Adaptive Model-Based Assistive Control for Pneumatic Direct Driven Soft Rehabilitation Robots

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***Abstract*—Assistive behavior and inherent compliance are assumed to be the essential properties for effective robot-assisted therapy in neurological as well as in orthopedic rehabilitation. This paper presents two adaptive model-based assistive controllers for pneumatic direct driven soft rehabilitation robots that are based on separated models of the soft-robot and the patient's extremity, in order to take into account the individual patient's behavior, effort and ability during control, what is assumed to be essential to relearn lost motor functions in neurological and facilitate muscle reconstruction in orthopedic rehabilitation. The high inherent compliance of soft-actuators allows for a general human-robot interaction and provides the base for effective and dependable assistive control. An inverse model of the soft-robot with estimated parameters is used to achieve robot transparency during treatment and inverse adaptive models of the individual patient's extremity allow the controllers to learn on-line the individual patient's behavior and effort and react in a way that assist the patient only as much as needed. The effectiveness of the controllers is evaluated with unimpaired subjects using a first prototype of a soft-robot for elbow training. Advantages and disadvantages of both controllers are analyzed and discussed.**

I. INTRODUCTION

Robot-aided (or motorized) movement therapy is a well-established method of deployed treatment for nearly every functional disorder of musculoskeletal system with neurological as well as with orthopedic syndromes. In orthopedic rehabilitation, continuous passive motion (CPM) machines are used for more than 30 years, because treatment times of physiotherapists are limited and expensive. These simple and cost-effective preprogrammed devices provide only passive treatment, guiding the patient's motion and ignoring their own effort. In neurorehabilitation, since the late 90s, position controlled gait machines like GaitTrainer GT1, Locomat and LokoHelp [1] are used to intensify repetitive task specified training and different studies indicate the effectiveness of interactive robot-assisted therapy in neurorehabilitation after stroke [2]–[4].

However, the stiffness of position controlled electromechanically driven devices limits the effect to relearn lost motor functions in neurological and to facilitate muscle reconstruction in orthopedic rehabilitation. To allow small deviations from the desired trajectory, several devices for neurorehabilitation based on electrical drives that uses impedance control have been developed [5]–[8], the first one was the MIT-Manus [9] that has now been marketed. Active compliance has been realized using mostly expensive force/torque sensors. But impedance control is limited in the ability to complete movements against gravity, tracking error increases if stiffness will be reduced and load is increasing.

Patient-cooperative control strategies [10], [11] have been developed for the Lokomat and the ARMin, including path-control [12], allowing free timing of movements in definable desired limits.

The Assist-as-Needed controller presented in [13] allows to learn on-line a model of the patient's arm and to control impedance and assistance separately, providing compliance and assistance force to complete spatial movements. The controller has been developed for the robotic system Pneu-WREX, which is based on pneumatic cylinders.

Soft-actuators with inherent compliance like pneumatic muscles are very suited to work in direct environment of humans [14]. The pneumatic rotary-type soft REC-actuators are used to develop different prototpyes of assistive acting movement therapy devices [15]. The inherent compliance allows for a general human-robot interaction and provides the base for effective and dependable assistive control. An assistive controller based on a quasi-static model of the individual patient is implemented and tested for a 2 degrees of freedom (DoF) shoulder movement therapy device and for a 1 DoF assistive knee movement therapy device that is under clinical trials in the Clinic for Orthopaedics and Trauma Surgery at the Klinikum Stuttgart.

In this paper two adaptive model-based assistive controllers

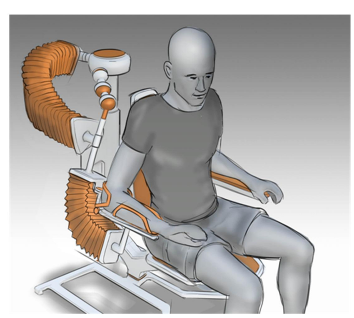

Fig. 1. Draft of a rehabilitation robot for upper extremity based on multi-axial pneumatic soft-actuators for neurological and orthopedic rehabilitation, in cooperation with i/i/d - Institute of Integrated Design, Bremen.

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for pneumatic direct driven soft rehabilitation robots are presented. Both controllers are based on separated models of soft-robots and of human's extremities. An inverse quasi-static model of soft-robot with estimated parameters is used to achieve robot transparency during treatment. Adaptive inverse models of the individual patient's extremity allow both controllers to learn on-line the individual patient's behavior and effort and react in a way that assist patients only as much as needed. Due to the use of the models as feed-forward assistance, the high compliance of the soft-actuators can remain during control, while providing sufficient supportive force for movements against gravity.

The first presented assistive controller is based on prior information of model parameters estimation (MPE) for the human's extremity with a minimal number of pressure and position measurements. Time-depending model adaptation in a predefined velocity range allows patients to move supported but unimpeded into requested direction. The second presented assistive controller is based on function approximation technique using radial basis functions (RBF), allowing patients to make small deviations from the desired trajectory, while estimating on-line a dynamic model of the human's extremity that is adapted to the patient's behavior, effort and ability, without any prior knowledge, similar to [13].

The algorithms are implemented and tested using a first prototype of a soft-robot for elbow training, that is the first part of a rehabilitation robot for upper extremity based on multi-axial pneumatic actuators, see Fig. 1 and Fig. 2, and unimpaired subjects. The advantages and disadvantages of both controllers are analyzed and discussed.

II. Experimental Setup

A first prototype for elbow training (see Fig. 2) is used as initial experimental setup to test the functionality and the behavior of the assistive controllers. The prototype is a 1 DoF soft-robot based on a new generation of soft REC-actuators, possess inherent compliance, allowing direct rotary movement and modular design of soft-robot structures. A knee and shoulder movement therapy device based on a previous generation of soft REC-actuators are presented in [15]. The experimental determined actuator torque characteristic for the extension chamber is exemplarily shown in Fig. 2.(b). The elbow trainer allows elbow movement in extension and flexion direction. The moving range is between 0° (full extension) and 120°. The device can be adjusted to patients using a spherical joint at the robot basis whose position can be changed in x,y and z direction using sliders. The actuator axis of the robot is assumed to be coincide with the pivot axis of the human elbow. Two low noise high dynamic pneumatic servo valves (FESTO MPYE-5-1/8LF-010-B) are used for silent operation of the two independent working chambers. Two pressure sensors (AMSYS AMS5812) and one magnetic position sensor (ASM PRAS21) are used to measure actuator position and pressure in actuator chambers. A three axis accelerometer (Freescale Semiconductor MMA7361L) is used to determine the orientation of the robot basis after adjusting the device to the patient. No force or torque sensor is used.

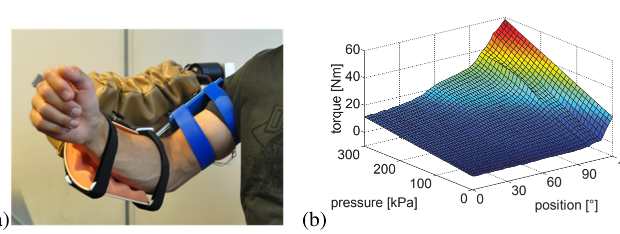
(a) (b)


Fig. 2. Soft-robot for elbow training as first part of a upper extremity rehabilitation robot (see Fig. 1): (a) First prototype used as experimental setup and (b) actuator torque characteristic of extension chamber.

III. Control

In this section, two adaptive model-based assistive controllers for direct driven soft rehabilitation robots are presented. To show the principle functionality, the controllers are developed for 1 DoF combined human-robot systems based on pneumatic soft-actuators (see section II), but they can be extended for more DoF systems. The overall assistive control concept has a cascade structure with a non-linear pressure controller and inverse models of actuator torque characteristics in the inner loop, see Fig. 3. This section briefly explains the dynamics of the combined human-robot system, the torque mapping, the innermost pressure control loop and presents both adaptive model-based assistive controllers.

A. Dynamics of Combined Human-Robot System

The general dynamics of the combined human-robot system with negligence of friction or other disturbances are assumed to be

$$\Theta_{RH}(q)\ddot{q} + C_{RH}(q,\dot{q})\dot{q} + G_{RH}(q) = \tau_R + \tau_H, \qquad (1)$$

where $\Theta_{RH}(q)\ddot{q}$ describes the inertia torque, $C_{RH}(q,\dot{q})\dot{q}$ the centrifugal and Coriolis torques and $G_{RH}(q)$ the gravity torque of the combined human-robot system, τ_R represents the actuator torque of the robot and τ_H the torque provided by the human.

B. Torque Mapping and Pressure Control

In order to avoid the use of mostly expensive torque and force sensors, an actuator torque characteristic is used, that has been determined in experimental manner. The characteristics for both actuator chambers are non-linear functions of actuator position and chamber pressure

$$\tau_1 = f\left(q, p_1\right), \;\; \tau_2 = f\left(-q, p_2\right). \qquad (2)$$

The determined actuator torque characteristic for the extension chamber is exemplarily shown in Fig. 2.(b). Based on pressure dynamics, the pressure control law for each actuator chamber is defined as

$$\dot{m}_i = \frac{V_i}{\gamma RT}\left(K_p\left(p_{id} - p_i\right) + \gamma p_i \frac{\dot{V}_i}{V_i}\right) \;\text{ for } i = 1, 2, \qquad (3)$$

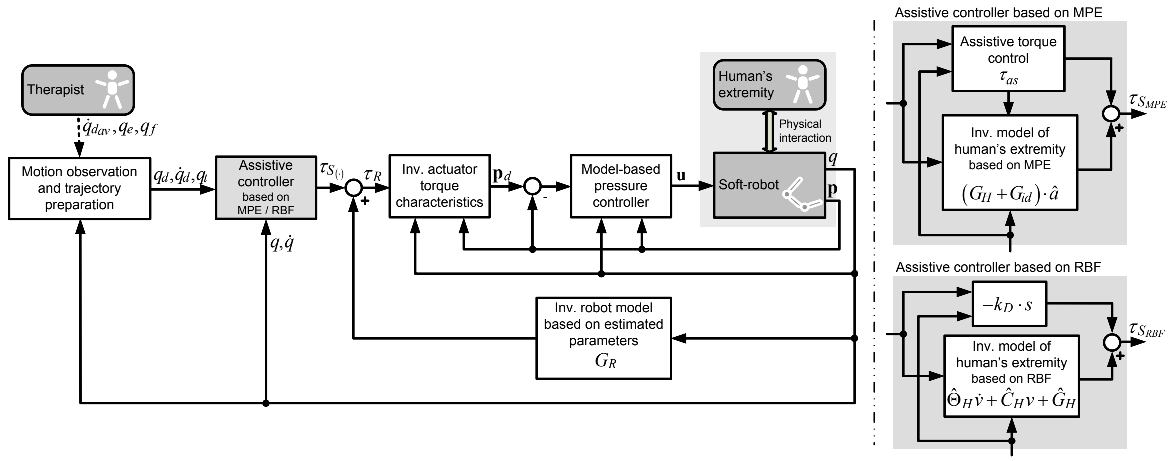


Fig. 3. General structure of assistive control concept with a non-linear pressure controller and inverse models of actuator torque characteristics in the inner loop. An inverse robot model is used to achieve robot transparency and an adaptive model-based assistive controller is used to learn on-line a model of the human's extremity. Two adaptive assistive controllers (based on MPE and RBF) are developed and compared in experiments.

where V_i is the chamber volume, R is the universal gas constant, T is the temperature in the chamber that is assumed to be constant, $\dot{m}_i$ is the air mass flow rate, p_i is the actual chamber pressure and γ is the polytropic coefficient. Experimental determined inverse characteristics of mass flow rate of servo valves are used to compensate corresponding non-linearities and obtain the control voltage for the valves

$$u_i = f^{-1}\left(\dot{m}_i, p_i\right) \text{ for } i = 1, 2. \tag{4}$$

C. Asistive Controller based on MPE

The desired torque is assumed to be

$$\tau_R = G_R + \tau_{S_{MPE}}, \tag{5}$$

where G_R is the gravity torque of the robot, used to achieve robot transparency. $\tau_{S_{MPE}}$ is the desired supportive torque for the human, that is calculated as

$$\tau_{S_{MPE}} = (G_H + G_{id}) \cdot \hat{a} + \tau_{as}, \tag{6}$$

where G_H is the gravity torque of the human's extremity, $\hat{a}$ is the estimated parameter and τ_{as} the assistive torque. The gravity torque for the robot and the human's extremity are calculated as

$$G_{(\cdot)} = \mathbf{e}^T \left(m_{(\cdot)} \mathbf{p}_{c(\cdot)} \times \mathbf{g} \right), \tag{7}$$

where $m_{(\cdot)}$ is the body mass and $\mathbf{e}^T \in \Re^3$ is a unit vector with origin in the body coordinate system and direction in joint axis. $\mathbf{p}_{c(\cdot)} \in \Re^3$ is a vector from the body coordinate system to the center of mass of the body. $\mathbf{g} \in \Re^3$ represents the gravitational acceleration in body coordinate system. The product $m_{(\cdot)} \mathbf{p}_{c(\cdot)} \in \Re^3$ is the first moment of inertia that is assumed to be an unknown vector of parameter estimates $\boldsymbol{\chi}_{(\cdot)} \in \Re^3$. The parameters for the human's extremity are identified for the individual patient before treatment starts. For parameter estimation, no prior information about length or mass parameters is required. At least two pressure and position measurements in different system configurations (A and B) are required for model parameter estimation.

The parameters of the estimated vector for the robot and the human's extremity are calculated by solving the corresponding systems of equations

$$\tau_{E_{A,B}} = \mathbf{e}^T \left(\boldsymbol{\chi}_{(\cdot)} \times \mathbf{g}_{A,B} \right), \tag{8}$$

where the required torque for estimation $\tau_{E_{A,B}}$ equals the torque calculated by the actuator torque characteristics $\tau_{A,B}(q, p_1, p_2)$ to identify the model parameters for the robot and equals $\tau_{A,B}(q, p_1, p_2) - G_{R_{A,B}}$ to identify the model parameters for the human's extremity.

To compensate errors due to experimental determined non-linear actuator torque characteristics, an characteristic of patient's individual torque deviation is calculated during initial warm-up phase of treatment, whereat the patient has to behave passively. The controller is used without model adaptation. The error in torque that is calculated by the models is determined at specific positions and is used as gain factor in a network of RBF. The individual deviation torque characteristic is calculated as

$$G_{id} = \sum_{i=1}^{m} \left(\left(\tau_{R(i)} - G_{R(i)} - G_{H(i)} \right) e^{-(q - c_i)^2 / 2\sigma^2} \right), \tag{9}$$

where c_i is the location of the center of the i^{th} RBF and σ is a constant positive definite gain factor that has a direct influence on the wide of a RBF.

Time-depending model adaptation in a predefined velocity range is used to motivate patients to maximize their voluntary effort. Patients are allowed to move supported but unimpeded into the requested direction, no predefined trajectory profile is forced on patients. The update law is as follows

$$\dot{\hat{a}} = f_r\left(\dot{q}\right) \hat{a}, \tag{10}$$

where $f_r\left(\dot{q}\right)$ is a velocity-depending forgetting and remember factor that is calculated as

$$f_r(\dot{q}) = \begin{cases} -c_1 & \text{if } |\tau_{as}| = 0 \wedge |\dot{q}| \leq \dot{q}_r \wedge \hat{a} > 0 \\ c_2(\dot{q}) & \text{if } |\tau_{as}| > 0 \vee \dot{q}_r \leq |\dot{q}| \\ 0 & \text{if } |\tau_{as}| > 0 \wedge \hat{a} = 1. \end{cases} \quad (11)$$

In this equation is $\dot{q}$ the current velocity, c_1 a constant gain factor and $\dot{q}_r$ the limit of the velocity range. Within the limit, model forgetting reduces time-depending the influence of the human model and outside, model remembering increases the model influence. The gain factor $c_2(\dot{q})$ is velocity-depending and for safety reason, outside of a second limit, $c_2(\dot{q})$ is increased to a maximum value, in order to remember the whole model very quickly, allowing to controller to act like a parachute and provide sufficient support to hold patients at the current position.

Additional assistive torque is only calculated if the patient does not participate actively or moves into not requested direction. The assistive torque is calculated as

$$\tau_{as} = k_p(q_{md}(t) - q(t)) - k_d\dot{q}(t), \quad (12)$$

where $q_{md}(t)$ is a modified desired minimum jerk trajectory. This trajectory is defined as

$$q_{md}(t) = q_s(t) + (q_t - q_s(t))\left(10c_d^3 - 15c_d^4 + 6c_d^5\right), \quad (13)$$

where $c_d = \frac{t}{d}$, q_t is the current target angle and $q_s(t)$ is the current starting angle. If the patient moves with sufficient strength into requested direction, the desired angle and starting angle is set equal to the actual angle, which allows the patient to move further without counteraction of robot. The starting angle is calculated as

$$\begin{gathered} q_s(t+\Delta t) = \begin{cases} q(t) & \text{if } \Delta q_{md}(t) \geq \Delta q(t) \\ q_s(t) & \text{if } \Delta q_{md}(t) < \Delta q(t) \end{cases} \\ \Delta q_{md} = |q_t - q_{md}| \wedge \Delta q = |q_t - q|, \end{gathered} \quad (14)$$

where Δt is the discrete sample time.

D. Assistive Controller based on RBF

The desired torque is assumed to be

$$\tau_R = G_R + \tau_{S_{RBF}}, \quad (15)$$

where G_R is the gravity torque of robot, see equation (7). $\tau_{S_{RBF}}$ is the required desired supportive torque, that is calculated as follows

$$\tau_{S_{RBF}} = \hat{\Theta}_H\dot{v} + \hat{C}_H v + \hat{G}_H - k_D s, \quad (16)$$

where $\hat{\Theta}_H$,$\hat{C}_H$ and $\hat{G}_H$ are estimations of Θ_H,C_H and G_H, representing an inverse dynamic model of the human's extremity that is on-line adapted to the individual patient's behavior, effort and ability. k_D is a positive definite gain factor, v is the reference trajectory and s the sliding condition developed in [16]. $\hat{\Theta}_H$,$\hat{C}_H$ and $\hat{G}_H$ are estimated using a proper number of RBF and are defined as

$$\hat{\Theta}_H = \mathbf{z}_\Theta^T\hat{\mathbf{w}}_\Theta, \hat{C}_H = \mathbf{z}_C^T\hat{\mathbf{w}}_C, \hat{G}_H = \mathbf{z}_G^T\hat{\mathbf{w}}_G, \quad (17)$$

where $\mathbf{z}_\Theta^T \in \Re^{1\times m}$, $\mathbf{z}_C^T \in \Re^{1\times m}$ and $\mathbf{z}_G^T \in \Re^{1\times m}$ are matrices of RBF and $\hat{\mathbf{w}}_\Theta \in \Re^m$,$\hat{\mathbf{w}}_C \in \Re^m$ as well as $\hat{\mathbf{w}}_G \in \Re^m$ are matrices of parameter estimates. The sliding condition and reference trajectory are calculated as

$$s = \dot{\tilde{q}} + k_s\tilde{q}, v = \dot{q}_d - k_v\tilde{q}, \quad (18)$$

where $\tilde{q} = (q - q_d)$ and k_s as well as k_v are positive definite gain parameters. The matrices of RBF are calculated as

$$\mathbf{z}_{(\cdot)}^T = \left[z_{(\cdot)1}, z_{(\cdot)2}, ..., z_{(\cdot)m}\right], \quad (19)$$

$$z_{(\cdot)i} = e^{-(q-c_i)^2/2\sigma^2} \text{ for } i = 1, ..., m. \quad (20)$$

The RBF are evenly distributed over the whole robot workspace by defining the center c_i of the i^{th} RBF. The final control law is

$$\tau_R = G_R + \mathbf{z}_\Theta^T\hat{\mathbf{w}}_\Theta\dot{v} + \mathbf{z}_C^T\hat{\mathbf{w}}_C v + \mathbf{z}_G^T\hat{\mathbf{w}}_G - k_D s. \quad (21)$$

The update laws are defined as

$$\begin{aligned} \dot{\hat{\mathbf{w}}}_\Theta &= -f_\Theta\mathbf{z}_\Theta\left(\mathbf{z}_\Theta^T\mathbf{z}_\Theta\right)^{-1}\mathbf{z}_\Theta^T\hat{\mathbf{w}}_\Theta - \\ &\quad +\mathbf{Q}_\Theta^{-1}\left(\mathbf{z}_\Theta\dot{v}s + \boldsymbol{\sigma}_\Theta\hat{\mathbf{w}}_\Theta\right), \\ \dot{\hat{\mathbf{w}}}_C &= -f_C\mathbf{z}_C\left(\mathbf{z}_C^T\mathbf{z}_C\right)^{-1}\mathbf{z}_C^T\hat{\mathbf{w}}_C - \\ &\quad +\mathbf{Q}_C^{-1}\left(\mathbf{z}_C vs + \boldsymbol{\sigma}_C\hat{\mathbf{w}}_C\right), \\ \dot{\hat{\mathbf{w}}}_G &= -f_G\mathbf{z}_G\left(\mathbf{z}_G^T\mathbf{z}_G\right)^{-1}\mathbf{z}_G^T\hat{\mathbf{w}}_G - \\ &\quad +\mathbf{Q}_G^{-1}\left(\mathbf{z}_G s + \boldsymbol{\sigma}_G\hat{\mathbf{w}}_G\right), \end{aligned} \quad (22)$$

where $f_{(\cdot)}$ is a constant forgetting factor. The first part of the update laws is a modification in order to reduce torque when errors are small, with the objective to motivate patients and prevent them of relying on the assistance, due to slacking, similar to [13]. The second part is an adjusted update law based on function approximation techniques, presented in [17].

IV. Experimental Results

The objective of this section is to validate both controllers as well as to analyze the controllers reactions to different subject's behavior. The experiments are performed using the first prototype for elbow training and an unimpaired subject with a body weight of 76 kg and a height of 1.78 m. The target angles for the movement are set to 20° for extension and 90° for flexion. The task is performed in a skew position, depending on adjustment to the subject, see Fig. 2.

During the experiments the subject was asked to behave passively for 3 periods (passive phase) and then participate actively (active phase). The experimental results with the assistive controller based on MPE are presented in Fig. 4 and with the assistive controller based on RBF in Fig. 6. The same experiment was repeated four times with each controller to confirm the controller reaction. To compare supportive torque between passive and active phase, the recorded data of each experiment was separated. Mean values and standard deviations of supportive torque for the active and the passive phase are shown in Fig. 4.(a) for the assistive controller based on MPE and in Fig. 6.(a) for the assistive controller based on RBF, calculated as $\bar{\tau}_{S_{(\cdot)}} = \frac{1}{T}\sum_{i=1}^{T}\tau_{S_{(\cdot)}}^{(i)}$.

Fig. 4.(b) and Fig. 6.(b) shows one of the four experiments in detail. In the first time-segments (see 0s-60s) the subject

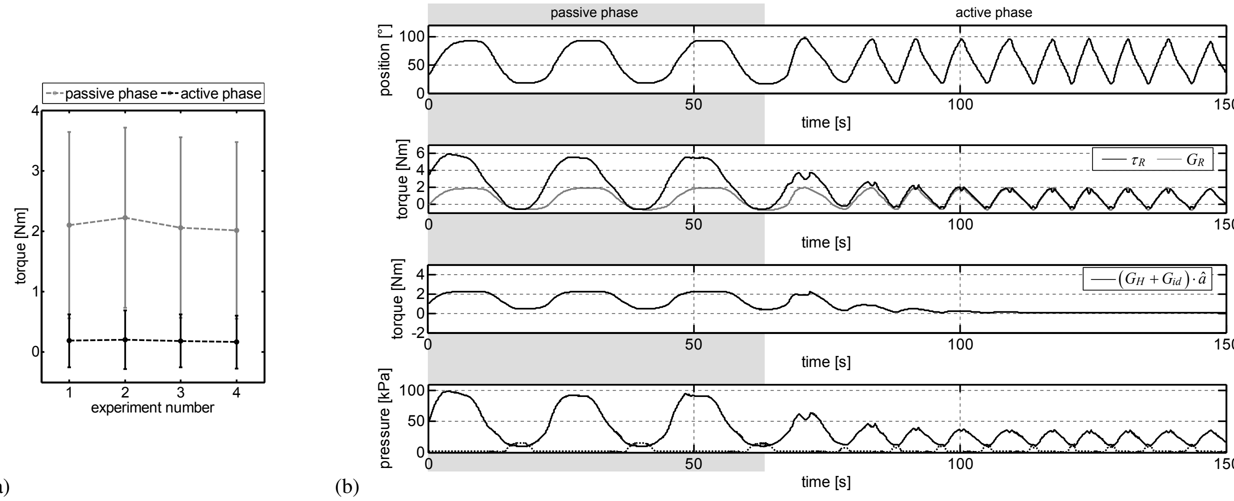


Fig. 4. Results of the four experiments using the assistive controller based on MPE. In the first three periods the subject behaved passively and thereafter actively. Time-depending on-line adaptation of the inverse model of human's extremity in a predefined velocity range allowed the subject to move supported but unimpeded into the requested direction: (a) Mean values and standard deviations of supportive torque provided by the robot and (b) detailed information of one experiment as an example.

behaved passively and in the second time segment (see 60s-150s) the subject participated actively. The first plot in both figures shows the position of the elbow joint, the second plot the total desired torque (black line) and the torque calculated by the model of robot (gray line). The third plot represents the torque calculated by the inverse adapted model of the human's extremity separately and the fourth plot the pressure in the actuator chambers. In the passive phase, the controllers calculate sufficient torque to guide the subject and in the active phase, the inverse models of human's extremity were adapted depending on the changing subject's behavior.

A. Assistive Controller based on MPE

Due to the velocity-depending adapted model of human's extremity, the subject was support but allowed to move unimpeded into the requested direction. The influence of the inverse human model was reduced time-depending when the subject moved actively into the requested direction within the predefined velocity range. The mean value of supportive torque for all four experiments is quite similar and it can be concluded that the assistive behavior of the controller is repeatable and confirmable, see Fig. 4.(a). The mean value of supportive torque is reduced from about 2.1 Nm when the subject behaved passively to 0.19 Nm when the subject behaved actively.

Fig. 5 shows the controller reaction to an unimpaired subject who is trying to imitate the behavior of an impaired person. The first plot shows the torque calculated by the human model (gray line) and the torque calculated by the adapted version of this model (black line). The second plot shows the estimated parameter an the third plot the current velocity. Due to velocity-depending model forgetting and remembering, the controller adapts to different subject's behavior and for safety reason reacts quickly in case of high velocity to provide sufficient torque to hold the subject at the current position.

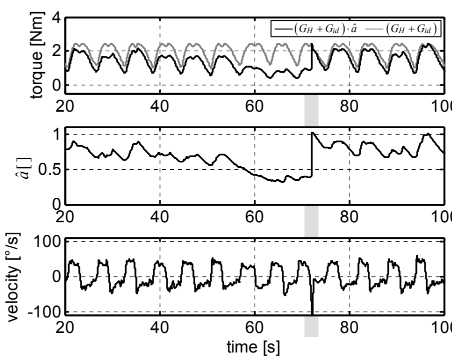


Fig. 5. Controller reaction in case of an impaired person imitating unimpaired subject. The controller reacts quickly in case of high velocity.

B. Assistive Controller based on RBF

The subject was allowed to make small deviations from the desired trajectory and as long as the subject participated actively, the overall torque was reduced until the torque that was calculated to compensate for the weight of the robot. Consequently, the pressure in actuator chambers was reduced when the subject participated actively. The mean value of supportive torque for all four experiments is quite similar, see Fig. 6.(a). The mean torque is reduced from about 1.87 Nm in the passive phase to 0.23 Nm in the active phase.

V. CONCLUSION

Two adaptive model-based assistive controllers for direct driven soft rehabilitation robots based on pneumatic soft-actuators are presented. The controllers are based on inverse models of the human's extremity, that are on-line adapted in order to take into account the individual patient's behavior, effort and ability as well as to motivate patients to maximize

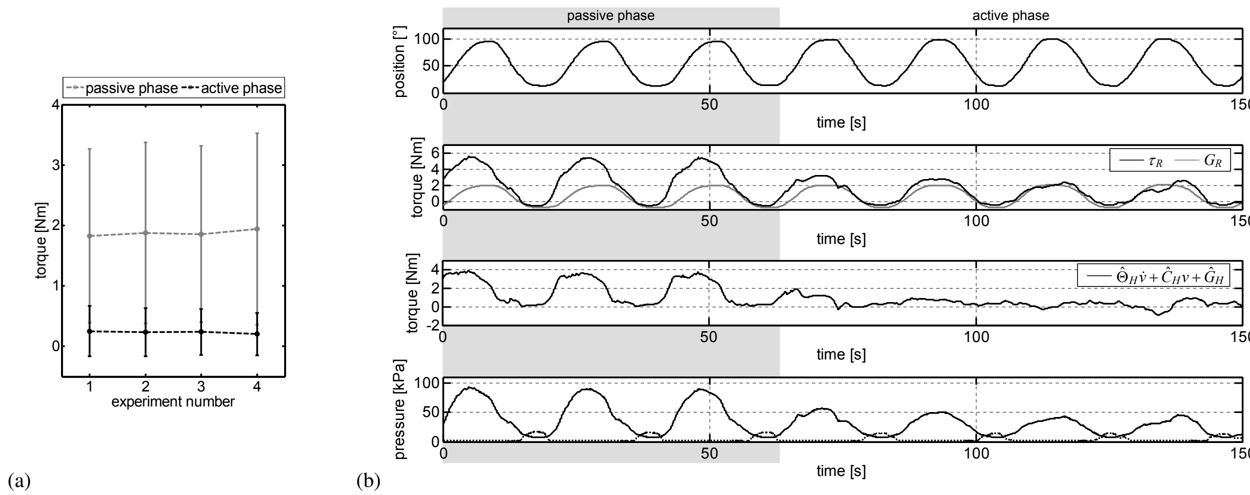


Fig. 6. Results of the four experiments using the assistive controller based on RBF. In the first three periods the subject behaved passively and thereafter actively. The subject was allowed to make small errors from the desired trajectory while an inverse dynamic model of the human's extremity was on-line calculated: (a) Mean values and standard deviations of supportive torque provided by the robot and (b) detailed information of one experiment as an example.

their voluntary effort and to prevent them of relying on assistance.

The assistive controller based on MPE allows patients to move supported but unimpeded within a predefined velocity range into the requested direction. No predefined trajectory profile is forced on patients when they participate actively. Patient are sufficiently supported due to the time-depending adaptive feed-forward model. This behavior allows patients to find their individual trajectory, what is assumed to be advantageous in order to motivate patients to maximize their effort. The disadvantage is that the controller is based on prior information about the human's extremity model parameters, but they can be identified using an approach for model parameter estimation with a minimal number of position and pressure measurements.

In contrast, for the assistive controller based on RBF no prior information is required, but this controllers only allows small deviations from the desired trajectory, while calculating on-line the inverse dynamics of the patient's extremity.

In the next step both controllers will be tested with the soft-robot for elbow training in the Clinic for Orthopaedics and Trauma Surgery as well as in the Neurological Clinic at the Klinikum Stuttgart.

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