Interaction Force, Impedance and Trajectory Adaptation: By Humans, for Robots

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Abstract. This paper develops and analyses a biomimetic learning controller for robots. This controller can simultaneously adapt reference trajectory, impedance and feedforward force to maintain stability and minimize the weighted summation of interaction force and performance errors. This controller was inspired from our studies of human motor behavior, especially the human motor control approach dealing with unstable situations typical of tool use. Simulations show that the developed controller is a good model of human motor adaptation. Implementations demonstrate that it can also utilise the capabilities of joint torque controlled robots and variable impedance actuators to optimally adapt interaction with dynamic environments and humans.

1 Background

When the famous tennis player Chris Evert jokingly said: "when I was younger, I was a robot", she may have been closer to reality than she thought. Similar to the robots that they may build when they get older, infants have sensors and actuators that they can utilize to read the environment and make actions. They are required

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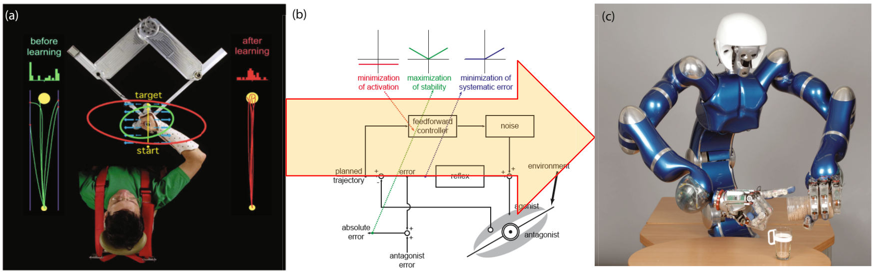

Fig. 1 Observation of how humans learn to perform successful movements in novel environments created with the help of a haptic device (a), led to computational modeling of this learning (b), and to a novel algorithm for adaptive robot interaction with the environment (c).

to learn how to assimilate the sensory signals into useful information, what actions to perform and how to control these actions, which are the very questions that drive robotics research. The study of motor control and learning in humans is thus closely related to robotics as it looks to understand how the humans motor system addresses the same questions that roboticists ask.

Neuroscience realized this close connection early, and has utilized robotic and engineering tools such as haptic devices and theories of structural mechanics, optimal control, iterative learning etc. to study and explain the observations in human experiments. Robotics, on the other hand, is still largely naive about the results from motor neuroscience which could advance robotics. Though some works have implemented biomimetic design for humanoid robots, and ‘human-like’ decision algorithms in robot vision or to select gait and grip choice, low-level movement control strategies developed by the humans central nervous system await translation to robotics applications.

Humans have an amazing ability to adapt and interact with changing external environments and internal dynamics by tuning the force and impedance of limbs [1, 2]. This ability enables humans to perform a variety of complex tasks ranging from holding an egg between fingers, requiring fine control of force, to the use of tools like chisels and screwdrivers, requiring precise control of impedance. In order to understand how humans perform such actions, the neuroscientists have studied movement control and adaptation in humans movements in the last decades , e.g. [3, 4, 1, 5, 6].

Our goal is to endow robots with an adaptable motor behavior as humans have. In this purpose we have modeled humans motor learning from a robotics point of view. This led to a computational model that could be implemented as a new robot controller (Fig.1). This article gives an overview of this project and illustrates the main robotic results. It first summarizes results on interaction control in humans, then describes their modeling and how this leads to an adaptive motion behavior enabling robots to perform efficient control in interaction with novel dynamic environments. Finally we discuss the scope of these results in human-robot interaction tasks such as that encountered in rehabilitation robotics.

2 Modelling Humans Motor Learning

2.1 Feedforward and Feedback Control

When the humans hand is slightly perturbed during arm movements it tends to return to the undisturbed trajectory, as if the hand would be connected to a spring along the planned trajectory [7]. This spring-like property stems mainly from muscle elasticity and the stretch reflex, which produce a restoring force towards the undisturbed trajectory.

Further, the strength of this spring-like property, or mechanical impedance, increases with muscle activation [8] or with endpoint force [9], such that the damping ratio is kept constant [10]. Therefore, both stiffness and damping can be adapted to compensate for dynamic environments [11], though not independently.

To manipulate objects or use tools we have to interact with the environment and compensate for forces arising from it. To perform skillful control using pure feedback control with the relatively low impedance produced by musculoskeletal system, the human central nervous system (CNS) would require a complex desired trajectory [12]. Further, the stabilization provided by reflexes is limited by a time delay of at least 60*ms*, which means that in some cases reflexes can create instability [13]. Therefore, there must be some feedforward mechanism to plan the forces for a task in advance.

In summary, we can assume that the motor commands for the muscles involved in a movement are composed of a feedforward and a feedback terms.

2.2 Motor Learning

In contrast to most robots, humans excel in the ability to adapt rapidly to the variable dynamics of their arm as the hand interacts with the environment. Mussa-Ivaldi and his collaborators have studied this adaptation by letting subjects perform planar arm reaching movements while interacting with a velocity dependent force field [4]. They could show that the CNS adapts feedforward control during repeated trials by compensating for the environment forces, which can be modeled by nonlinear adaptive control (Fig.2, [14, 15, 16]).

However, this does not explain how humans can learn unstable tasks common in daily life, e.g. many tasks involving tool use [17]. In the last ten years, we have addressed learning of unstable tasks in humans, in a series of experimental studies (Figs. 1a, 2, 3, e.g. [1, 2, 18, 19, 20]). We could show that humans are also able to adapt impedance independently from force by selective activation of suitable muscles groups. Humans adapt both force and impedance to perform stable and unstable tasks skillfully [21]. This can be modelled through a control law with feedforward and feedback, both of which are adapted during movements.

Human joints are actuated by a redundant set of single directional muscle actuators, each of which can only pull, not push. The resultant activation of different muscles provides torques on the joint (Fig.4a), while muscle forces producing co-contraction are internally canceled out and do not contribute toward joint torque.

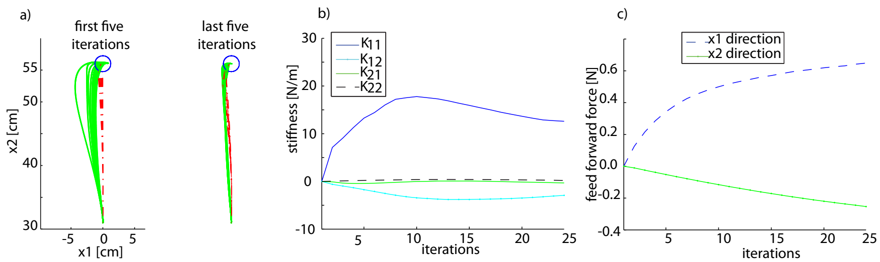

Fig. 2 Motor control experiments involve human subjects who learn to perform reaching movements from a start to a target point, against force perturbations provided by a haptic device (Fig. 1a), which they hold with their hand. (a) shows simulation of the hand trajectories performed by an individual in the early trials in a *velocity dependent force field* where the subjects experience a x-force to the left proportional to the y-velocity. With practice, the subject learns to compensate for this force and is able to make almost straight movements to the target (right panel of a). Comparison with [18, 2] shows that the biological behavior, i.e trajectories (a) and stiffness (b) and force (c) at the end point are well predicted by our model (Section 3).

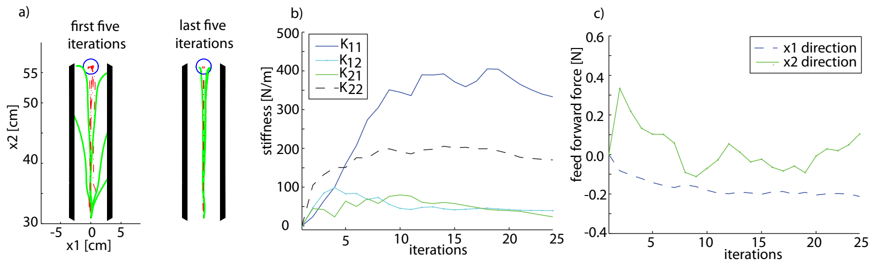

Fig. 3 The model can similarly predict well in case of a ‘divergent force field‘ where the subjects experienced a x-force proportional to their x deviation. This field requires the subjects to learn to increase their arm impedance in order to succeed. Evolution of simulated trajectories (reference in dotted red and actual in green) (a), stiffness (b) and feedforward force (c) correspond well to the observations of humans motor learning in [1, 18].

However, co-activation contributes towards the joint impedance, because in each muscle impedance increases with activation [8], and impedance add in antagonist muscles, i.e. parallel actuators.

How do humans use these muscle properties to adapt to novel environments? By analyzing the modifications of muscle activation trial after trial (Fig.4b), we could identify the following *principles of motor learning* [20]:

(i) Motor commands to perform a desired action are composed of both the feedforward command, defined as the component of the motor command learned by repeating an activity, and the feedback command,

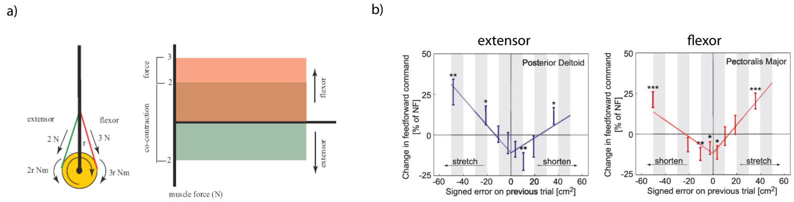

Fig. 4 How humans muscles control force and impedance. A cartoon of a human joint (a) shows how the differential activation of the two antagonist muscles can moderate force and impedance in the joint. (b) The average muscle activity from two antagonist muscle (Posterior Deltoid and Pectoralis Major) of each trial from a representative subject during learning of different environments is plotted against trajectory error [20]. Note that each muscle is activated for error in either direction.

(ii) learning is performed in muscle space,
(iii) feedforward increases with the muscle stretch in previous trial,
(iv) it also increases with antagonist muscle stretch,
(v) and decreases when the error is small.

These simple principles enable adaptation of both force and impedance (as was summarized in Fig. 5). It was shown in [22] that they yield *concurrent minimization of error and effort while maintaining a fixed stabilitity margin in presence of destabilizing environments*.

A question that is still the subject of research is that of the adaptation of trajectory in novel dynamics. In the pioneering work of Mussa-Ivaldi et al. [5], it was observed that in presence of an obstacle the reference trajectory is modified with learning, preventing too large forces against the surface. While the neuro-physiological mechanisms of trajectory adaptation are still to be further analyzed, a plausible explanation is that the reference trajectory would drift trial after trial to minimize motion error.

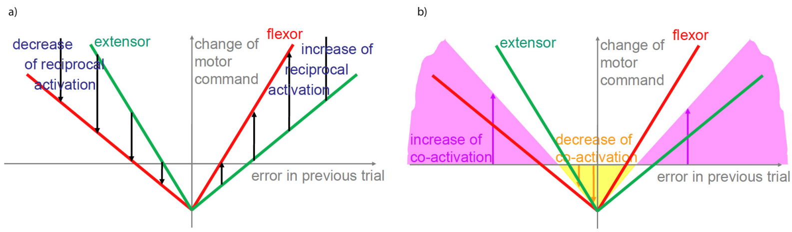

Fig. 5 Adaptation model. The activation change of the two muscles of Fig.4 are combined in (a) such that the difference in the activation (black arrows) represents the torque change in the joint while the common activation (pink region in (b)) represents the impedance change.

3 Adaptation of Force, Impedance and Trajectory

Expressing control in joint space [23], *the dynamics of a rigid body model of the humans arm or of a robot interacting with the environment* can be described as

$$M(q)\ddot{q}+N(q,\dot{q}) = \tau(t)+\nu+F(q,\dot{q},t) \tag{1}$$

where $M(q)$ is the mass matrix, $N(q,\dot{q})$ the joint torque vector due to the centrifugal, Coriolis, gravity and friction forces, $F(q,\dot{q},t) \equiv F_q$ (where t is time) is the interaction force with environment, τ the vector of joint torques produced by muscles/actuators, and ν is motor output variability or robotic system noise.

The principles of Section 2 yield the following *control law* for the force produced by the humans muscles / robot actuators:

$$\tau_u(t) = -\left(K_0(t)+K(t)\right)\varepsilon(t) - \tau(t) \tag{2}$$

where

$$\varepsilon \equiv \dot{e}(t)+\Gamma e(t)\,, \quad \Gamma = \Gamma^T > 0\,, \tag{3}$$

is the *tracking error* and

$$e(t) \equiv q(t)-q_r(t), \;\; \dot{e}(t) \equiv \dot{q}(t)-\dot{q}_r(t) \tag{4}$$

are the *position and velocity errors* relative to the *reference trajectory* $q_r(t)$, $t \in [0,T]$. The first term $-K_0\varepsilon$ is the *minimal feedback* (in the human arm produced by passive mechanical properties of muscles without co-contraction), τ is the *learned feedforward*, and $-K\varepsilon$ the *feedback* due to additional impedance *learned through interaction with the environment*.

We assume a *task* characterized by trajectory $q^*(t)$, $t \in [0,T]$. According to the principles of Section 2, the humans central nervous system / a robot will fulfill this task by adapting the movement reference trajectory q_r, feedforward τ and feedback K. This adaptation will be guided by concurrent minimization of interaction force and trajectory error

$$J = \int_0^T \|F_q(\sigma)\|_Q^2 + \|q(\sigma)-q^*(\sigma)\|_R^2 \, d\sigma \tag{5}$$

using a linear second order impedance model [24] ($\|\cdot\|_R$ and $\|\cdot\|_Q$ are the norms defined by $\|A^T R A\|$ and $\|A^T Q A\|$ for a matrix A, with positive definite weighting matrices Q and R, respectively), while maintaining stability through

$$\int_0^T V(\sigma)\,d\sigma \le \eta, \;\; V \equiv \varepsilon^T M(q)\,\varepsilon \tag{6}$$

where $\eta > 0$ is a small constant.

It is shown in [25] that this yields the following *adaptation algorithm for the reference trajectory*:

$$\begin{aligned} q_r^0 &= q^* \,, \\ q_r^{i+1} &= q_r^i - Lz^i, \quad i = 0, 1, 2, \ldots \end{aligned} \tag{7}$$

where

$$z = (\dot{q} - \dot{q}^*) + \Lambda(q - q^*) - f_q \tag{8}$$

with filtered force f_q defined through

$$\dot{f}_q + \Gamma f_q = K_F F_q \tag{9}$$

and L a constant matrix satisfying

$$\|I - K\Gamma^{-1} L M^{-1}(q)\| < 1\,. \tag{10}$$

Further, *feedforward adaptation* yields [26]

$$\tau^{i+1}(t) = \tau^i(t) + Q_\tau \left(\varepsilon^i(t) - \gamma^i(t)\tau^i(t)\right) \tag{11}$$

where $Q_\tau \equiv Q_\tau^T > 0$ and

$$\gamma^i(t) = \frac{1}{1 + \|\varepsilon^i(t)\|^2} \tag{12}$$

a forgetting factor of learning, and *impedance adaptation*

$$K^{i+1}(t) = K^i(t) + Q_K \left(\varepsilon^i(t) e^{iT}(t) - \gamma^i(t) K^i(t)\right) \tag{13}$$

where $Q_K = Q_K^T > 0$.

4 Simulations

Simulations were carried out to compare the prediction of the above adaptation algorithm with the results of human motor control. The simulations were conducted based on the two joint model of human arm biomechanics of [21].

The task consisted in performing a point to point movement, with minimal jerk nominal task trajectory $x^*(t)$ from $x(0) = [0, 0.31]m$ to $x(T) = [0, 0.56]m$:

$$\begin{aligned} x^*(t) &= x(0) + (x(T) - x(0))\, p(t)\,, \\ p(t) &= 10\left(\frac{t}{T}\right)^3 - 15\left(\frac{t}{T}\right)^4 + 6\left(\frac{t}{T}\right)^5, \end{aligned} \tag{14}$$

assuming a movement duration $T = 0.7s$.

We first investigated the adaptation to the *velocity dependent force field* (VF) used in [2]:

$$F_{VF} = \begin{bmatrix} 13 & -18 \\ 18 & 13 \end{bmatrix} \dot{x}\,. \tag{15}$$

Then we simulated the adaptation to the *divergent force field* (DF) used in [1, 2]:

$$F_{DF} = \begin{bmatrix} 450 & 0 \\ 0 & 0 \end{bmatrix} x, \quad \text{if} - 0.03 \le x_1 \le 0.03 \tag{16}$$

$$\text{otherwise} \;\; F_{DF} = \mathbf{0} \tag{17}$$

where the force is replaced by lateral damping when the distance to the straight line from start to target exceeds $5cm$ for safety in the human experiment.

Finally, we studied the adaptation to a *radial force field* (RF) used in [5], corresponding to a circular object:

$$F_{RF} = \begin{cases} k_E(R-r)\mathbf{n} & r \le R \\ 0 & r > R, \end{cases} \tag{18}$$

where R is the radius of the circle, r the distance from the circle center to the end effector, $\mathbf{n}$ is the unit vector pointing from circular center to the end effector and $k_E = 1000$ is a spring constant. We see that force F_{RF} is always pointing from circle center to outside along the normal direction.

All the three simulations were carried out for 24 iterations, using the following control parameters:

$$\begin{aligned} K_0 &= \begin{bmatrix} 60 & 28 \\ 28 & 70 \end{bmatrix}, K_F = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix}, \\ \Gamma(t) &= \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} + \begin{bmatrix} 30 & 0 \\ 0 & 30 \end{bmatrix} p(t), \\ \Lambda(t) &= \begin{bmatrix} 5 & 0 \\ 0 & 5 \end{bmatrix} + \begin{bmatrix} 20 & 0 \\ 0 & 20 \end{bmatrix} p(t)\,. \end{aligned} \tag{19}$$

Figs. 2 and 3 contrast the learning in VF and DF, respectively. Learning in VF shows monotonic adaptation of the hand trajectory trial after trial towards roughly the free trajectory. The trajectories in DF diverge in initial trials due to the unstable interaction, but then converge to the straight line while stability is gradually acquired during learning. Stiffness increases both in VF and DF. However, while it remains small in VF and rapidly decreases, it increases in DF to roughly compensate for the environment instability. Conversely, force increases marginally and rapidly decreases in DF, while it compensates for the external force in VF, together with some impedance force. These results are similar to the results of human adaptation as observed in [1, 27].

Simulation results of the adaptation to the radial force field as in [5] are shown in Fig.6. In this simulation the force field is on during trials 1-12, and off during

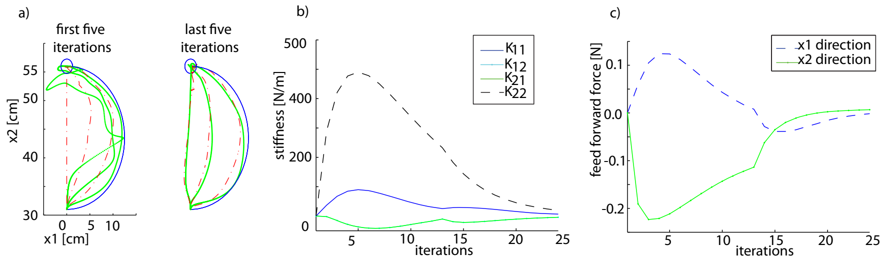

Fig. 6 Adaptation in a radial force field [5] of trajectory (a, trials No 1, 4, 12 left, and 13, 16, 24 right), stiffness (b) and feedforward force (c). While these results obtained with the simulation of model 3 correspond to the observation of adaptation to obstacle in [5], the drift of reference trajectory (dashed trace in a) is a prediction which needs experimental testing.

trials 13-24, so that both learning and unlearning can be analyzed. We observe a continuous drift of the reference trajectory towards the boundary of the circular haptic object which is plausible with the experimental findings of [5], though the data of that experiment cannot be used to test this prediction. Both stiffness and force increase in the initial trials but remain bounded and rapidly decrease as the reference trajectory drifts right towards the object boundary, bringing the interaction force to a relatively low level.

5 Implementation

The algorithm was tested in postural control and trajectory control experiments on a 1-degree of freedom DLR light weight robot (LWR) test-bed, on the DLR 7 degrees-of-freedom LWR arm and on a new variable impedance actuator (DLR quasi-antagonistic joint) and gave humans-like adaptation of feedforward force, impedance and trajectory/posture in these robots. Videos of these experiments are available at *http://www.cns.atr.jp/∼gganesh/robot_learning.rar*.

In the posture control task shown in Fig.7, the 1-DOF VIA joint attends to maintain its initial position at $0 rad$ (Fig.7a) while perturbations of low (green) or high (orange) frequency are applied on the robot. The robot counters slow perturbations using torque (Fig.7b) and fast perturbation by increased stiffness (Fig.7c), similar to behavior observed in humans doing a similar task [28].

In order to test trajectory adaptation by the algorithm, we use a ramp up and down as obstacle (green trace in Fig.8) added to the original plan (dashed red trace) of the robot movement. When the obstacle is suddenly removed in the fifth adaptation trial, the movement mirrors the obstacle (dashed blue trace) showing that the robot initially tries to increase the torque to counter the obstacle. However, if the obstacle remains till the 25th trial, the robot movement (blue trace) and plan (red trace) can be clearly seen to have adapted to the shape of the obstacle. The robot movement (blue trace) lies to the right of the plan (red trace), indicating that the robot still

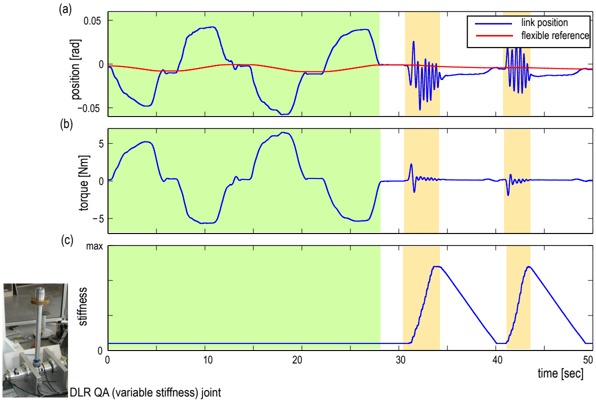

Fig. 7 Adaptation in posture control on the variable impedance actuator (VIA). The robot automatically maintains its position (blue trace of (a)) in the presence of low frequency (green region) by adapting the torque (b), and reacts to high frequency (orange) perturbations by increasing stiffness (c).

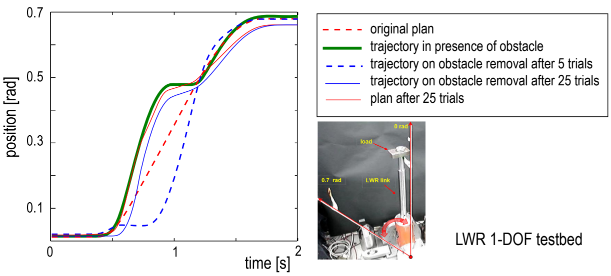

Fig. 8 Obstacle avoidance. The robot was presented with a (rigid) obstacle (green trace), such that the reference trajectory (dashed red trace) cannot be followed. On removal of the obstacle after 5 trials, robot movement (dashed blue trace) mirrored the obstacle. After 25 adaptation trials the robot movement (blue trace) and reference (red trace) adapt to the shape of the obstacle.

applies some contact force onto the obstacle. This behavior is again similar to the adaptation observed in humans [5].

Finally, a joint space implementation of the algorithm on the 7-DOF robot exhibited the ability of the algorithm to adapt feedforward and impedance, not only in magnitude, but also in direction. Fig.9 shows how direction and magnitude adaptation of task space stiffness are adapted according to the external perturbation, similar to observations in humans [1], and it yields smooth control on a surface similar to force control.

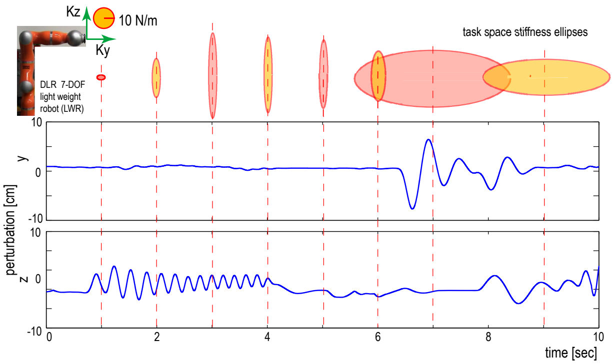

Fig. 9 Task stiffness shaping. The joint space implementation on the 7-DOF arm exhibited the ability of the algorithm to shape the task stiffness in magnitude and direction while maintaining a posture (shown in the photo) against disturbances applied at the end effector by a humans. The 2-dimensional projection on the *y-z* plane of the translational task space stiffness matrix is presented at different time instances.

6 Discussion

While robotics has been a very efficient tool to investigate humans motor control in the last 30 years, and has allowed significant advances such as described in [3, 4, 1], this paper presents one of the very few examples where neuroscience findings directly translate into robotics advances (Fig.1).

Specifically, we presented here *a novel adaptive motor behaviour*, which is both a successful model of human motor adaptation and is able to predict many published observations [1, 2, 18, 5], as well as a robotic controller, which:

- is the first controller able to simultaneously adapt force, impedance and trajectory in the presence of unknown dynamics;
- can deal with unstable situations due to interactions and gradually acquire a desired stability margin;
- is strictly derived from the minimization of motion error and effort;
- leads to better performance than fixed gains controllers in tasks with tools such as drilling, cutting or polishing [29];
- can learn a large range of dynamics models such as rigid body dynamics, neural networks, muscle synergies, and generalise in multiple movements [30];
- yields compliant following of unknown surfaces with controlled force.

This controller was validated in implementations with one and multidof industrial robots and can utilize the new possibilities offered by variable impedance actuators. We note that the goal of our implementations was not to reproduce exact motion adaptation as observed in humans, but to test and demonstrate the new robot capabilities enabled by the new adaptation behavior.

This controller can also be used to realize an intuitive adaptive human-robot interaction, such as needed in rehabilitation, physical training and teleoperation. One example consists of using this adaptive algorithm to tune the tremor attenuation offered by robotic devices [31] or functional electrical stimulation [32] so as to prevent excessive impedance in the system.

Another example is for the adaptive control of rehabilitation robots [33]. While still little is known about how to best assist patients recover motor function after a stroke, it appears that a condition of success is that the patient provides as much motion effort as possible [34, 35], otherwise he or she will not learn. Algorithms have thus been proposed to adapt guidance stiffness [36] or the feedforward force provided by the robot [37]. Our algorithm can provide adaptation of trajectory, force and impedance in a simple and automatic way.

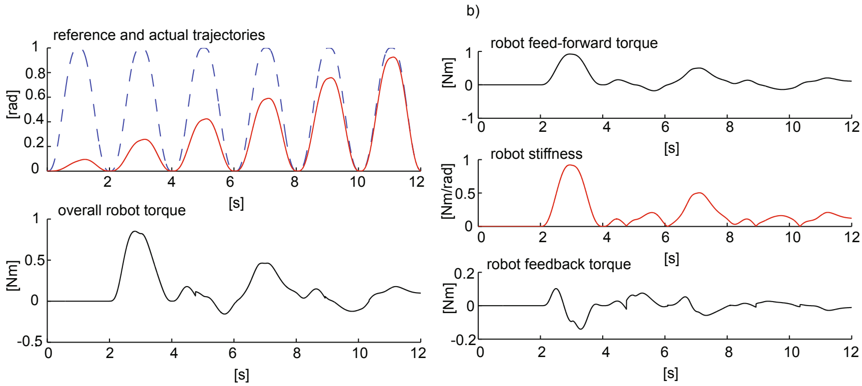

Fig. 10 Simulation of adaptive assistance provided by humans-like adaptation of the robot control to a stroke affected wrist. Assuming that the motor function is improving, the range of motion will increase. Assistance provided by the robot will enable to improve the outcome of the motor action, and decrease when the affected limb is able to provide motion, i.e. feedforward and feedback forces provided by the robot decrease.

To illustrate this, we simulated wrist flexion/extension training with the Bi-Manu-Track (*http://www.reha-stim.de/cms/index.php?id=12*). With this robotic device, the non-affected arm accompanies oscillatory movements of the affected arm, and can provide force and guidance to help these movements, directly or through the help of a computer controlled torque actuator.

However in the sub-acute phase after a stroke, many patients cannot move the affected limb yet [38] or cannot control movement well. What we develop is a strategy in which the trajectory amplitude, the feedforward force and guidance strength are adapted to the motor condition of the affected limb using the learning algorithm presented above.

The principle of this adaptation is simulated as follows. The torque applied by the robot on the affected limb will assist the affected wrist movement to follow a trajectory provided by a healthy wrist, which is represented in this simulation as a minimal jerk trajectory.

We see in Fig.10 that in the first iteration $t \in [0, T = 2s]$, the feedforward torque $\tau(t) = 0$ and stiffness $k(t) = 0$. The affected limb is not able to move well in the first iteration so there will be large error. In the second iteration, the stiffness and feedfoward torque provided by the robot will increase to assist the wrist movement, which is assumed to improve gradually. We observe that as the position tracking error decreases, the robot feedforward and feedback torques contributed by impedance decrease as well.

Though only experiments with patients will be able to decide on the success of this algorithm, this simple simulation illustrates that our algorithm fulfills the design objectives. The robot device only provides minimal required assistance to the patient, who will thus have to provide as much effort and as good performance as possible to keep successful motion.

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