient biomechanical and physiological (EMG) performance to update an adaptive robot control system. A specific module for arm-weight support is designed to provide the patient with adaptive support against gravity. The module is designed according to clinicians requirements in order to extend therapy to stroke patients and its validation is actually reformed.

Further experiments on healthy subjects are being carried out to test the reliability of the complete platform before moving to the clinical validation on post-stroke subjects.

As evident from the reported analysis of the literature and from our experience, the bio-cooperative systems offer the real challenge to depict a complete picture of the user and use this picture to real-time shape the therapy on the user's features. This is possible thanks to the multimodal information about physiological, biomechanical as well as psychological measurements, the novel machine learning techniques for data processing, the non-invasive interfaces for user detection intention, the sensory feedback to the patient.

Notwithstanding their potential, the validation of bio-cooperative systems in the clinical settings is still very limited (except for a few preliminary studies [33–35,45,46,56,57]) and represents the real keystone to assess the efficiency of bio-cooperative approach in rehabilitation robotics.

5. Conclusions

This paper has provided an overview of the bio-cooperative systems for upper-limb robot-aided rehabilitation and has presented a case study of bio-cooperative system developed by the authors for the delivery of 3D motion tasks and ADLs. The provided definition of bio-cooperative system is extended to include non-invasive human–machine interfaces for detection of human intention, context and environmental factors, and augmented sensory feedback for the patient (in addition to the multimodal signal acquisition for the patient state). The main expected advantage is to close the control loop on the patient and enhance his/her active role in the rehabilitation treatment, also in case of severe neurological damages. The technologies and techniques developed in this context have been presented and largely discussed as well as their pros and cons. The proposed bio-cooperative system partly developed within the ECHORD/MAAT project wants to represent an example of bio-cooperative system relying on an end-effector machine. It allows providing assistance in the 3D space with a patient-tailored approach but it also requires a module for guaranteeing arm-weight support. The overall system has been briefly presented, including the novel approach to overcome patients' difficulty to self-sustaining their own arm, based on a mechatronic arm-weight support. The adaptive control of the arm-weight support is currently being developed and an extensive validation of the complete system in the clinical setting is envisaged.

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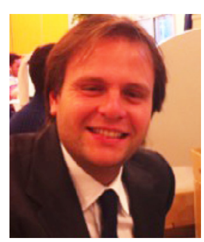

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