Accepted Manuscript

Anticipatory assistance-as-needed control algorithm for a multijoint upper limb robotic orthosis in physical neurorehabilitation

Rodrigo Pérez-Rodríguez, Carlos Rodríguez, Úrsula Costa, César Cáceres, Josep M. Tormos, Josep Medina, Enrique J. Gómez

PII: S0957-4174(13)00989-5
DOI: http://dx.doi.org/10.1016/j.eswa.2013.11.047
Reference: ESWA 9079

To appear in: Expert Systems with Applications

Please cite this article as: Pérez-Rodríguez, R., Rodríguez, C., Costa, Ú., Cáceres, C., Tormos, J.M., Medina, J., Gómez, E.J., Anticipatory assistance-as-needed control algorithm for a multijoint upper limb robotic orthosis in physical neurorehabilitation, Expert Systems with Applications (2013), doi: http://dx.doi.org/10.1016/j.eswa.2013.11.047

This is a PDF file of an unedited manuscript that has been accepted for publication. As a service to our customers we are providing this early version of the manuscript. The manuscript will undergo copyediting, typesetting, and review of the resulting proof before it is published in its final form. Please note that during the production process errors may be discovered which could affect the content, and all legal disclaimers that apply to the journal pertain.
Title

Anticipatory assistance-as-needed control algorithm for a multijoint upper limb robotic orthosis in physical neurorehabilitation

Names

Rodrigo P´erez-Rodr´ıguez1,2, Carlos Rodr´ıguez3, Úrsula Costa4, C´esar C´aceres1,2, Josep M. Tormos1, Josep Medina4, Enrique J. G´omez1,2

Complete postal addresses of affiliations

1 Telemedicine and Bioengineering Centre, ETSI Telecomunicaci´on - Universidad Politec´nica de Madrid, 28040, Madrid, Spain
2 Centro de Investigaci´on Biom´edica en Red, Biomateriales y Nanomedicina (CIBER-BBN)
3 Fundaci´on Cartif, 47151, Valladolid, Spain
4 Institut Universitari de Neurorehabilitaci´o Guttmann adscrit a la UAB, 08916, Barcelona, Spain

Full telephone number, fax number and e-mail address of the corresponding author

Tel.: +34 91 549 57 00; ext.: 3407
Fax: +34 91 336 68 28
Email: rperez@gbt.tfo.upm.es (Rodrigo P´erez-Rodr´ıguez)

Present address of authors: Grupo de Bioingeniería y Telemedicina, ETSI Telecomunicación, Universidad Politécnica de Madrid, Ciudad Universitaria, Avda. Complutense 30, 28040, Madrid, Spain.
Anticipatory assistance-as-needed control algorithm for a multijoint upper limb robotic orthosis in physical neurorehabilitation

Rodrigo Pérez-Rodríguez 1,2, Carlos Rodríguez 3, Úrsula Costa 4, César Cáceres 1,2, Josep M. Tormos 4, Josep Medina 4, Enrique J. Gómez 1,2

1 Telemedicine and Bioengineering Centre, ETSI Telecomunicación - Universidad Politécnica de Madrid, 28040, Madrid, Spain
2 Centro de Investigación Biomédica en Red, Biomateriales y Nanomedicina (CIBER-BBN)
3 Fundación Cartif, 47151, Valladolid, Spain
4 Institut Universitari de Neurorehabilitació Guttmann adscrit a la UAB, 08916, Barcelona, Spain

Abstract

Robotic devices are becoming a popular alternative to the traditional physical therapy as a mean to enhance functional recovery after stroke; they offer more intensive practice opportunities without increasing time spent on supervision by the treating therapist. An ideal behavior for these systems would consist in emulating real therapists by providing anticipated force feedback to the patients in order to encourage and modulate neural plasticity. However, nowadays there are no systems able to work in an anticipatory fashion. For this reason, the authors propose an anticipatory assistance-as-needed control algorithm for a multijoint robotic orthosis to be used in physical ABI neurorehabilitation. This control algorithm, based on a dysfunctional-adapted biomechanical prediction subsystem, is able to avoid patient trajectory deviations by providing them with anticipatory force-feedback. The system has been validated by means of a robotic simulator.

Obtained results demonstrate through simulations that the proposed assistance-as-needed control algorithm is able to provide anticipatory actuation to the patients, avoiding trajectory deviations and tending to minimize the degree of actuation. Thus, the main novelty and contribution of this work is the anticipatory nature of the proposed assistance-as-needed control algorithm, that breaks with the current robotic control strategies by not waiting for the trajectory deviations to take place. This new actuation paradigm avoids patient slacking and increases both participation and muscle activity in such a way that neural plasticity is encouraged and modulated to reinforce motor recovery.

© 2013 Published by Elsevier Ltd.

Keywords: Neurorehabilitation, Acquired Brain Injury, Assistance-as-needed, Rehabilitation robotics, Robotic simulation

1. Introduction

1.1. Research context

ABI (Acquired Brain Injury) is defined as an injury to the brain that has occurred after birth but it is not related to congenital defects or degenerative diseases [1]. The WHO (World Health Organization) estimated that in 2005, stroke accounted for 5.7 million deaths worldwide, equivalent to 9.9% of all deaths, and it was the main cause of disability, affecting 30.7 million people [2]. These days, nine million people suffer from a cerebrovascular disease every year in the world [2] and globally, stroke is the second leading cause of death and the eighth cause of severe
disability in the elderly. By the year 2020, as the WHO predicts, it will be among the ten most common causes of disability in the developed world. These injuries, due to their physical, sensory, cognitive, emotional and socioeconomic consequences, considerably change the life of both the patients and their families. The cause of ABI can be either traumatic (car accidents, falls, etc.) or non-traumatic (strokes, brain tumors, infections, etc.). The most common ABIs are stroke and TBI (Traumatic Brain Injury) [3].

New techniques of early intervention and the development of intensive ABI care have noticeably improved the survival rate [4]. However, in spite of these advances, brain injuries still have no surgical or pharmacological treatment to re-establish lost function. Neurorehabilitation therapies address this problem by restoring, minimizing or compensating the functional alterations in people with disabilities of neurological origin. Medical evidence in neurorehabilitation is scarce and the assessment methods, especially those dealing with upper limb function, depend on clinician experience and subjectivity. Moreover, motion analysis assessments, which are more sensitive and provide objective data, are mainly centered on gait analysis, whereas upper limb tests are still not widely performed; current trend in development towards individualised and more complex models needs to be justified by demonstrating their ability to answer questions that cannot already be answered by existing models [5]. Besides, the lack of standardized protocols due to the large variety of movements, complexity of the upper extremity and lack of international consensus to validate the protocols hampered the advance on this area [6].

One of the main objectives of neurorehabilitation is to provide patients with the capacity to perform specific ADL (Activity of the Daily Life) required for an independent life, taking into account that continual practice of fundamentally inappropriate compensatory strategies may be a critical factor limiting recovery after brain damage [7, 8]. Although traditional physical therapy can enhance functional recovery after stroke, robotic devices may offer more intensive practice opportunities without increasing time spent on supervision by the treating therapist [9]. This, along with the assertion that traditional therapies are expensive and likely dosage dependant, have caused a remarkable increase in research aimed at creating, controlling and using robotic devices [10, 11].

1.2. Related work

Robotic neurorehabilitation is attractive because of its potential for easy deployment, its applicability across a wide range of motor impairment and its high measurement reliability and thus, there is an increasing interest in using these devices to support neurorehabilitation therapies [12]. Moreover, it is also believed that robotic therapy during the acute and sub-acute phase of stroke recovery could augment changes in impairment driven by spontaneous biological recovery processes [13].

To provide patients with ADL-based functional rehabilitation under the assistance-as-needed paradigm [14] (which means to assist the subject only as much as is needed to accomplish the task) and without the presence of a therapist but under his/her supervision, is one of the main challenges of the current neurorehabilitation technologies. Current assistance-as-needed strategies face one crucial challenge: the adequate definition of the desired limb trajectories regarding space and time that the robot must generate to assist the user during the exercise [15].

Rehabilitation robotic control algorithms can be grouped according to the strategy taken to facilitate motor recovery: assisting, challenge based, haptic simulation and non-contact coaching [16]. Assistive controllers actively help the patients to achieve certain goals; challenge-based ones provide resistance to the performed movements. Haptic simulation consists in practising ADL movements in virtual environments. Coaching robotic systems do not physically interact with the patients but provide them with help and motivation.

Besides, there is a scientific theory, called the "Slacking Hypothesis", that suggests that active guidance may decrease motor learning because, in some cases, it can cause patients to decrease their own effort during the training session [17]. Thus, assistance-as-needed neurorehabilitation paradigm, which consists in providing the patients only with the assistance they need to perform certain activity, appears as a strong alternative to enhance the therapy outcomes. This actuation paradigm has been proven to be successful in previous motor rehabilitation studies [18].

Several approaches to the assistance-as-needed paradigm can be found in the scientific literature. Some robotic systems provide an assistance that is proportional to the deviation of the patient given a predefined trajectory. Well known examples of this control strategy are MIT-MANUS [19, 20, 21], MIME [22, 23, 24], GENTLE/G [25], ARMin [26, 27, 28], L-EXOS [29, 30], ReoGo [31] or NeReBot [32]. Other systems that apply the aforementioned control strategy are also [33, 34, 35, 36, 37]. These assistive robotic therapy controllers focus on the following idea: when the subject moves along a desired trajectory (and an artificially created virtual tunnel), the robot should not intervene, and if the participant deviates from the desired trajectory, the robot must create a restoring force [16].
Dynamic control systems, that are able to adapt to the current needs of the patient based on online performance measurements, can be also found in the scientific literature. The basis of these control strategies is to adapt their configuration parameters tuning the system to the subject changing needs. Rienert et al. [38] developed such system for gait rehabilitation by recognizing the patient intention and adapting the level of assistance to the subject’s contribution. Regarding the upper limb, inter-session parameter adaptation methods that allow the selection of the working parameters once a previous performance measurement is available can be found [20, 39]. Recently, Guidali et al. developed a method that made the robotic device able to react in real time to the performance of the subject by updating a dynamic model of the upper limb [40]; even though this work supposes a clear step forward to the work presented by Wolbretch et al. [10] (whose method was movement-specific) their ‘assistance-as-needed’ strategy is not focused on the provision of anticipatory force-feedback to the patients, in contrast, their aim is to perform an online adaptation of the amount of support depending on the activity. Finally, some assistance strategies introduce a forgetting factor to keep a challenging assistance level for the patient in order to avoid slacking [17, 14, 40, 41].

Anticipatory control is still a relatively unexplored niche in the field of rehabilitation robotics. No works have been found that try to anticipate patient intention in order to avoid trajectory deviations. However it is worth to mention the work developed by Everarts et al. [42], who proposed an anticipatory algorithm to enhance robotic transparency for gait rehabilitation taking advantage of the cyclic nature of the gait; in this work a predictive layer is incorporated to the control architecture to compensate the computational delays, the mechanical response of the robot and the limited bandwidth.

In relation with intention detection, there are several robotic control mechanisms that rely on the information provided by EMG (Electromyography) signals [43, 44]. In these works, based on single DoF (Degree of Freedom) orthoses, patient intention is detected in such a way that the motion is supported, saving physical effort but leaving full control to the subject, as a consequence, potential trajectory deviations are not corrected. Other authors, with the hypothesis that motor learning is stimulated by correlating motor commands with feedback signals to the somatosensory cortex, propose control schemas based on non-invasive BCIs (Brain Computer Interfaces) to restore lost motor function by routering movement related signals from the brain to external effectors [45, 46, 47, 48]; the use of these interfaces are still at a very early stage of development and need further experimentation [47].

Nowadays, there are not many robotic devices specifically oriented for practising ADLs, being the ADLER orthosis [49] the most relevant amongst them. This device uses the HapticMaster [50] robot to assist the patient along programmed ADL trajectories providing customized forces through three active DoFs (the other three remain passive). ADLER system is able to work under both assistive and challenge-based strategies. A limiting factor of this device is its small range of motion.

Full and more exhaustive reviews of rehabilitation robotics control strategies can be found in [16] and [51].

1.3. Aim and scope

As it can be noticed by reading previously cited bibliography, although several adaptive methods have been developed, there are no upper limb-centered control algorithms intended to anticipate the patients in order to avoid deviations from those considered as healthy motions. The main goal of this research work is the design and definition of an anticipatory assistance-as-needed control algorithm to emulate, throughout a robotic orthosis, a therapist that is in direct contact with the patient when he/she is carrying out an ADL-based neurorehabilitation session. This algorithm is based in the fact that healthy individuals continuously select and weight different proprioceptive feedback to adjust their motion [52], describing an anticipatory motor control for the production of movement [53]. The anticipatory component of the algorithm refers to the ability to predict the trajectory of the patient to online adapt the response.

In this way, the major novelty and contribution of this research work is the breaking with the traditional control strategies: from reactive systems to an anticipatory system that takes into account the patient’s dysfunctional profile.

2. Methods

The used biomechanical model is an extended version of that one previously used by the authors in [54, 55], with eight DoFs. Human upper limb motion is approximated as the articulated motion of rigid body parts [56]: scapula (from the clavicle to the shoulder joint), upper arm (between the shoulder and elbow joints), forearm (between the
elbow and wrist joints) and hand (from the wrist joint on). For this field of application, the precise modeling of the involved biological components, such as bones or muscles, is secondary. That is why a simplified approach of the human arm can be sufficient [57]. The proposed kinematic model includes the following simplifications of the physiological upper limb:

- Each joint is defined from a joint center. In particular, the shoulder joint is considered as a simple spherical joint that maintains functional shoulder movements but does not preserve the real physiological configuration
- The forearm is considered as a rigid body, meaning that pronation and supination movements must be considered around the elbow
- The hand is modeled as two rigid bodies to allow grasping

Every joint has its own local axis. The scapula is modeled as a single joint with just one DoF. Shoulder is modeled as a ball and socket joint with three DoFs, located in the center of the humeral head. Movements are calculated between the vector representing the humerus and the trunk. Elbow is modeled as a rotating hinge joint with two DoF with a single joint in the distal humerus. The wrist is modeled as a single joint with only one DoF, that is calculated between the vector representing the hand and a fixed point representing the center of the wrist (between radial and cubital stiloid spinas). Finally, grasping is considered as a hand DoF.

2.1. Assistance-as-needed control algorithm

Many studies have proposed computational models of the motor control function associated to the human brain when the subject is performing a goal directed movement [58, 59, 60, 61, 62]. Based on the schematic of motor control shown in Figure 1, inspired in the model presented by Shadmehr et al. [60], the authors propose an equivalent diagram for the case when the therapist is directly contacting the subject’s upper limb (to provide the patient with certain amount of assistance or force-feedback). This diagram is the one governing the global behaviour of the proposed anticipatory assistance-as-needed control algorithm.

As Figure 1 depicts, there are 5 different modules in the computational model of voluntary movements:

- Sensory system: senses the environment
- Forward models: transform motor commands into sensory consequences to estimate the state of the body and the world around it. These models are necessary to compensate the delayed sensory information provided by our transmission lines (axons), that move information slower than the speed of sound
- Integration: combination of what we predict and what we sense
- Motor commands generator: cause the body to change
- Body: changes its configuration depending on the received motor commands

The key component of the aforementioned motion generation computational model are the forward models [63, 64], that correspond to the computational approach of the function associated to the cerebellum, which predicts the state of the limb allowing one to act on this estimate of state rather than relying solely on a delayed sensory feedback.

In this study, the body is substituted by the patient’s upper limb and the forward models are implemented by a biomechanical prediction module that, given the current biomechanical configuration of the patient, estimates the evolution of that configuration to reach a specific target. With this estimation (that would be carried out by the therapist), that depends on both the motion purpose of the patient (ADL specific) and the dysfunctional profile (understood as a representation of the motion deficits related to the patient), anticipatory force-feedback can be provided to the subject when a non-adaptive motion (movement considered clinically incorrect) is going to take place, increasing the patient participation and the associated muscle activity, and thus encouraging and modulating neural plasticity [10, 65].

Figure 2 depicts the flow chart that summarizes the behavior of the proposed assisted-as-needed algorithm, where we can find three subsystems: a biomechanical prediction module that emits predictions evaluated by a decision system which provides input to a command generation module. On the other hand, Figure 3 shows the statechart diagram corresponding to the proposed assistance-as-needed control algorithm. For each DoF of the multijoint upper limb robotic orthosis there are three possible states:
Monitoring: the system reads the current biomechanical angular value of certain DoF

Evaluation: both the current biomechanical configuration and the estimation of its evolution are analyzed to determine if the patient requires assistance

Assistance: in case the patient needs force-feedback, a motor command is generated

Finally, it is important to highlight that the proposed assistance-as-needed control algorithm is designed to support as many DoF as the robotic orthosis is designed to have. The statechart diagram presented in Figure 3 is applicable to every DoF of the biomechanical model.

2.1.1. Biomechanical prediction subsystem

In order to emulate the so called forward models and thus, to allow anticipatory actuation, the assistance-as-needed control algorithm counts with a biomechanical prediction subsystem that, taking into account both the patient dysfunctional profile and the ADL that is being performed, makes an estimation of the biomechanical evolution adapted to the given subject. This estimation is later evaluated to determine if physical assistance is required.

Figure 4 shows the biomechanical prediction system block diagram, which consists in three subsystems:

- End effector trajectory generator: makes an estimation of the end-effector (hand) trajectory applying a minimum-jerk algorithm [66]
- IK (Inverse Kinematics) solver: solution to the IK problem to obtain a normal biomechanical evolution departing from a 3D end-effector trajectory. To solve the IK problem, a MLP (Multilayer Preceptron)-based solution is applied following the procedure described in authors' previous work [55]
- Dysfunctional profile adaptation: adaptation of the estimated healthy biomechanical evolution to the dysfunctional profile of the patient

The use of compensatory strategies may be related to the degree of motor impairment; severely to moderate impaired compensate for motor deficits while mildly impaired subjects employ healthy movement patterns [67]. When a patient attempts to move and encounters a deficit, the natural reaction is to compensate with the available motor strategies, exploiting the redundancy of the upper limb by creating pathological movement synergies [67, 68, 69]. Due to the lack of dysfunctional motion models that accurately define how a certain patient or group of patients move, in this work we have used our own individual pathological models. To create the so called dysfunctional report, we have applied the following methodology:

1. Analysis of the patient's affected DoF when performing goal directed movements without any assistance
2. Exhaustive evaluation of the main biomechanical compensations

To build these reports we need both the motion features associated to a given patient and a healthy reference to compare it with. In this work, healthy motion models (ADL-specific) are obtained by averaging the biomechanical evolution of each DoF of at least 40 subjects [70] performing certain activity. In this way, each model DoF has three components: the biomechanical pattern and the upper and lower limits, that are due to the inter-subject variability. The dysfunctional motion features corresponding to the patient are extracted from a previously recorded execution of the ADL under study.

In this way, the adaptation of the predicted healthy biomechanical evolution (output of the IK solver) to the patient-specific dysfunctional profile is performed for each DoF separately depending on the morphological characteristics of the patient motion. This adaptation is carried out by calculating a transfer function between the pattern and the dysfunctional motion; there are three possible options: the DoF is affected and modeled using a polynomial transfer function, the DoF is affected and modeled by a simple offset operation and finally, the DoF is considered without affectation. Figure 5 shows an example where all the affectation cases take place.

Hence, for each patient and ADL, a data structure containing his/her dysfunctional profile is created. Figure 6 shows the template used for the rows that compose the dysfunctional profile data matrix: positions 3 and 4 are used to identify compensations; if the DoF under study compensates any other, position 3 will contain a true flag; if the DoF is compensated, position 3 will have a false flag and position 4 will point to the DoF identifier that compensates
the current kinematic variable. Position 5 indicates with a flag if the patient is not able to perform the motion at a normal speed. Position 6 indicates how the adaptation must be performed (code 0 means no adaptation, code 1 an offset operation and code 2 a polynomial adaptation) and finally, the last positions (7 to 10) contain the adaptation parameters.

The adaptation algorithm, is the following:

1. DoF selection
2. Adapt evolution of the current DoF according to the profile
3. Evaluate DoF using the assistance decision subsystem
   - if feedback is needed then
     - Search for compensated DoFs
     - Do not perform any adaptation (the compensation will not be allowed)
   - else
     - Search for compensated DoFs
     - Adapt evolution of those DoFs according to the profile
   end if

To obtain a more accurate analysis of the affected limbs and for the evaluation of the compensations, an ADL modeling methodology has been applied. Both the ADL logical landmarks (for instance, when certain object is picked up) and its associated angular features are taken into account in such a way that for each ADL a state-chart diagram is obtained. Following this methodology, the activity gets partitioned into several transitions that are studied independently.

### 2.1.2. Assistance decision subsystem

Once the dysfunctional motion prediction is available, the system has to take a decision about the convenience of providing the patient with force-feedback. Bayesian statistics [71] provides a systematic way of solving problems in the presence of uncertainty. This mathematical tool defines how our beliefs should be combined with our objectives to make optimal decisions. In planning a goal-directed movement, the motor system is required to pick one of many possible motor programs [72]; this assertion can be extrapolated to our case, where a virtual therapist has to decide which alternative will result in the best outcome: provide physical assistance or not. The selection of an alternative can be described as the rational choice of the decision that maximizes utility. This kind of decision mechanisms, where their outcome is generally uncertain, have been previously used to emulate human decision making [73, 74, 75, 72, 76]. In this work the uncertainty resides in the possible positive effects (from a therapeutical point of view) that a physical assistance decision would bring based on the evaluation of a predicted motion in terms of adaptability.

Prior to take the force-feedback decision, the adaptability of the predicted motion (how healthy is considered certain movement) has to be measured (for each DoF independently). According to the clinical criteria of the therapists belonging to the Institut Guttmann Neurorehabilitation Hospital, there are two major characteristic that have to be taken into account: the morphologic similarity with the healthy motion reference and the angular deviation from the model. To meet the given requirements we propose the adaptability coefficient given by Equation 1, where $C$ corresponds to the Pearson correlation coefficient existing between the prediction and the reference (capturing the morphologic similarity) and $D_p$, the measured angular deviation, is given by Equation 2; in this expression the RMSE (Root Mean Squared Error) is calculated by applying Equation 3, being $\hat{\theta}$ and $\theta$ the estimated and the model angular values for a given DoF respectively. Variable $T$ corresponds to the angular deviation threshold obtained as the mean of the measured RMSE between the lower and upper limits relative to the pattern (this threshold value is necessary to consider the inter-subject variability). Variable $p$ represents the permissivity concept, whose influence is related to the amount of RMSE that is allowed before the coefficient $K_p$ starts tending to zero. Parameter $m$ is related to the shape of the last part of the deviation function and determines how $D_p$ grows with the measured RMSE. Figure 7 shows an example of function $D_p$ where $m$ takes a value of 1 and $T$ and $p$ are set to 10 and 0 respectively.

$$K_p = C / D_p$$

$$D_p(RMSE) = \begin{cases} 1 & \text{if } RMSE \leq T + p \\ e^{(RMSE-(T+p))/m} - e^{1/m} + 1 & \text{if } RMSE > T + p \end{cases}$$

$$\text{Figure 7 shows an example of function } D_p \text{ where } m \text{ takes a value of 1 and } T \text{ and } p \text{ are set to 10 and 0 respectively.}$$
Given the definition of the adaptability coefficient (Equation 1), it can be observed that it is equivalent to the measured correlation when the angular deviation is equal to 1. In case the angular deviation grows, $K_p$ decreases. In this way, the closer to the unity is the coefficient, the healthier the motion is considered because it is both morphologically similar to the reference and little or no angular-deviated.

Based on the described adaptability coefficient, in this work the authors propose a fuzzy Bayesian decision system [77] which comprises the following steps:

1. Definition of the singleton states of nature $s_1$, $s_2$ and $s_3$ and their associated prior probabilities $p(s_1)$, $p(s_2)$ and $p(s_3)$, whose value depend on the measured adaptability coefficient.

2. Definition of the fuzzy states of nature:
   - $\tilde{F}_1$: low measured adaptability
   - $\tilde{F}_2$: medium measured adaptability
   - $\tilde{F}_3$: high measured adaptability

3. Definition of the fuzzy alternatives:
   - $\tilde{A}_1$: not provide assistance
   - $\tilde{A}_2$: provide assistance

4. Definition of the information to be handled: in this case we establish that there are five different possible real measurements determined by the therapists (used to see the equivalence between the adaptability coefficient measured over the prediction and that one that would be obtained if the patient were allowed to perform the motion):
   - $x_1$: real adaptability of 100%
   - $x_2$: real adaptability of 80%
   - $x_3$: real adaptability of 60%
   - $x_4$: real adaptability of 40%
   - $x_5$: real adaptability of 20% or less

5. Definition of the orthogonal fuzzy information system:
   - $\tilde{M}_1$: low real adaptability
   - $\tilde{M}_2$: medium real adaptability
   - $\tilde{M}_3$: high real adaptability

6. Identification of the utility values for each of the given alternatives.

7. Definition of the membership values.

8. Definition of the conditional probabilities for the uncertain information $p(x_k/s_i)$.

The posterior probabilities of fuzzy states $\tilde{F}_s$, given probabilistic information, can be derived using the Equation 4. Also, the expected utility, given the fuzzy information, can be calculated using Equation 5, where parameters $u_{js}$ correspond to the utility values of each fuzzy state of nature.

\[
p(\tilde{F}_s/\tilde{M}_t) = \frac{\sum_{i=1}^{3} \sum_{k=1}^{5} \mu_{\tilde{F}_s}(k) \cdot \mu_{\tilde{M}_t}(k) \cdot p(x_k/s_i) \cdot p(s_i)}{\sum_{k=1}^{5} \mu_{\tilde{M}_t}(k) \cdot p(x_k)}
\]

\[
E(\tilde{A}_j/\tilde{M}_t) = \sum_{i=1}^{3} u_{js} \cdot p(\tilde{F}_s/\tilde{M}_t)
\]

The alternative to be chosen, independent for each DoF, is that one that maximizes the expected utility.
2.1.3. Command generation subsystem

The command generation subsystem is the responsible of creating assistance commands depending on the underlying hardware. In our case, where we focus on an upper-limb robotic orthosis with haptic capabilities, the command generation subsystem selects a desired angular value along with a desired torsional stiffness value (rigidity) to feed an impedance controller for every DoF independently achieving a desired level of compliance.

Two different possibilities come up: if the current patient’s DoF needs assistance the required rigidity is calculated by using Equation 6, and, on the other hand, if that DoF does not need assistance, Equation 7 is used to calculate the commanded rigidity (the assistance intensity also starts decreasing when the angular value of the DoF reaches the target). In both cases, the commanded angular values are those corresponding to the motion model (described in Section 2.1.1) of the ADL that is being executed at the current time instant. In the mentioned equations, \( \kappa_t \) corresponds to the rigidity to be commanded at the current time instant, \( \kappa_{t-1} \) is the rigidity commanded to the DoF in the previous time instant, \( \kappa_{\text{max}} \) is the maximum rigidity that the robot is able to provide for the evaluated DoF, \( \kappa_{\text{min}} \) is the minimum rigidity configured for the DoF, and \( f_a \) and \( f_r \) are the assistance and releasing factors used to increment or decrement the commanded rigidity.

\[
\begin{align*}
\kappa_t &= \min(\kappa_t - 1 + \kappa_{\text{max}} * f_a, \kappa_{\text{max}}) \\
\kappa_t &= \max(\kappa_t - 1 - \kappa_{\text{max}} * f_r, \kappa_{\text{min}})
\end{align*}
\]

As it can be noticed, the assistance is provided in an incremental basis in such a way that the applied force does not abruptly reach its maximum or minimum.

Synchronization between the motion performed by the subject and the reference model is always kept due to the fact that, depending on the configured task duration, the motion model is adjusted to have the required number of samples so, for each time instant, the pattern configuration is always known. It is important to remark at this point that apart from trajectory deviations, this algorithm also corrects patients when they do not perform the ADLs at a desired speed; for instance, if the patient remains in the same position for a certain amount of time, as the model will be going forward, the issued predictions will be considered as non-adaptive at some point so that force-feedback will be provided.

2.2. Robotic simulator

2.2.1. Orthosis simulator

An orthosis simulator has been developed in order to allow a better understanding of the algorithm results and performance by creating a virtual reality model which is easily manipulable from either MATLAB® or Simulink® environments. Using this simulator it is possible to modify several parameters from the haptic control layer such as the target impedance per joint \( Z_d \), the desired angles \( q_{d,i} \) and velocities \( \dot{q}_{d,i} \) and the external torques \( \tau_{ext} \). It is also helpful in determining the required hardware, based on the performance (maximum velocities, accelerations and torques needed for each joint) demanded by the haptic requirements to be compliant with the assistance-as-needed criteria.

The robotic simulator was created using MATLAB®, Simulink® and the Robotics Toolbox v8.0 [78]. It features a simplified 3 DoF impedance controlled model [79] with the DH (Denavit-Hartenberg) configuration [80] presented in Table 1, where \( L_s \) values correspond to the segment lengths. This simplified model allows making modifications and seeing the robot behavior in real time (Figure 8). This is crucial in order to have a good understanding of the robot reactions to the assistance-as-needed and haptic layer commands.

Besides, the orthosis also features a haptic control layer which is responsible for transforming the otherwise rigid, non-backdrivable mechanism, into a compliant robot by means of a joint space impedance controller. The haptic control layer is also capable of rendering several haptic primitives like virtual springs, dampers, walls, and force fields, within the device’s workspace boundaries.

The controlled torque \( \tau_{c,i} \) for each joint \( i \) is then computed as:

\[
\tau_{c,i} = \tau_{ext} + \tau_{\text{inv}}(q_r, \dot{q}_r, \ddot{q}_r) + \tau_{\text{imp}}(q_r, \dot{q}_r)
\]

where \( \tau_{ext} \) is the sum of any external torque acting on the \( i \)th joint, \( q_r \), \( \dot{q}_r \), and \( \ddot{q}_r \) the measured (real) joint angle, velocity and acceleration and \( \tau_{\text{inv}} \) is the computed torque using the inverse dynamics method represented by Equation 9, being \( M \) the inertia matrix, \( C \) the coriolis and centripetal terms and \( g \) the forces due to gravity (9.8 m/s²).
\[ \tau_{\text{inv}} = M(q_r)q_r + C(q_r, \dot{q}_r)\dot{q}_r + g(q_r) \] (9)

Finally, the commanded torque \( \tau_{\text{imp}} \) is calculated from the virtual target impedance as follows:

\[ \tau_{\text{imp}} = \kappa_i(q_{di} - q_{ri}) + B_i(\dot{q}_{di} - \dot{q}_{ri}) \] (10)

being \( q_{di} \) and \( \dot{q}_{di} \) the desired angular position and velocity, \( \kappa_i \) the torsion coefficient (rigidity) in \( \text{Nm rad}^{-1} \) and \( B_i \) the damping rotational coefficient in \( \text{Kg m}^2\text{s}^{-1}\text{rad}^{-1} \) for each joint \( i \) respectively.

However, and both for simplification reasons and because the wanted response is critically damped, Equation 10 can be simplified by assuming a desired velocity of \( \dot{q}_i = 0 \) in such a way that for any value of \( \kappa_i \) the target impedance \( Z_{di} \) can be computed as:

\[ Z_{di} = \kappa_i(q_{di} - q_{ri}) - 2\sqrt{\kappa_i}(\dot{q}_{ri}) \] (11)

Therefore, the only inputs needed to calculate \( Z_{di} \) are \( \kappa_i \) and \( q_{di} \), as \( q_{ri} \) and \( \dot{q}_{ri} \) are directly available from the sensors.

The simulator has been configured to provide a maximum rigidity per joint of 1000 \( \text{Nm rad}^{-1} \); this relatively high initial value is meant to be adjusted to real hardware limitations and saturation points when experimental data becomes available.

2.2.2. External torques simulator

To carry out a full simulation it is also necessary to emulate the external torques that the patient provides to the robotic orthosis. To calculate these moments of force, information of previous executions of the performed ADL is used in such a way that the torques are proportional to the angular difference between the current biomechanical configuration and its equivalent in the recorded motion.

To obtain the maximum external torque values (\( \tau_{\text{max}} \)) that the subjects can externally apply to the orthosis, Equation 12 is applied, where \( m \) is the upper limb mass, \( \text{load} \) is the extra mass that the patient could move with the studied joint, \( g \) is the acceleration due to gravity (9.8 \( m/s^2 \)) and \( c \) corresponds to the center of mass of the segment.

\[ \tau_{\text{max}} = (m + \text{load}) \cdot g \cdot c \] (12)

Given the maximum torque that can be applied by every joint, the provided external torque is calculated through the linear relation privedided by the Equation 13, where \( \Delta \) corresponds to the absolute value of the difference between the angular values of the recorded motion and the model and \( s \), given by Equation 14, the applied slope, being \( V \) an angular difference threshold to lower the output torque once it is surpassed.

\[ \tau = \Delta \cdot s \] (13)

\[ s = \begin{cases} \frac{\tau_{\text{max}}}{V} & \text{if } \Delta \leq V \\ \frac{\tau_{\text{max}}}{4V} & \text{if } \Delta > V \end{cases} \] (14)

Once known the mathematic formulation, the following algorithm is run:

1. **DoF selection**
   - **if** the DoF is compensated **then**
   - Select the compensation DoF
   - **if** the compensation DoF angular value is inside the model boundaries **then**
   - Assume that the value of the current DoF in the recorded motion is equal to the pattern’s
   - **end if**
   - **end if**
2. Calculate the corresponding external torque
2.2.3. Configuration parameters

Given the assistance-as-needed simulator, the following parameters can be configured to adapt its behaviour to the specific clinical needs:

1. ADL duration
2. Permissivity per DoF (associated to the calculation of the adaptability coefficient $K_p$)
3. Minimum assistance (rigidity) per DoF
4. Assistance utility per DoF (given by the utility matrix)
5. Assistance factor ($f_a$)
6. Releasing factor ($f_r$)

As many of the previously mentioned parameters can be difficult to be set by the therapists, it could be recommendable to create several configuration sets that try to match the pursued clinical targets.

2.3. Experimental work

Two different ADLs designed by therapists from the Institut Guttmann Neurorehabilitation Hospital have been used to validate the assistance-as-needed control algorithm: 'serving water from a jar' and 'picking up a bottle'. 'Serving water from a jar' setup is shown in Figure 9(a); in this ADL, a glass jar (with a capacity of 1.5 L) with 150 mL of water was placed to the right (and a bit behind) of the glass (with a capacity of 170 mL); two solid red dots indicate the correct position for the glass and the jar. The subject was asked to fill the glass with the water and leave the jar in the initial position. Figure 9(b) depicts the 'picking up a bottle' setup; an empty plastic bottle with a capacity of 330 mL is located in a shelf that is placed on a table. The subject is asked to put the bottle in the closest right corner of the table (a solid red dot indicates the exact place).

To build the motion models, data from 73 healthy subjects, 34 men and 39 women with a mean age of 37.97 ± 12.44 years old were captured for the 'serving water from a jar' ADL. For the 'picking up a bottle' ADL, data from 40 healthy subjects, 17 men and 23 women with a mean age of 30.45 ± 5.25 years old, were captured.

Regarding the ABI patients, dysfunctional reports of five different subjects have been created. Table 2 depicts the data associated to patients P01 to P05.

The proposed assistance-as-needed control algorithm has been given a standard configuration for the different simulations carried out over healthy and pathological subjects in such a way that significant behaviour differences can be observed for validation purposes. First, as there is not formal elicitation of utilities for the assistance decision subsystem, the set of values present in Table 3, determined by clinical experts, have been used. Second, a permissivity $p$ of 0 degrees has been configured for all the DoF for both healthy and pathological subjects (factor $m$ has been set to 1). Third, the minimum assistance $\kappa_{\text{min}}$ (rigidity) has been set to 0 for all the DoFs. Fourth, the assistance and releasing factors $f_a$ and $f_r$ have been both set to 1. And fifth, the duration of the ADLs have been set to the observed normal speed (9 seconds the ADL 'serving water from a jar' and 7.5 seconds the ADL 'picking up a bottle').

Figure 10 shows how the a priori probabilities are calculated depending on the measured adaptability coefficient and Tables 4, 5 and 6 contain the fuzzification values for the fuzzy states of nature, those ones related to the orthogonal fuzzy information system (all these fuzzification values have been set by the clinical experts) and the needed conditional probabilities respectively. It is important to remark here that the conditional probabilities have been estimated and then, they have not been set experimentally since, at this point of the research, there are not enough dysfunctional data to accurately calculate them.

Regarding the external torques simulation, standard values of 3.35 Kg and 1.513 Kg have been used for the arm and the forearm masses respectively (an extra load of 2 Kg for the shoulder abduction/adduction and 10 Kg for the shoulder and elbow flexion/extension has been used); the angular difference threshold has been set to 5 degrees. All these values have been selected in order to obtain values coherent with [81].

After the simulations, the following parameters are obtained for each DoF:

- Pearson correlation coefficient (C) between the motion pattern and the motion performed
- RMSE between the motion pattern and the motion performed following Equation 3
• Assistance percentage, considering that a value of 100% would correspond to the case of providing the maximum rigidity value during all the time instants.

As commented previously in the manuscript, the two ADLs under study have been partitioned into several identifiable states taking into account both the ADL landmarks and its associated angular features, obtaining for each ADL a state-chart diagram. In this way, the 'serving from a jar' ADL has been fragmented into 6 time intervals and 'picking a bottle from a shelf' into 3 as Figure 11 depicts. For each time interval, correlation coefficient, RMSE and assistance percentage can be also measured.

To obtain the motion data for both creating the healthy motion models and the dysfunctional reports, BTS SMART-D [82] system has been used. The system consisted of 6 infrared cameras with a recording rate of 140 Hz and two video cameras to register the entire subjects movement. Smart Capture, Smart Tracking and Smart Analyzer Software were used. A sixteen-marker model derived from [6] was created for this purpose (Figure 12). Furthermore, a MATLAB® r2011b running on a 64-bit computer with a 3 GHz Intel® Core™ 2 Duo processor with 8 GB RAM has been used for running the simulations.

3. Results and Discussion

Table 7 shows the mean assistance percentage that the system has provided to the healthy subjects working with the standard configuration in the performed simulations. If these values are compared with those ones presented by Table 8, that contains the assistance percentage given to each of the pathological subjects that participated in this study, it can be clearly seen that the assistance-as-needed control algorithm almost do not assist healthy subjects while it behaves completely different when dealing with the pathological ones (the amount of assistance provided to these subjects depends on their dysfunctional profile). It is important to highlight that the force feedback that the system provides to the healthy subjects is mainly due to the fact that the motion models used to evaluate the predictions are independent of the anthropometric measurements while the manipulated objects are in the same position in every case. This can cause the RMSE between the predicted and the pattern motions to increase and then, to obtain a lower adaptability coefficient. Anyway, considering that the force feedback is provided in an incremental/decremental basis (due to use of the assistance and releasing factors $f_a$ and $f_r$ when generating motion commands), this amount of assistance (given the configured values for $f_a$ and $f_r$) would really correspond to a half of it.

Tables 9 and 10 present the obtained results for both ADL under study (fragmented into their corresponding time intervals and averaged for all the patients) when the pathological subjects perform them using the orthosis (under the defined standard configuration) and without using it. When the patients use the orthosis, it can be observed that in all the time intervals the performed motions are very similar in shape to the reference ones, being the kinematic evolutions’ RMSEs lower than those corresponding to the model boundaries almost in every case (those where the RMSE is higher than the limits, the difference is very low). It is evidenced that the (simulated) patients perform much better when the robotic orthosis is working, and thus, when the neural plasticity is being encouraged.

Figure 13 graphically shows how the assistance-as-needed control algorithm works along with the robotic orthosis using P01 as an illustrative example (note that the provided rigidity is scaled to the maximum angular value) when he is performing the ADL 'serving water from a jar'. It can be seen how the system anticipates to the non-adaptive motions of the patient causing him not only to perform a motion very similar in shape to the reference one but also to remain within the model upper and lower limits during the whole execution of the ADL. In particular, the main motion deficit that patient P01 has is present in the reaching phase (initial seconds of the task): he needs to perform an excessive shoulder abduction to attain the shoulder flexion needed to reach the jar. In this Figure, it can be seen how the system anticipates to this wrong compensation and guides his shoulder abduction, so the reaching movement is successfully completed.

4. Conclusions

In this paper, the authors present an assistance-as-needed control algorithm able to provide ABI patients with anticipatory force-feedback only when it is strictly needed, avoiding the subjects to slack by increasing their participation and muscle activity in such a way that neural plasticity is encouraged and modulated to reinforce motor recovery. Although the algorithm presented here are designed and presented using the simulator, the realism that have
been given to the developed robotic simulator assures the certainty of the previously stated reasonings and interpretations. Nevertheless, when transferring this system to the real world some problems are expected: on one hand, as the simulator does not guarantee an accurate patients’ response to feedback, differences might be observed when real persons are involved with the device; this fact could force a readjustment in the amount of force that is provided to the subjects. On the other hand, and regarding the simulation of the robot itself, one have to be careful when porting the algorithm to a real world platform; when dealing with real world robots, constraints are imposed by the capabilities of the robots themselves, for instance low actuator bandwidths, speeds and torques are limiting factors that could make the strategies presented here decay in performance or being not realizable at all. As in our case there is not an available hardware target we opted for using nonlinear speed and torque limits rather than a full parametric model of each motor. However, once the hardware is available, those nonlinear constraints can be substituted by more complex models that provide accurate information for a specific platform.

The main novelty and contribution of the proposed assistance-as-needed control algorithm presents is the breaking with the current robotic control strategies: it does not wait the trajectory deviations to take place. Obtained simulation results demonstrate that the assistance-as-needed control algorithm is able to provide anticipatory actuation to the patients tending to minimize the degree of actuation.

Also, and assuming the fact that the patients will recover some abilities while they are under a rehabilitation treatment, the predicted movements that the system uses to decide the need of providing force-feedback will tend to be more similar to the healthy ones. This fact will presumably cause a decrease in the amount of assistance with the course of the therapy, which makes this system to match the faded guidance principle [83], that is, less guidance is provided as practice progresses. For this reason, this algorithm could be also considered as a dynamic approach to the assistance-as-needed control strategy, since it dynamically adapts to the evolution of the patients’ dysfunctional profiles during the neurorehabilitation therapy.

Thus, the main advantages of the proposed assistance-as-needed control algorithm are: it is a multijoint system, meaning that it can work with as many DoF as desired; multihardware, since it does not depend on the robotic (or non-robotic) hardware underneath; and, maybe the most important, it is able to provide patients with anticipatory actuation thanks to the implementation of the so called forward models by means of a biomechanical prediction subsystem.

Next steps will mainly address the implementation of an eight DoF detailed robotic simulator including scapular elevation, shoulder flexion/extension, abduction/adduction and rotation, elbow flexion/extension and pronation/supination, wrist flexion/extension and grasping (as stated previously, the assistance-as-needed control algorithm is already prepared to work with a variable number of DoF). In addition, authors will also focus on the validation of the proposed system with a wider range of therapeutically-defined ADLs. Future work will also tackle the experimental determination of the decision system’s a priori probabilities. Additionally, healthy motion models will be enhanced to take into consideration the anthropometric ranges, which will reduce the amount of assistance provided due to adaptability measurement errors. Furthermore, future research will also undertake dysfunctional modeling with the aim of generalizing the patient and ADL-specific dysfunctional reports to be applied to any ADL. Finally, the assistance-as-needed control algorithm will be integrated in a real eight DoF robotic orthosis.

5. List of abbreviations

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABI</td>
<td>Acquired Brain Injury</td>
</tr>
<tr>
<td>ADL</td>
<td>Activity of the Daily Life</td>
</tr>
<tr>
<td>BCI</td>
<td>Brain Computer Interface</td>
</tr>
<tr>
<td>C</td>
<td>Pearson Correlation Coefficient</td>
</tr>
<tr>
<td>DH</td>
<td>DenavitHartenberg</td>
</tr>
<tr>
<td>DoF</td>
<td>Degree of Freedom</td>
</tr>
<tr>
<td>EMG</td>
<td>Electromyography</td>
</tr>
<tr>
<td>IK</td>
<td>Inverse Kinematics</td>
</tr>
<tr>
<td>MLP</td>
<td>Multilayer Perceptron</td>
</tr>
<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
</tr>
<tr>
<td>TBI</td>
<td>Traumatic Brain Injury</td>
</tr>
<tr>
<td>WHO</td>
<td>World Health Organization</td>
</tr>
</tbody>
</table>

6. Author’s contributions

RPR contributed in the research, design and validation of the proposed control algorithm and collaborated with UC in the interpretation of the obtained results. UC contributed with the data acquisition and worked together with RPR in the data formalization and modeling process. CR contributed in the development of the orthosis simulator. RPR, CC, JMT, JM and EJG contributed with the original study design.

Finally, all authors participated in the drafting of the manuscript and approved its final version.
7. Acknowledgements

This research work was partially funded by CDTI (project: REHABILITA; CIN/1559/2009), Spanish Government. The authors would like to thank all the REHABILITA consortium members, project ECNI-Estimulación Cerebral Invasiva y Rehabilitación asistida por robots for acelerar la rehabilitación en TCE, Instituto de Salud Carlos III, Ministry of Science and Innovation-P1082004, project 3e+D and ACC10 (Department of Industry, Generalitat de Catalunya).

8. Competing interests

The authors declare that they have no competing interests.

References


Table 1. DH parameters for the 3 DoF anthropomorphic robot. Notice that the robot base is previously rotated by $\frac{\pi}{2}$ to be compliant with the world coordinate system.

<table>
<thead>
<tr>
<th>Link</th>
<th>$a_i$</th>
<th>$\alpha_i$</th>
<th>$d_i$</th>
<th>$\theta_i$</th>
<th>Offset</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$L_1$</td>
<td>$-\frac{\pi}{2}$</td>
<td>0</td>
<td>$\theta_1$</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>$L_2$</td>
<td>0</td>
<td>0</td>
<td>$\theta_2$</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>$L_3$</td>
<td>0</td>
<td>0</td>
<td>$\theta_3$</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 2. Patient data (M=Male; F=Female; \( l_A \)=arm length; \( l_F \)=forearm length; \( l_T \)=total length; II=Isquemic Ictus; IH = Hemorrhagic Ictus; E=Encephalopathy; L=Left; R=Right)

<table>
<thead>
<tr>
<th>ID</th>
<th>Gender</th>
<th>Age</th>
<th>Height (cm)</th>
<th>( l_A ) (cm)</th>
<th>( l_F ) (cm)</th>
<th>( l_T ) (cm)</th>
<th>Etiology</th>
<th>Focality</th>
<th>Fugl-Meyer</th>
</tr>
</thead>
<tbody>
<tr>
<td>P01</td>
<td>M</td>
<td>69</td>
<td>182</td>
<td>32.5</td>
<td>27</td>
<td>62</td>
<td>II</td>
<td>L</td>
<td>55</td>
</tr>
<tr>
<td>P02</td>
<td>F</td>
<td>46</td>
<td>167</td>
<td>27.5</td>
<td>25</td>
<td>59.5</td>
<td>E</td>
<td>R</td>
<td>62</td>
</tr>
<tr>
<td>P03</td>
<td>F</td>
<td>64</td>
<td>156</td>
<td>29</td>
<td>24.5</td>
<td>58.5</td>
<td>HI</td>
<td>L</td>
<td>58</td>
</tr>
<tr>
<td>P04</td>
<td>M</td>
<td>63</td>
<td>163</td>
<td>31</td>
<td>24</td>
<td>65</td>
<td>HI</td>
<td>R</td>
<td>42</td>
</tr>
<tr>
<td>P05</td>
<td>F</td>
<td>47</td>
<td>149</td>
<td>31</td>
<td>19</td>
<td>55.5</td>
<td>II</td>
<td>L</td>
<td>55</td>
</tr>
<tr>
<td>$F_1$</td>
<td>$F_2$</td>
<td>$F_3$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-------</td>
<td>-------</td>
<td>-------</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_1$</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$A_2$</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Utility matrix
Table 4. Fuzzyfication values for the fuzzy states of nature

<table>
<thead>
<tr>
<th></th>
<th>$s_1$</th>
<th>$s_2$</th>
<th>$s_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\tilde{F}_1$</td>
<td>0.9</td>
<td>0.2</td>
<td>0</td>
</tr>
<tr>
<td>$\tilde{F}_2$</td>
<td>0.1</td>
<td>0.6</td>
<td>0.1</td>
</tr>
<tr>
<td>$\tilde{F}_3$</td>
<td>0</td>
<td>0.2</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Table 5. Fuzzyfication values for the orthogonal fuzzy information system

<table>
<thead>
<tr>
<th></th>
<th>x1</th>
<th>x2</th>
<th>x3</th>
<th>x4</th>
<th>x5</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1</td>
<td>1</td>
<td>0.8</td>
<td>0.3</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>M2</td>
<td>0</td>
<td>0.2</td>
<td>0.5</td>
<td>0.3</td>
<td>0.1</td>
</tr>
<tr>
<td>M3</td>
<td>0</td>
<td>0</td>
<td>0.2</td>
<td>0.7</td>
<td>0.9</td>
</tr>
</tbody>
</table>
Table 6. Conditional probabilities

<table>
<thead>
<tr>
<th></th>
<th>x_1</th>
<th>x_2</th>
<th>x_3</th>
<th>x_4</th>
<th>x_5</th>
</tr>
</thead>
<tbody>
<tr>
<td>p(x_k</td>
<td>x_1)</td>
<td>0.8</td>
<td>0.2</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>p(x_k</td>
<td>x_2)</td>
<td>0.1</td>
<td>0.2</td>
<td>0.5</td>
<td>0.2</td>
</tr>
<tr>
<td>p(x_k</td>
<td>x_3)</td>
<td>0</td>
<td>0</td>
<td>0.1</td>
<td>0.1</td>
</tr>
<tr>
<td>Object</td>
<td>fexS(%)</td>
<td>abdS(%)</td>
<td>fexE(%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------</td>
<td>---------</td>
<td>---------</td>
<td>---------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>jar</td>
<td>11.10</td>
<td>15.24</td>
<td>7.36</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bottle</td>
<td>5.64</td>
<td>2.48</td>
<td>19.24</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7. Mean assistance percentage provided to the healthy subjects using a standard configuration of the simulated system.
Table 8. Assistance percentage provided to the pathological subjects using a standard configuration of the simulated system

<table>
<thead>
<tr>
<th></th>
<th>fexS(%)</th>
<th>abdS(%)</th>
<th>fexE(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>jar</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P01</td>
<td>50.94</td>
<td>37.60</td>
<td>44.81</td>
</tr>
<tr>
<td>P02</td>
<td>66.12</td>
<td>71.07</td>
<td>94.31</td>
</tr>
<tr>
<td>P03</td>
<td>22.49</td>
<td>57.33</td>
<td>5.49</td>
</tr>
<tr>
<td>P04</td>
<td>42.59</td>
<td>58.33</td>
<td>92.82</td>
</tr>
<tr>
<td>P05</td>
<td>37.24</td>
<td>41.45</td>
<td>28.68</td>
</tr>
<tr>
<td><strong>bottle</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>P01</td>
<td>3.58</td>
<td>29.62</td>
<td>49.04</td>
</tr>
<tr>
<td>P02</td>
<td>29.33</td>
<td>55.96</td>
<td>55.41</td>
</tr>
<tr>
<td>P03</td>
<td>45.17</td>
<td>19.35</td>
<td>44.68</td>
</tr>
<tr>
<td>P04</td>
<td>58.70</td>
<td>23.97</td>
<td>74.43</td>
</tr>
<tr>
<td>P05</td>
<td>30.24</td>
<td>92.98</td>
<td>69.46</td>
</tr>
</tbody>
</table>
Table 9. ADL 'serving water from a jar' simulation results

<table>
<thead>
<tr>
<th></th>
<th>$\mu_C$</th>
<th>$\mu_{RMS_E}$</th>
<th>$RMS_E \leq RMS_{E_{limits}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>fexS</td>
<td>abdS</td>
<td>fexE</td>
</tr>
<tr>
<td>with robot</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_1$</td>
<td>0.98</td>
<td>1</td>
<td>0.82</td>
</tr>
<tr>
<td>$T_2$</td>
<td>1</td>
<td>1</td>
<td>0.97</td>
</tr>
<tr>
<td>$T_3$</td>
<td>0.97</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>$T_4$</td>
<td>0.80</td>
<td>0.84</td>
<td>0.78</td>
</tr>
<tr>
<td>$T_5$</td>
<td>0.99</td>
<td>0.97</td>
<td>0.97</td>
</tr>
<tr>
<td>$T_6$</td>
<td>0.98</td>
<td>0.99</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>without robot</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$T_1$</td>
<td>0.7</td>
<td>1</td>
<td>0.28</td>
</tr>
<tr>
<td>$T_2$</td>
<td>1</td>
<td>1</td>
<td>0.94</td>
</tr>
<tr>
<td>$T_3$</td>
<td>0.51</td>
<td>0.76</td>
<td>0.49</td>
</tr>
<tr>
<td>$T_4$</td>
<td>0.19</td>
<td>0.36</td>
<td>0.46</td>
</tr>
<tr>
<td>$T_5$</td>
<td>1</td>
<td>0.97</td>
<td>0.75</td>
</tr>
<tr>
<td>$T_6$</td>
<td>0.86</td>
<td>0.98</td>
<td>0.15</td>
</tr>
</tbody>
</table>
### Table 10: ADL 'picking up a bottle' simulation results

<table>
<thead>
<tr>
<th>With robot</th>
<th>μC</th>
<th>μRMSE</th>
<th>RMSE ≤ RMSE_{limits}</th>
</tr>
</thead>
<tbody>
<tr>
<td>T&lt;sub&gt;1&lt;/sub&gt;</td>
<td>0.97</td>
<td>0.96</td>
<td>0.89</td>
</tr>
<tr>
<td>T&lt;sub&gt;2&lt;/sub&gt;</td>
<td>0.99</td>
<td>0.95</td>
<td>0.99</td>
</tr>
<tr>
<td>T&lt;sub&gt;3&lt;/sub&gt;</td>
<td>0.98</td>
<td>1.00</td>
<td>0.99</td>
</tr>
<tr>
<td>Without robot</td>
<td>T&lt;sub&gt;1&lt;/sub&gt;</td>
<td>0.93</td>
<td>0.87</td>
</tr>
<tr>
<td>T&lt;sub&gt;2&lt;/sub&gt;</td>
<td>0.92</td>
<td>0.84</td>
<td>0.39</td>
</tr>
<tr>
<td>T&lt;sub&gt;3&lt;/sub&gt;</td>
<td>0.75</td>
<td>0.91</td>
<td>0.43</td>
</tr>
</tbody>
</table>
Highlights

- We propose a new anticipatory assistance-as-needed robotic control algorithm
- The control algorithm adapts its behavior to the patient dysfunctional profile
- The algorithm anticipates to trajectory deviations to encourage neural plasticity
- We validated the proposed algorithm throughout a robotic simulator