Patient-Cooperative Control: Adapting Robotic Interventions to Individual Human Capabilities

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Abstract— **Patient-cooperative control strategies aim at improving the efficacy of current rehabilitation robots. The key aspects of these strategies are the transparency of the robots, constraints for safety and guidance, and individual interventions. Within the frame of transparency and constraints, interventions of challenging or facilitating nature can be applied. In this paper, we propose a way of providing facilitating interventions by force fields or global parameters, which are adapted by iterative learning control. We evaluate this approach in two scenarios with the rehabilitation robot Lokomat; first, to assist knee extension during stance phase, and second, to modulate how actively human subjects participate in bearing their own body weight. Both examples show that iterative learning control algorithms provide a feasible way to allow patients to train at a continuously challenging level according to their individual capabilities.**

Keywords— **Rehabilitation robotics, patient-cooperative control, assist-as-needed, iterative-learning control**

I. INTRODUCTION

Neurological conditions such as stroke and spinal cord injury frequently cause walking disabilities. Body weight supported treadmill training (BWSTT) is successfully applied to the rehabilitation of patients suffering from these conditions [1], [2].

Robotic rehabilition devices such as the Lokomat (Hocoma AG, Switzerland) [3], the ReoAmbulator (Motorika, USA), and the Gait Trainer (Reha-Stim, Germany) automate BWSTT by moving patients repetitively along pre-defined walking trajectories. However, recent studies indicate that the way in which these devices are currently used in therapy is not optimally effective for all groups of patients [4], [5]. The strong guidance of the robots allows patients to remain completely passive, which leads to reduced activity of muscles and metabolism [6].

Therefore, patient-cooperative control strategies are being developed by numerous research groups [7]–[15]. These strategies aim at empowering patients to influence their movements, while still providing sufficient guidance and support to ensure successful walking. We can summarize the desired properties of cooperative controllers in three key terms: Transparency, constraint, and intervention.

Transparency means the ability of the robot to "get out of the way": Movements that can be achieved by the patient's own efforts should not be distorted by the interaction with the robot. This property can be either achieved by very lightweight mechanical design as e. g. in the LOPES robot [16], or by means of control algorithms such as the recently developed approach of "Generalized Elasticities" [17].

Constraints restrict the possible movements with the robot such that the patient is safe and can only move in physiologically meaningful ways. This concept originates from the idea of "virtual fixtures" [18], and has led to a number of control strategies which provide spatial guidance, but allow free timing of movements [11]–[13].

Transparency and constraints are apparently competing interests: The presence of constraints violates transparency. However, a patient being able to train with a completely transparent rehabilitation robot would not need any therapy at all. Patient-cooperative control needs to find the right balance between transparency and control to provide a safe frame that enables the patient to train.

Within this safe and enabling frame, the robot can apply an individual *intervention* to the patient. Two fundamental types of interventions are possible: challenging and facilitating interventions.

Challenging interventions are e. g. velocity-dependent resistance, which has been shown to increase muscle activity and generate beneficial after-effects [19], or error augmentation, which has led to improved motor learning in upper extremity training of stroke survivors [20].

However, during gait training, patients first and foremost have to be enabled to walk successfully. This aim may be compromized by challenging interventions. Therefore, facilitating interventions are being favored for gait rehabilitation robots.

A direct way to realize facilitating interventions is to immediately reduce movement errors, as with impedance control [8], [21]. Variants of this approach generate reference trajectories which are more individual, e. g. by minimizing interaction forces [7], or by inferring movement intentions from other limbs of the patient [14].

Based on the assumption that patients benefit most from rehabilitation if they participate as actively as possible, there is a general consensus that facilitating interventions should ideally assist only as much as needed [9]. For impedance control, this can be achieved by locally adapting the controller stiffness according to the control errors [15].

In contrast to methods with immediate error reduction,

O. Dössel and W.C. Schlegel (Eds.): WC 2009, IFMBE Proceedings 25/IX, pp. 271–274, 2009.
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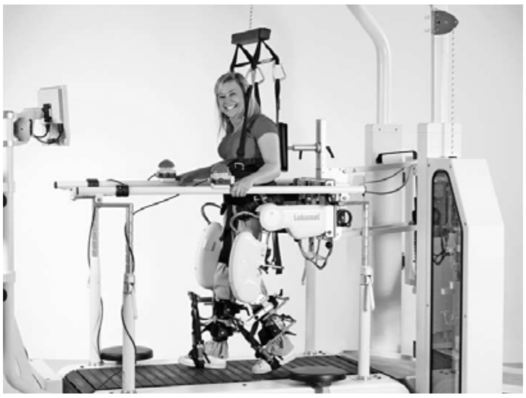

Fig. 1. The Lokomat gait rehabilitation robot with Lokolift body weight support system (Photo courtesy of Hocoma AG, Switzerland)

individual interventions can also be realized by adaptive force fields. An intriguing advantage of this approach is the possibility to read out the adapted force field after the training and interpret it as a model of the patient's weaknesses [22]. To adapt such force fields, we can exploit the highly repetitive nature of rehabilitation training. Iterative learning control [23] algorithms can be used to adapt robotic support from repetition to repetition. This way, all available information from a complete cycle can be taken into account for the adaptation.

In this paper, we propose an adaptive algorithm based on iterative learning control that adjusts the support to the amount needed to maintain walking, but keeps the patient constantly challenged to participate as much as possible in the training. We will demonstrate the use of the algorithm in two different applications for the rehabilitation robot Lokomat: first, to shape an assistive force field applied at the knee joint to assist weight bearing during stance phase, and second, to automatically adjust the amount of body weight support provided to the patient.

II. MATERIALS & METHODS

A. Rehabilitation Robot

Experiments were performed with the gait rehabilitation robot Lokomat (Fig. 1). The robot has been developed to automate body weight supported treadmill training of patients with locomotor dysfunctions in the lower extremities such as spinal cord injury and hemiplegia after stroke [3]. It comprises two actuated leg orthoses that are attached to the patient's legs. Each orthosis has one linear drive in the hip joint and one in the knee joint to induce flexion and extension movements of hip and knee in the sagittal plane. Knee and hip joint torques can be determined from force sensors integrated inside the Lokomat. A closed-loop controlled body weight support system ("Lokolift") relieves the patient from a definable amount of his or her body weight via a harness, which is attached to the patient's trunk [24].

B. Iterative Learning Support

An adaptation algorithm based on iterative learning control (ILC) is used to adjust the amount of support provided to the patient. The basic idea of ILC is the iterative improvement of an input function for a cyclic process. The input function for the $(k+1)^{\text{th}}$ cycle $\mathbf{u}^{(k+1)}(t)$ is determined by adding a correction term to the input function of the k^{th} cycle

$$\mathbf{u}^{(k+1)}(t) = \mathbf{u}^{(k)}(t) + \Gamma(t)\mathbf{e}^{(k)}(t) \tag{1}$$

where $\mathbf{e}^{(k)}(t)$ represents the control error during the k^{th} cycle, and $\Gamma(t)$ is the "learning gain" of the process.

Emken et al. [9] showed that an adaptive controller which is supposed to assist only as much as needed must incorporate a forgetting factor in order to keep patients continuously challenged. Introducing such a factor $k_{\text{f}} \in [0,1]$ in eq. (1) yields

$$\mathbf{u}^{(k+1)}(t) = (1-k_{\text{f}})\mathbf{u}^{(k)}(t) + \Gamma(t)\mathbf{e}^{(k)}(t). \tag{2}$$

Adaptive stance support: When the compliance of the Lokomat is increased to let patients move more freely, many patients are not capable of keeping their knee joints extended during stance phase. Therefore, we applied additional supportive torques to prevent knee buckling. For this particular case, the control error $e^{(k)}(t)$ during the k^{th} cycle is a scalar function of the control deviation in the knee joint during stance phase. Based on this error, a scalar supportive torque for the knee joint is calculated.

$$\tau_{\text{knee}}^{(k+1)}(t) = (1-k_{\text{f,knee}})\tau_{\text{knee}}^{(k)}(t) + \gamma_{\text{knee}} e^{(k)}(t) \tag{3}$$

This supportive torque is added to the output of the closed-loop impedance controller of the Lokomat [8] as a feedforward term.

Adaptive BWS: To modulate how actively a human subject participates in the Lokomat training, we adapted the body weight support F_{unload} provided by the Lokolift.

With dynamic models of human leg and Lokomat leg during single support stance phase, we can determine the theoretically needed contribution of the subject $\tilde{A}_{\text{needed}}$ and the actual contribution of the subject A_{actual} to the forces the subject needs to bear his/her own body weight [25].

We define the ratio of the actual human contribution to the theoretically needed contribution during the k-th stride as *relative human activity* $A_{\text{rel}}^{(k)}$.

$$A_{\text{rel}}^{(k)} = A_{\text{actual}}^{(k)} / \tilde{A}_{\text{needed}}^{(k)} \tag{4}$$

The error function $\mathbf{e}^{(k)}(t)$ is now replaced by the activity tracking error $\Delta A^{(k)}$.

$$\Delta A^{(k)} = A_{\text{des}} - A_{\text{rel}}^{(k)} \tag{5}$$

with A_{des} being the desired level of relative human activity. Then, the learning law for adapting the body weight support becomes

$$F_{\text{bws}}^{(k+1)} = (1-k_{\text{f,bws}})F_{\text{bws}}^{(k)} + \gamma_{\text{bws}} \cdot \Delta A^{(k)} \tag{6}$$

with $\gamma_{\text{bws}} > 0$ being the learning gain that determines how much the deviation from the desired activity $\tilde{A}_{\text{des}}$ during the current stride affects the update of the unloading force $F_{\text{bws}}^{(k+1)}$ for the next stride.

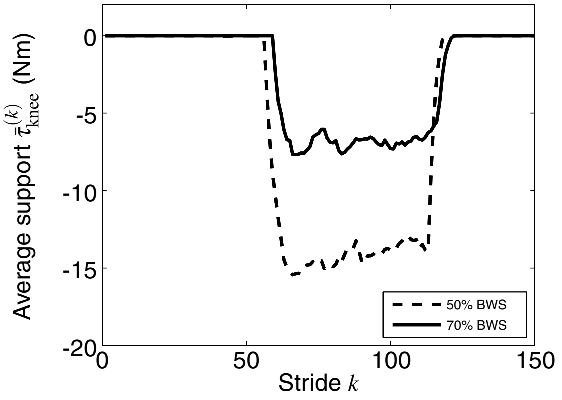

Fig. 2. Adaptive stance support $\bar{\tau}^{(k)}_{\mathrm{knee}}$ for a test subject during walking with different levels of BWS. The graph shows the average knee support during stance phase for each step. The subject was active during the first 50 steps (phase A1), passive during the next 50 steps (phase P), and active again during the last 50 steps (phase A1).

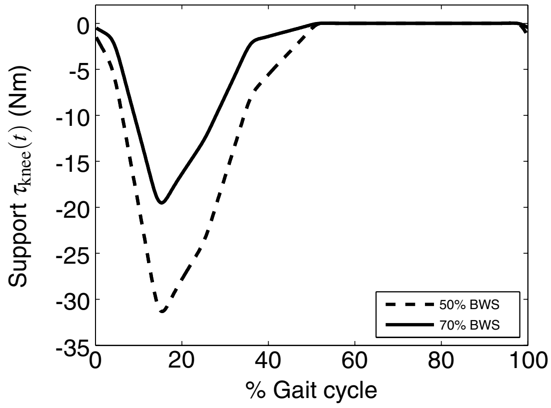

Fig. 3. Output τ_{knee} of adaptive feedforward support component during the 100$^{\mathrm{th}}$ stride for a test subject walking with 50% body weight support (dashed line) and 70% body weight support (solid line).

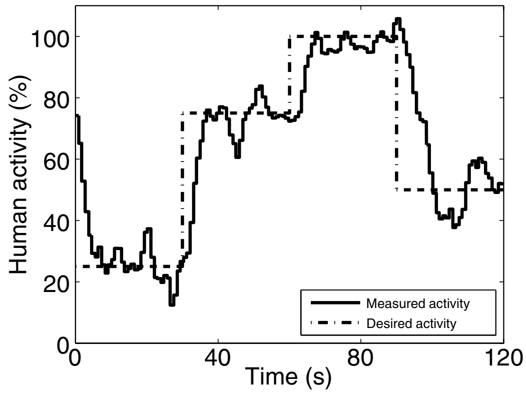

Fig. 4. Activity tracking for one exemplary subject walking with the adaptive BWS controller. The measured human activity $A^{(k)}_{\mathrm{rel}}$ (solid line), and the desired level of activity A_{des} (dash-dotted line) are plotted over the time course of the experiment.

C. Experimental evaluation

Adaptive stance support: Three healthy, male subjects were instructed to walk in the Lokomat under 2 different conditions: with 50% body weight support and adaptive support for knee extension, and with 70% body weight support and adaptive support for knee extension. Under each condition, the subjects walked actively for 2 minutes (phase A1), followed by 2 minutes of passive walking (phase P) and another 2 minutes of active walking (phase A2). For phase A1 and A2, the subjects were instructed to actively extend their knees during stance phase. For phase P, they were instructed to simulate not being able to carry their body weight on their own. The resulting support $\tau_{\mathrm{knee}}(t)$ was recorded for the left leg, and the average support $\bar{\tau}^{(k)}_{\mathrm{knee}}$ was calculated for each stride.

Adaptive BWS: Eight healthy subjects participated in the evaluation. After an acclimation phase of 30 seconds with a BWS level of 30% of the subjects' body mass, the adaptive BWS controller was enabled. The controller modified the provided BWS to make the subjects walk with the desired level of activity. Four different levels of activity were targeted (25%, 50%, 75%, and 100%). The order of the levels of activity was randomized and not revealed to the subjects.

III. RESULTS

Adaptive stance support: When the subjects walked with the Lokomat while adaptive support during stance phase was provided, the support stayed at a minimal level during active walking, increased to a high level during passive walking, and returned back to the initial level when the subjects walked active again (Fig. 2).

During the passive walking phase, the support model adapted to a unimodal output profile with a maximum of support during mid stance phase (Fig. 3).

In all subjects, the knee support during passive walking with 50% body weight support was significantly higher than during passive walking with 70% body weight support.

Adaptive BWS: The iterative learning algorithm for adapting the body weight support successfully tracked the desired levels of physical activity in the test subjects (Fig. 4).

IV. DISCUSSION

The adaptive stance support for the knee joint reacted as desired to the simulated weakness of the human subjects. The resulting output of the controller can be interpreted as a model of the simulated weakness. The model produced the highest output during mid stance phase when in fact most support is needed. Furthermore, the model output also reflected the changes in environment conditions: When the BWS system took over more body weight, the adaptive feedforward support contributed less.

The latter observation demonstrates that in the presence of other potentially active components of the cooperative controller, the model fitted by the adaptive support component does not necessarily represent the absolute weakness of the patient. Thus, the outputs of the fitted model may only be used as an assessment of patient performance if the contributions of all other components of the system are either taken into account or kept constant for all measurements that are supposed to be compared.

The example of the adaptive BWS controller shows that it is not only possible to react to the state of a human subject but also to manipulate the state of a human subject in a targeted way. The cycle-to-cycle update of the iterative learning controller makes it possible to use complex model-based calculations which rely on information from a longer time horizon for the update of the adaptive support.

More comprehensive support models may be realized by taking results from the field of "robot learning" into account, where excellent controller performance has been achieved when the controller learned a feedforward model of the—*a priori* unknown—dynamics of a robot even in high-dimensional spaces [26].

V. CONCLUSION

Individual interventions in patient-cooperative control approaches can be realized by supportive force fields or single support parameters, such as the level of body weight support. Iterative learning control algorithms are well suited to adapt these means of support to the individual capabilities of a human subject. Thus, they provide a feasibly way to train at a continuously challenging level.

ACKNOWLEDGMENTS

The authors would like to thank all subjects who participated in the evaluation. The contents of this publication were developed in part under a grant from the US Department of Education, NIDRR grant number H133E070013. However, those contents do not necessarily represent the policy of the US Department of Education, and you should not assume endorsement by the Federal Government of the United States of America.

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