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Adaptive Impedance Control for Robot-Aided Rehabilitation of Ankle Movements

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***Abstract*— This paper summarizes our on-going efforts to design adaptive assist-as-needed impedance controllers for ankle rehabilitation. Two robot assistance control strategies were evaluated: the first one attempted to normalize the combined robot and patient impedance via a complementary robot stiffness based on the estimate of the patient's stiffness and the second one searched for an optimal solution that minimized a cost function relating the rehabilitation goal and the interaction between patient and robot. For both strategies, the robot level of assistance was adapted based on patient's performance on distinct video games (serious games). Preliminary experimental results, employing the Anklebot in one stroke patient, confirmed the feasibility of the proposed control schemes in helping the subject to complete the tasks with optimal assistance from robot.**

I. Introduction

Stroke is the leading cause of permanent disabilities in the world with over 15 million new stroke cases occurring every year. About 35 percent of people who suffer a stroke die within 30 days (stroke is the third leading cause of death in developed countries and the first cause of death in the developing world); about 50 percent of stroke survivors are left permanently disabled and in need of rehabilitation [1]. Stroke generally damages neural areas that control the movement of both upper and lower limbs. Although the improvement of clinical post-stroke care has increased the survival rate, the number of people who need rehabilitation has increased significantly because of the aging of the population (e.g., in 1995 there were 450,000 new strokes in the US while presently over 795,000 occur annually). The natural course of recovery for the survivors affords some respite; however, a program for physical and occupational therapy is always required to promote additional gains. Post-stroke therapy is labor intensive with one therapist interacting one-on-one with a patient during several hours per day [2]. Rehabilitation robotics is a novel solution to assist with the increasing demands in rehabilitation services and to augment the potential of patient recovery [3]-[6].

Different control schemes have been tried with the assist-as-needed approach leading to best overall results and effectiveness [4]. Assist-as-needed imparts external forces to aid the patient to reach a desired target only when s/he cannot complete the movement unassisted [7].

Assist-as-needed paradigm can be seen as a minimization problem [8], where the control algorithm should minimize a cost function relating the rehabilitation goal and the interaction between robot and patient. In a rehabilitation process, the robot/patient interaction is equivalent to the teacher/student relationship as described in [9]. The best results are achieved when the teacher (robot) aims to minimize the student (patient) error, while also seeking to minimize its own effort [10].

In this paper, we tested two distinct adaptive control strategies intended to increase patient's participation and to assist only as needed during strength training. Initially, we present an error-based patient's stiffness estimation as a valid measurement of patient's participation. Then, both schemes determine the necessary robot assistance. The first approach attempts to normalize the combined robot and patient impedance while achieving an admissible target error. In the second case, the optimal robot assistance is estimated from the cost function minimization. The cost function is defined as the weighted sum between the force exerted by the robot on the patient (to reduce the robotic assistance) and the patient motion error (to complete the task). We monitor patient's performance while playing the serious game to reduce the robot assistance and challenge the patient to do more. We will present the results with both approaches in pilot tests during ankle therapy.

The paper is organized as follows: Section II presents the Anklebot characteristics and the interactive environment; Section III presents the procedure to estimate the patient's stiffness; Section IV presents both the complementary impedance and optimal control strategies for robot assistance; Section V presents the experimental results; and Section VI presents the conclusions.

II. System Description

A. Robotic Device: Anklebot

We employed the Anklebot (Interactive Motion Technologies, Inc., Watertown, MA, USA), which acts on the ankle joint via two linear actuators mounted in parallel to the leg, allowing movement in all three degrees of freedom (dof) of the foot with respect to the leg and actuating two of these dof [11]. The actuated movements are dorsi/plantarflexion (DP) in the sagittal plane, when the actuators move in the same direction, and inversion/eversion (IE) in the frontal plane, when the actuators move in opposite directions. The anklebot can apply up to 23 N/m in DP and 15 N/m in

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IE. Although not sufficient to support the weight of the user, these torques can properly position the ankle during the swing phase and assist during toe-off and heel-strike gait phases, minimizing foot drop and slap in stroke patients. We employed an impedance controller with a controllable torsional stiffness and damping.

Fig. 1. Anklebot.

B. Interactive Environment

The anklebot can be employed in seated position or during walking over a treadmill or overground. In this work, we employed a set of visually-guided, visually-evoked serious games in seated position (Figure 1) to guide the patient to make the maximum effort at each movement.

The patient must hold the weight of a watermelon or control the upward trust of a balloon in the interactive environment, and then dorsi- or plantarflex (DP) the ankle to hit the desired target (Figure 2). The goal is to reach the largest number of targets in the shortest possible time.

(a) (b)

Fig. 2. Interactive environment. (a) Downward force (watermelon's weight), dorsiflexion movement; (b) Upward force (balloon's thrust), plantarflexion movement. The arrows in the figure represent the resistive forces (they do not appear during the game) and the blue circle is the target.

The objective of these simple games is to train plantarflexion during push-off and dorsiflexion during toe-off.

III. Estimation of Patient's Ankle Stiffness

In order to estimate the patient's ankle stiffness, a dynamic model of the patient-robot system is proposed. Considering only the DP degree of freedom and the dynamic proprieties of the foot and robot, the model is given by:

$$I\ddot{\theta} + B\dot{\theta} = \tau_r + \tau_h + \tau_p, \tag{1}$$

where θ is the DP angular position, I is the combined patient-robot inertia, B is the combined system damping, τ_r is the torque generated by the robot's impedance control, τ_h is the torque generated by the patient, τ_p is the external torque simulating the object weight (watermelon) or upward thrust (balloon). The external torque is artificially generated by the robot motors by adding a constant value to the applied torque (assumes small values of θ).

The Anklebot's PD controller is defined as:

$$\tau_r = K_r \theta_e - B_r \dot{\theta}, \tag{2}$$

where $\theta_e = \theta_d - \theta$ is the position error, θ_d is the desired DP angular position, $\dot{\theta}$ is the DP angular velocity, and K_r and B_r are, respectively, the desired stiffness and damping of the impedance controller.

Assuming the patient adopts a position error-based control solution similar to the robot controller, we can model the patient behavior as:

$$\tau_h = K_h \theta_e - B_h \dot{\theta}, \tag{3}$$

where K_h and B_h are, respectively, the patient stiffness and damping.

Replacing (2) and (3) in (1), and assuming steady state condition, the patient's stiffness can be estimated as:

$$\hat{K}_h = \frac{\tau_p}{\theta_e} - K_r, \tag{4}$$

where $\hat{K}_h$ assumes only positive values, that is, $\hat{K}_h = min\{\frac{\tau_p}{\theta_e} - K_r, 0\}$. Equation (1) indicates that the ratio between the external torque and the steady state position error minus the stiffness imposed by the robot defines the stiffness of the patient. This makes sense, since the sum of patient and robot stiffnesses must reflects the ratio between the external torque and the position error.

IV. Adaptive Control Strategies

In this paper, we propose two strategies to compute the robot stiffness according to the patient behavior, leading s/he to perform the best effort and complete successfully the task imposed by the game. The robot stiffness is adapted online based on the patient's stiffness estimate.

A. Complementary Adaptive Control

The first assistance strategy is based on the necessary stiffness the patient-robot system must achieve to obtain an acceptable performance. To this end, we define an admissible error, θ_e^{adm}, and compute the necessary combined stiffness as:

$$K^{adm} = \frac{\tau_p}{\theta_e^{adm}}. \tag{5}$$

Thus, the robot stiffness is determined by the following equation:

$$K_r^c = K^{adm} - \hat{K}_h, \tag{6}$$

where K_r^c also assumes only positive values and $\hat{K}_h$ is the patient's estimate stiffness, computed in the previous section.

B. Optimal Adaptive Control

This strategy proposes to generate the robot stiffness so as to minimize a cost function that characterizes the assist-as-needed paradigm. Interaction between patient and robot is equivalent to the teacher-student relationship, where the best result is achieved when the teacher (robot) minimizes the student error (patient), while minimizing its own effort [11].

The cost function associated with the robot behavior in a patient learning process is as follows:

$$J = \theta_e^2 + \beta \tau_r^2, \tag{7}$$

where $\beta > 0$ is weighting parameter. Assuming again steady state condition, $\tau_r = K_r \theta_e$, hence:

$$J = \theta_e^2 \left(1 + \beta K_r^2\right). \tag{8}$$

From (4), the final form of the function to be optimized is given by:

$$J = \tau_p^2 \frac{\left(1 + \beta K_r^2\right)}{\left(K_r + \hat{K}_h\right)^2}. \tag{9}$$

Differentiating J with relation to the robot stiffness, K_r, and equating to zero, we can find the minimum of the cost function:

$$\frac{\partial J}{\partial K_r} = 2\tau_p^2 \frac{(\beta K_r K_h - 1)}{\left(K_r + \hat{K}_h\right)^3}. \tag{10}$$

Solving for K_r:

$$K_r = \frac{1}{\beta \hat{K}_h}. \tag{11}$$

Thus, the robot stiffness should be inversely proportional to the estimated stiffness of the patient. A similar result is obtained in [8], however, in that work the patient's stiffness is assumed to be constant.

In the above solution, since no admissible error is defined and considering no patient participation ($\hat{K}_h \approx 0$), the best way to achieve the desired position is to increase indefinitely the robot stiffness. In order to prevent such a situation, the following constraint is defined:

$$K_r^o = min\left\{K^{adm} - \hat{K}_h, \frac{1}{\beta \hat{K}_h}\right\}. \tag{12}$$

Figure 3 shows a schematic representation of (6) and (12), for $\beta = 0.5$, with relation to the patient's estimate stiffness.

C. Performance-based Adaptation

Regarding (6) and (12), if the patient does not participate during a given target appearance ($\hat{K}_h \approx 0$), the robot will completely assist the movement within an error threshold, which is defined in the interactive environment as the condition to the next target appearance. In order to impose a necessary participation of the patient, an assistance factor

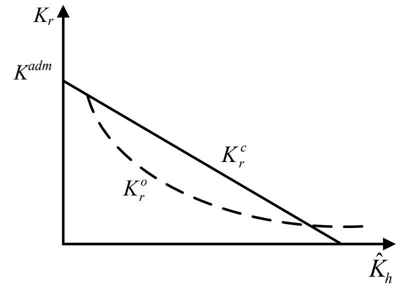


Fig. 3. Schematic representation of the assistance strategies.

is defined, limiting the robot action. The practical robot stiffness, $\overline{K}_r$, is given by:

$$\overline{K}_r = \alpha K_r, \tag{13}$$

where $0 < \alpha < 1$ is the assistance factor. If α is defined, for example, as 0.5, the robot will assist up to the double of the admissible error in case of no patient participation.

The proposed adaptive strategy is a simple performance-based strategy of the form:

$$\alpha_{k+1} = f\alpha_k + g(1 - P), \tag{14}$$

where k is a given game sub-section consisting of a set of target appearances, f and g are, respectively, the forgetting and gain factors, and P is the performance measurement given by:

$$P = \frac{N_s}{N}, \tag{15}$$

where N_s is the number of successfully completed movements during a given game section and N is the number of targets in that sub-section. If the patient has a good performance during the section ($P \approx 1$), the robot assistance decreases by reducing α, due to the forgetting factor, challenging the patient in the next section. On the other hand, if the patient has a poor performance ($P \approx 0$), the robot assistance increases due to the gain factor g.

The block diagram of the proposed adaptive stiffness control solution is presented in Figure 4.

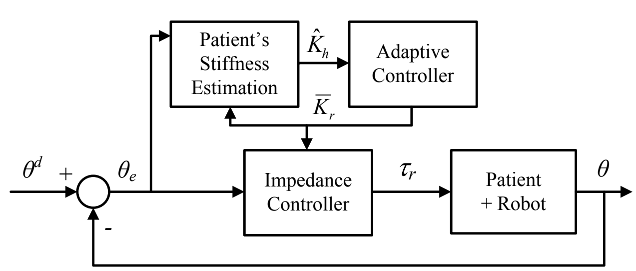


Fig. 4. Adaptive Impedance Control.

V. RESULTS

The proposed control schemes for robot stiffness adaptation were first evaluated on a patient-robot system simulator. We then tested, as a proof of concept, in one person with stroke during two sessions. This study was approved by the Ethics Committee of the Federal University of São Carlos (Number 26054813.1.0000.5504) and was conducted at their clinic.

A. Simulation

The patient-robot system was modeled using the SimMechanics toolbox of Matlab/Simulink, according to the actuation principle of Anklebot, which considers two linear actuators mounted in parallel to the leg, Figure 5. The adaptation and control laws, as well as dynamic trajectories generator, were implemented in embedded Simulink blocks. In this paper, it is assumed a model of the ankle, as defined by (3).

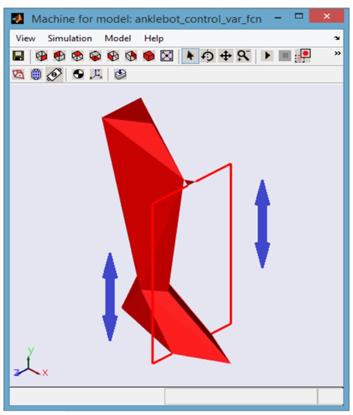


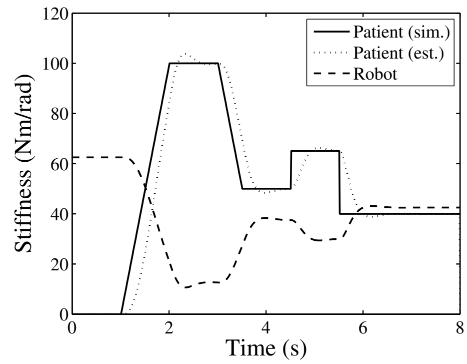
Fig. 5. SimMechanics model of Anklebot-patient system.

Figure 6 shows the patient's stiffness estimate and adapted robot's stiffness for a given profile for the actual patient's stiffness. Note that the estimated value converges to the actual one in the steady state condition. The estimation dynamics can be adjusted by properly adjusting the damping control parameter, B_r, of the robot controller.

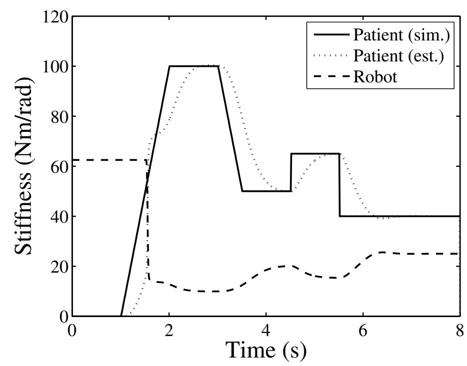
B. Impaired Subject

Two sessions were performed by a stroke patient: male, 57 years old, 62 kg, 84 months since onset, right hemiparesis, right-side dominant, no Ankle-Foot Ortheses use, Barthel score 19, Berg score 38, Timed Up and Go test (TUG) 29.7 s, walking speed 0.56 m/s (10 m - limited community ambulator).

The evaluations occurred at the same day, with an interval of 30 min between them. The experimental protocol consists of the evaluation of the two adaptive solutions, complementary and optimal, with the patient performing 100 movements (50 dorsiflexions and 50 plantarflexions) during each game section (a 5 min rest time is given to the patient between games).



(a)



(b)

Fig. 6. Simulated patient's stiffness, estimated patient's stiffness, and robot's stiffness: (a) complementary adaptive control and (b) optimal adaptive control.

The external torque simulating the watermelon's weight or balloon's thrust, τ_p, is defined as 3 Nm, representing approximately 20 N of weight (thrust) at the forefoot. Actually, the external torque changes gradually from -3Nm (dorsiflexion) to 3Nm (plantarflexion), and vice-versa, after the subject hits the targets or after the available time period (3 s) expires. The desired positions representing the targets, θ_d, are defined as 7° rad (dorsiflexion) and -7° rad (plantarflexion). The admissible error is defined as 20% of the desired position, ie., θ_e^{adm} = 1.4°. From (5), the necessary combined stiffness is K^{adm} = 125 Nm/rad.

The performance-based adaptation procedure, Section IV-C, starts with $\alpha = 0.5$ and updates its value every 10 movements, defined as a game sub-section, that is, N = 10 in (15). The following parameters are used: f = 0.95, g = 0.1, $B_r = 1$ Nms/rad, and β = 0.0005.

Figure 7 shows typical responses for patient's stiffness estimate, robot's stiffness, and ankle DP position for both adaptive control strategies. The figures shows a successful movement attempt and only the period of time where the patient's stiffness estimate is not zero, that is, only when there is an estimated active participation of the patient. The robot's stiffness starts with the maximum allowed value, αK^{adm} = 62.5 Nm/rad (computed from (6), (12), and (13), with $\hat{K}_h = 0$) and decreases according to the increase of patient participation following the same set of equations.

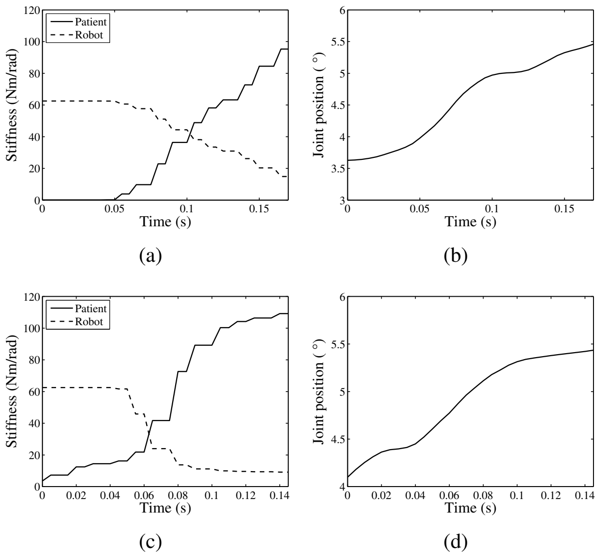


Fig. 7. Typical responses for patient's stiffness estimate, robot's stiffness, and ankle DP position: (a) and (b) complementary adaptive control, (c) and (d) optimal adaptive control.

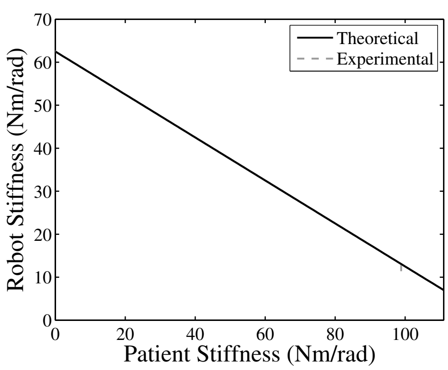


Fig. 8. Robot's stiffness versus patient's stiffness estimate, complementary adaptive control.

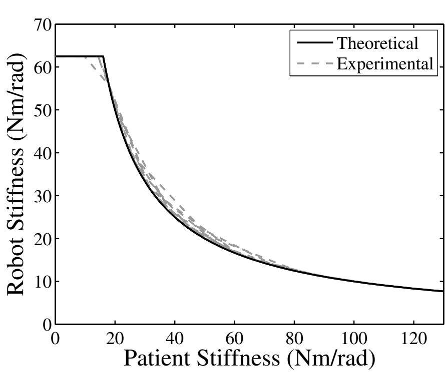


Fig. 9. Robot's stiffness versus patient's stiffness estimate, optimal adaptive control.

The decrease rate of the complementary adaptive solution is lower than of optimal one. This behavior could be predicted, since Figure 3 shows a greater declination rate for the optimal adaptive curve for small values of $\hat{K}_h = 0$. Actually, Figures 8 and 9 show robot's stiffness versus patient's stiffness estimate experimental results, respectively, for complementary and optimal adaptive solutions, and the corresponding theoretical curves, for $\alpha = 0.5$.

The resulting robot's stiffness curves can explain a characteristic observed from the two evaluations. The mean time to complete the task (MT) for the optimal solution is lower than for the complementary one, Table I. As the robot decreases its actuation early in the optimal case, the patient detected the change in the level of assistance and he had also to increase his participation early, completing the task in a shorter time.

TABLE I

MEAN TIME TO REACH THE TARGET (MT) AND COST FUNCTION (J_T).

	Evaluation 1		**Evaluation 2**	
	MT (ms)	J_T	MT (ms)	J_T
Complementary	387	0.107	497	0.121
Optimal	306	0.059	386	0.070

Table I also shows the computed cost function over time, J_T, considering only the time periods where we have active participation of the patient, i.e.:

$$J_T = \sum_{i=1}^{n} \int_{T_0^i}^{T_f^i} (\theta_e^2 + \beta\tau_r^2)dt, \qquad (16)$$

where $n = 100$, T_0 and T_f are the time instants where the patient, respectively, starts his active participation and reaches the target (in Table I, $MT = \sum_{i=1}^{n} (T_f - T_0)/n$). Note that the optimal solution presents, as expected, the lowest value of cost function for the two schemes.

Regarding the performance-based adaptation, Figure 10 shows the values of α and P obtained at the first evaluation of the optimal adaptive control solution. The results for the other evaluations are similar. Figure 11 shows the computed cost function over time for the game sub-sections, that is,

$$J_{10}(k) = \sum_{i=1+(k-1)N}^{kN} \int_{T_0^i}^{T_f^i} (\theta_e^2 + \beta\tau_r^2)dt, \qquad (17)$$

for $k = 1, ..., 10$ and $N = 10$. Note that the patient's performance is sustained at a high level during the game section and the level of robot assistance, represented by α, is decreased according to (14). As consequence, the optimal solution imposes a higher participation of the patient which, in the given example, results in an increase of the cost function, mainly due to the increase of the position error.

VI. CONCLUSIONS

In this paper, we proposed and evaluated two adaptive impedance control schemes for rehabilitation robotics, with

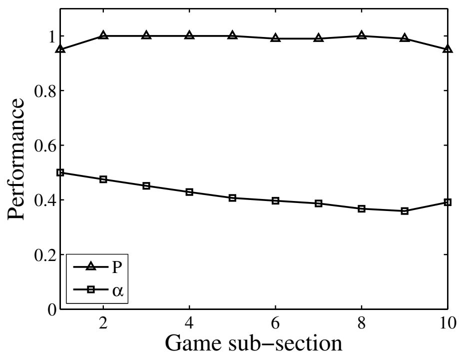


Fig. 10. Performance-based adaptation, α and P, evaluation 1, optimal adaptive control.

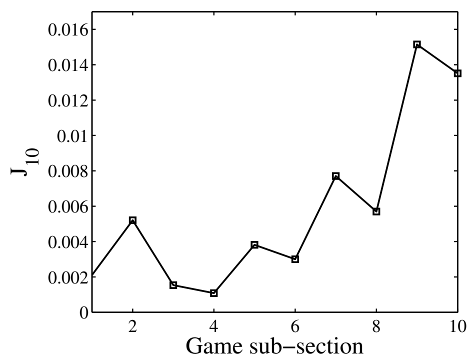


Fig. 11. Computed cost function over time for the game sub-sections, evaluation 1, optimal adaptive control.

experimental validation using the Anklebot. The two solutions, complementary and optimal, are based on an online estimation of the patient's stiffness (which, in some sense, represents an estimate of the active participation of the patient). Simulated and experimental results show that the proposed control strategies can effectively estimate the patient's stiffness and properly set the level of robot assistance in order to complete the task. The optimal solution seems to further stimulate the active participation of the patient by reducing the robot assistance early during the task.

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