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Adaptive body weight support controls human activity during robot-aided gait training

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Abstract— **Current clinical practice of robot-aided gait training is not as effective as expected. Cooperative control strategies aim at improving the effectiveness of robot-aided training by empowering patients to participate more actively. Our group has recently proposed the concept of bio-cooperative control, which explicitely considers the role of the human in the loop, as an extension of these strategies. A supervising controller adapts the cooperative control loops in a way that guarantees appropriate stimuli and prevents undue stress or harm for the patients. In this paper, we implement this concept with an adaptive body weight support algorithm. The algorithm was evaluated with the Lokomat gait rehabilitation robot and the Lokolift body weight support system. Experiments showed that human activity was successfully controlled during Lokomat walking. The desired level of activity was effectively limited when subjects simulated weakness in load bearing. The proposed algorithm may help to train patients with neurological gait impairments in a more engaging and, thus, hopefully more effective way.**

I. INTRODUCTION

Walking disabilities are a common consequence of neurological conditions such as stroke, spinal cord injury, traumatic brain injury, cerebral palsy, and multiple sclerosis. Body weight supported treadmill training is applied to the rehabilitation of patients suffering from these conditions, and it has been shown to be effective especially in stroke [1] and incomplete spinal cord injury [2].

However, this kind of training is strenuous and physically demanding for therapists; thus, it is usually limited by personnel shortage and fatigue of the therapist. Therefore, several robotic devices have been developed to overcome these deficiencies. The first generation of these devices has been in clinical use for several years: the Lokomat (Hocoma AG, Switzerland) [3], the ReoAmbulator (Motorika, USA), and the Gait Trainer (Reha-Stim, Germany) [4].

Recent studies indicate that the way in which these devices are currently used in the clinics is not optimally effective for all groups of patients [5]. The strong guidance of the robots allows patients to remain completely passive, which leads to reduced activity of muscles and metabolism [6].

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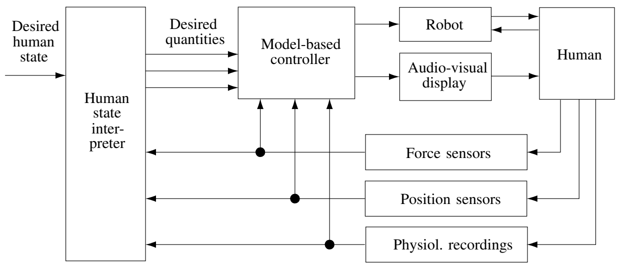

Fig. 1. The human subject as an integral component of the bio-cooperative control loop with respect to biomechanical and psycho-physiological aspects (adapted from [13]).

To ameliorate these shortcomings, cooperative control strategies are being developed by numerous research groups [7]–[12]. These strategies aim at empowering patients to influence their movements, while still providing sufficient guidance and support to ensure successful walking.

Recently, our group has proposed an extension of the cooperative paradigm by focusing on the role of the human in the control loop [13]. In the suggested *bio-cooperative* framework, the biomechanical and psycho-physiological states of the human subject are explicitly taken into account and interpreted by a supervising "state interpreter" (Fig. 1). This interpreter estimates aspects of the psycho-physiological state of the human subject which are relevant the training. Such aspects may be engagement, stress, fun, boredom, etc. Based on these estimates, the desired quantities for the subordinate (and potentially cooperative) controllers are adapted such that the human subject always receives appropriate stimuli and is challenged in a moderate but engaging and motivating way without causing undue stress or harm.

In this paper, we present a setup in which the bio-cooperative concept is applied to robot-aided gait rehabilitation. We focus in this setup on a key parameter of gait training: the (un)loading of the stance leg. Partial body weight support (BWS) is important to facilitate successful walking and to allow the patient to successfully employ their limited abilities [14]. On the other hand, it is desirable to load the patient's stance leg as much as possible to maximize afferent input to the nervous system [15] and physical activity [16]. A bio-cooperative controller for the BWS should fulfill two main requirements. First, it needs to be able to drive the human subject to a desired level of active participation. Second, it shall limit the desired level of active participation according to the capabilities and current state of the human subject, to avoid overloading and undue stress during the

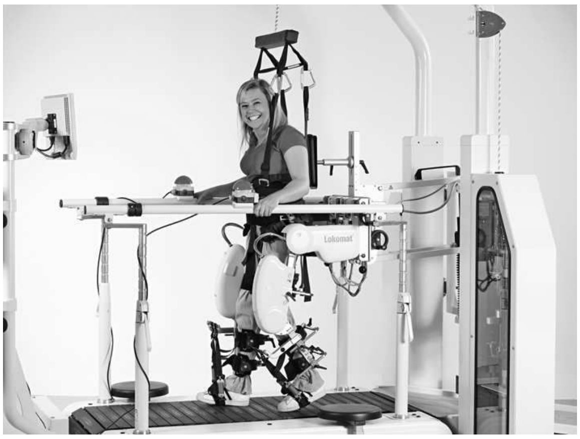

Fig. 2. The Lokomat gait rehabilitation robot with Lokolift body weight support system (Photo courtesy of Hocoma AG, Switzerland)

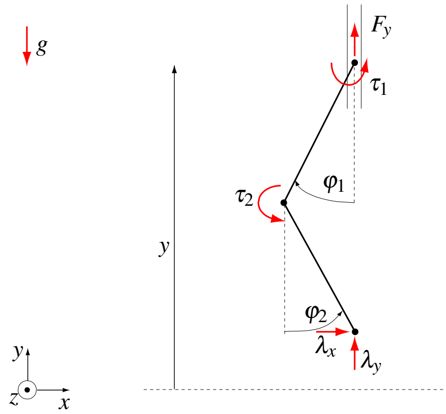

Fig. 3. 3-dof model with minimal coordinates y, φ_1 and φ_2, external forces F_y, τ_1, and τ_2, and contact forces λ_x and λ_y.

training.

In the following, we will sketch the development of an algorithm for adaptive body weight support (aBWS) and evaluate the algorithm with respect to these two requirements.

II. MATERIALS & METHODS

A. Gait Rehabilitation Robot

Experiments were performed with the gait rehabilitation robot Lokomat (Fig. 2). 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 [17]. 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 [18].

B. Model of the leg during stance phase

During gait training with the Lokomat system, a number of components interact with the human subject to facilitate walking. The treadmill, the BWS system, and the motors of the exoskeleton all apply forces to the human body. These components are controlled by independent closed-loop controllers. Thus, it is not immediately apparent how much the human subject actually contributes to the walking movements. To quantify how actively a human subject participates in bearing his or her own body weight, we developed a mechanical model for the single-support stance phase, i. e. when only one foot is in contact with the ground. In this phase, the load on the particular stance leg is the highest, thus, it contains the most decisive information on the subject's load bearing contribution.

To keep the model as simple as possible, the following assumptions were made. First, the subject does not introduce forces other than those produced by the leg muscles (i. e. the subject does particularly not interact with the parallel bars of the treadmill). Second, the exoskeleton legs and the human legs are considered as rigidly coupled, i. e. the joint angles of Lokomat and human subject match at all times. In our implementation, these assumptions were fulfilled by applying the following means: Subjects were instructed to not support their weight with their arms on the parallel bars of the treadmill. Compliant impedance control [7] was used for controlling the Lokomat exoskeleton to prevent high interaction forces between exoskeleton and human subject. Such high interaction forces would be able to displace exoskeleton and human legs by deforming the cuffs of the exoskeleton.

A model containing all major relevant aspects of Lokomat and human subject incorporates three degrees of freedom (3-dof) in the minimal coordinates y, φ_1 and φ_2, where y is the height of the center of rotation of the hip joint above the ground, φ_1 is the angle of the upper leg segment to the vertical and φ_2 is the angle of the lower leg segment to the vertical. Inputs to the model are the vertical force F_y (support by arms and BWS system), the joint torques in the hip joint τ_1 and in the knee joint τ_1 (caused by exoskeleton motors and human muscle activity), and the horizontal and vertical ground reaction forces λ_x and λ_y (Fig. 3).

However, not all relevant quantities for the model can be measured with the Lokomat system (y, λ_x, and λ_y cannot be determined directly). Therefore the model was reduced to a 1-dof model with the additional assumption that the foot of the subject does not slip on the treadmill and the foot sole stays flat on the ground. To fulfill this assumption, an automatic synchronization algorithm [19] kept Lokomat and treadmill perfectly synchronized, preventing foot slipping on the treadmill.

The coordinates of the 3-dof model can then be expressed by the single coordinate ϕ and the external excitation $e(t)$, which is the horizontal position of the subject's foot on the

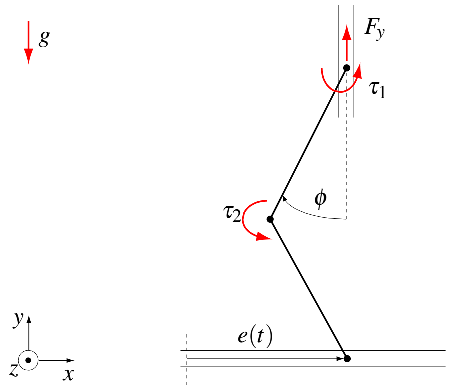

Fig. 4. 1-dof model with minimal coordinate ϕ, external excitation $e(t)$ and external forces F_y, τ_1 and τ_2.

treadmill (Fig. 4).

$$\varphi_1 = \phi \quad (1)$$

$$\varphi_2 = \arcsin\left(\frac{e(t) + l_1 \sin(\phi)}{l_2}\right) \quad (2)$$

$$y = l_1 \cos(\phi) + l_2 \sqrt{1 - \frac{(e(t) + l_1 \sin(\phi))^2}{{l_2}^2}} \quad (3)$$

where l_1 and l_2 are the length of the upper and the lower leg segment of the human leg, respectively.

By applying the second Lagrange method [20], we can then derive a one dimensional differential equation that completely describes the dynamics of the human subject.

$$f_{\mathrm{H}}(\phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t))\ddot{\phi} = h_{\mathrm{H}}(\tilde{\tau}_{\mathrm{hum}}, \phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t)) \in \Re^1 \quad (4)$$

The quantity $\tilde{\tau}_{\mathrm{hum}}$ is the projection of the forces and torques caused by human muscle activity to the remaining degree of freedom ϕ (i. e. to a torque in the hip joint). Dynamic properties of the human body—like segment lengths, segment masses, centers of gravity and moments of inertia—are estimated based on body height and body mass according to anthropometric approximations of Winter [21]. A similar modeling approach was used in [22] for the design of a passive swing assistive exoskeleton.

Analogously, a one dimensional differential equation for the Lokomat leg can be derived.

$$f_{\mathrm{L}}(\phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t))\ddot{\phi} = h_{\mathrm{L}}(\tau_{\mathrm{exo}}, \phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t)) \in \Re^1 \quad (5)$$

The quantity τ_{exo} is the projection of the forces and torques caused by the Lokomat motors in the hip and knee joint and the force applied by the BWS system to the remaining degree of freedom ϕ. Finally, equations (4) and (5) can be combined to one differential equation for the whole system

$$f(\phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t))\ddot{\phi} = h(\tau_{\mathrm{ext}}, \phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t)) \in \Re^1 \quad (6)$$

where τ_{ext} is the sum of the projected contributions of human subject and Lokomat system. The contributions of the Lokomat system τ_{exo} are known. Using an analytical solver, (6) can be solved for τ_{ext}

$$\tau_{\mathrm{ext}}(t) = g(\phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t)) \in \Re^1 \quad (7)$$

and the actual human contribution τ_{hum} can be determined.

$$\tau_{\mathrm{hum}}(t) = \tau_{\mathrm{ext}}(t) - \tau_{\mathrm{exo}}(t) \quad (8)$$

Analogously, we can solve (4) for $\tilde{\tau}_{\mathrm{hum}}$ to obtain the human contribution which would have been necessary to move only the isolated human subject along the trajectory $\phi(t)$.

$$\tilde{\tau}_{\mathrm{hum}}(t) = g_{\mathrm{H}}(\phi, \dot{\phi}, e(t), \dot{e}(t), \ddot{e}(t)) \in \Re^1 \quad (9)$$

Finally, we define the ratio of the actual human contribution to the theoretically needed contribution as *relative human activity* A.

$$A(t) = \frac{\tau_{\mathrm{hum}}(t)}{\tilde{\tau}_{\mathrm{hum}}(t)} \quad (10)$$

To obtain a representative value for the relative human activity during the whole single-support stance phase of a particular stride, we define

$$\bar{A}^{(i)} = \underset{t \in P^{(i)}_{\mathrm{stance}}}{\mathrm{median}}(A(t)) \quad (11)$$

as the overall relative human activity during the i-th stride, with $P^{(i)}_{\mathrm{stance}}$ being the time interval covered by the single-support stance phase during the i-th stride.

C. aBWS algorithm

The primary goal of the aBWS algorithm is to control the overall relative human activity of a human subject walking with the Lokomat to make the subject reach a desired level of activity A_{des}. However, the algorithm also needs to ensure that the subject is not overloaded. We assume that a walking-impaired subject can only reach a certain maximal level of activity A_{max}.

The desired adaptive behavior of the algorithm is implemented by two nested iterative-learning control (ILC) loops [23]. The inner loop uses the BWS system as "actuator" to drive the human subject to the level of activity $\tilde{A}_{\mathrm{des}}$ commanded by the outer loop (Fig. 5). The rationale behind the adaptation is that increasing the unloading force F_{unload} reduces the active participation of the human subject with respect to load bearing. Vice versa, if F_{unload} is decreased, the subject needs to be more active during stance phase. However, if the subject cannot contribute sufficiently because the desired level of activity is above his or her maximal capacity A_{max}, he or she will walk with reduced "gait quality". Therefore, the outer loop adjusts an estimated maximal level of activity $\tilde{A}_{\mathrm{max}}$ and keeps the desired level activity for the inner loop below this threshold .

If we define the activity tracking error in the i-th stride as

$$\Delta A^{(i)} = \tilde{A}_{\mathrm{des}} - \bar{A}^{(i)} \quad (12)$$

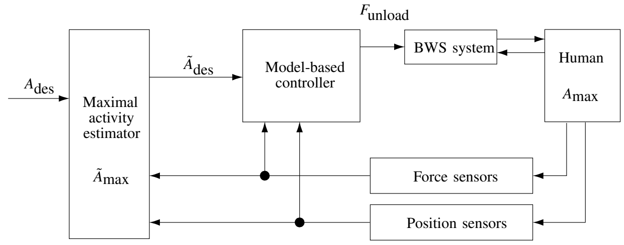

Fig. 5. The human subject in the adaptive BWS control loop

then the learning law for the inner loop can be stated as

$$F_{\text{unload}}^{(i+1)} = F_{\text{unload}}^{(i)} + \gamma_F \cdot \Delta A^{(i)} \tag{13}$$

with $\gamma_F > 0$ 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 $F_{\text{unload}}^{(i+1)}$ for the next stride.

For the outer loop, we need a measure for "gait quality" which is sensitive to a potential overloading of the human subject. If subjects walking in the Lokomat are not capable of carrying their own body weight during stance phase, they tend to walk with less extended legs, resulting in a lower position of the center of rotation of the hip joint above the ground. Using (3), we define the gait error Δy as follows

$$\Delta\tilde{y}(t) = y(\phi_{\text{ref}}(t)) - y(\phi(t)) \tag{14}$$

$$\Delta y(t) = \begin{cases} \Delta\tilde{y}(t), & \text{if } \Delta\tilde{y}(t) < m_{\text{err}} \\ 0, & \text{if } \Delta\tilde{y}(t) \geq m_{\text{err}} \end{cases} \tag{15}$$

with $\phi_{\text{ref}}(t)$ being the current point on the reference trajectory for the legs, which is used by the separate impedance controller [7] of the exoskeleton, and m_{err} is a threshold for the maximal tolerated deviation from the reference.

In accordance with the definition of the overall relative human activity in (11), we define the overall gait error $\overline{\Delta y}$ as

$$\overline{\Delta y}^{(i)} = \underset{t \in P_{\text{stance}}^{(i)}}{\text{median}} (\Delta y(t)) \tag{16}$$

In addition to the estimate of the subject's maximal level of activity $\tilde{A}_{\max}$, we also define B as the subject's "activity margin", i.e. the difference to the level of activity of 100%. Then, the update for the outer loop can be stated as

$$B^{(i)} = 1 - \tilde{A}_{\max}^{(i)} \tag{17}$$

$$B^{(i+1)} = \beta_A \cdot B^{(i)} + \gamma_A \cdot \overline{\Delta y}^{(i)} \tag{18}$$

$$\tilde{A}_{\max}^{(i+1)} = 1 - B^{(i+1)} \tag{19}$$

where $\gamma_A > 0$ is the learning gain that determines how much the gait error reduces the estimate of the subject's maximal level of activity, and $\beta_A \in [0, 1)$ is a forgetting factor that makes $\tilde{A}_{\max}$ increase again in the absence of gait errors.

Finally, the set point for the inner loop is determined by saturating the external set point A_{des} to the subject's estimated maximal level of activity $\tilde{A}_{\max}$.

$$\tilde{A}_{\text{des}} = \begin{cases} A_{\text{des}}, & \text{if } A_{\text{des}} \leq \tilde{A}_{\max} \\ \tilde{A}_{\max}, & \text{if } A_{\text{des}} > \tilde{A}_{\max} \end{cases} \tag{20}$$

D. Experimental evaluation

Eight healthy subjects (three female, five male, age: 32 ± 5 years, height 177 ± 11 cm, body mass: 76 ± 17 kg) participated in the evaluation. The experiment was conducted under three conditions. The subjects walked with the Lokomat at a treadmill speed of 2.5 km/h for 150 seconds. After an acclimation phase of 30 seconds with a BWS level of 30% of the subjects' body mass, the aBWS 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.

Under the ACTIVE condition, subjects were instructed to contribute actively to the walking movements induced by the Lokomat. Next, under the PASSIVE condition, subjects were instructed to relax their muscles during walking, relying as much as possible on the support of the Lokomat legs and the BWS system. Finally, subjects were instructed to aim for a medium activity during the SEMIPASSIVE condition.

The Lokomat legs were controlled by the impedance control algorithm described in [7], with the stiffness parameters $(K_{\text{hip}}, K_{\text{knee}}) = (300\,\text{Nm/rad}, 225\,\text{Nm/rad})$, and the damping parameters $(B_{\text{hip}}, B_{\text{knee}}) = (35\,\text{Nms/rad}, 22.5\,\text{Nms/rad})$ along a reference trajectory $\phi(t)$ recorded from healthy subjects [3].

During walking with the Lokomat, the joint angles of the hip and knee joint were recorded by the potentiometers located at the joints of the exoskeleton. Furthermore, the torques in the hip and knee joint were recorded from force sensors located at the Lokomat drives.

E. Data analysis

The estimate of the maximal level of activity $\tilde{A}_{\max}$ was averaged for each subject over each condition.

The first 10 seconds of each phase with a particular level of activity were cut out of the recordings of the activity tracking error ΔA to exclude the transitions phases between the different levels of activity. The remaining signal was considered as activity tracking error during the steady state. To assess the general controller performance at steady state, the mean and the standard deviation of this signal were calculated for each subject under each condition.

The different conditions were compared by a Kruskal-Wallis nonparametric ANOVA at the 5% significance level with Tukey-Kramer adjustment for multiple comparisons [24].

III. RESULTS

The control algorithm tracked the external reference for the level of activity A_{des} during the ACTIVE condition (Fig. 6, upper row) or the estimate of the subject's maximal level of activity $\tilde{A}_{\max}$, if $\tilde{A}_{\max}$ was below A_{des} (Fig. 6, middle and lower row).

The estimate of the subject's maximal level of activity $\tilde{A}_{\max}$ under the PASSIVE condition was significantly smaller than under the ACTIVE condition. The obtained estimates under the SEMIPASSIVE condition were distributed between

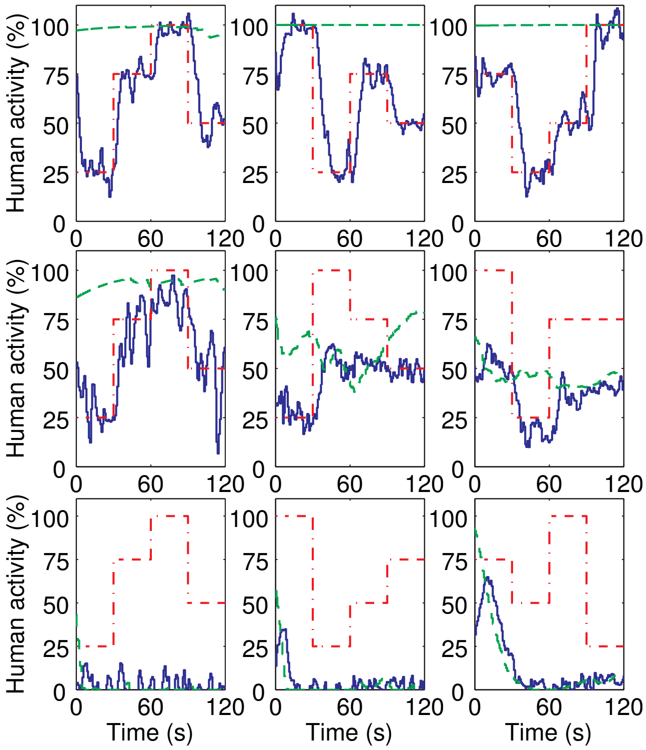

Fig. 6. Activity tracking for three exemplary subjects walking actively (condition ACTIVE, upper row), with medium activity (condition SEMI-PASSIVE, middle row), and passively (condition PASSIVE, lower row). The overall relative human activity $\bar{A}^{(i)}$ (solid blue line), the external reference for the level of activity A_{des} (dash-dotted red line), and the estimate for the subjects maximal level of activity $\tilde{A}_{\text{max}}$ (dashed green line) are plotted over the time course of the experiment.

those of the two more extreme conditions but not significantly different from them (Fig. 7).

The mean steady state tracking error was distributed around 0% under all conditions. (Fig. 8). The standard deviation during the steady state for the different subjects was distributed between 4.5% and 13% under all conditions with a median of approximately 6% (Fig. 9).

IV. DISCUSSION

The level of activity of the subjects $\bar{A}$ always followed the internal reference $\tilde{A}_{\text{des}}$ (Fig. 6). If the subjects walked actively, the internal reference matched the external reference A_{des}, otherwise the estimated maximal level of activity $\tilde{A}_{\text{max}}$ was tracked. The mean tracking errors during steady state were distributed around zero, indicating no systematic deviation from the reference activities. Thus, the aBWS algorithm can–within the limits of the capabilities of the human subject—achieve an arbitrary degree of active load bearing during robot-aided treadmill training.

Depending on how actively subjects participated, an adequate maximal level of activity was estimated: high when the subjects were walking actively, medium when the subjects were walking semi-passively, and low when the subjects were walking passively (Fig. 7). The high variance in the estimates can be explained by the fact that subjects interpreted the instructions to walk semi-passively and passively quite differently. Furthermore, it is not very easy for unimpaired subjects to walk passively in the Lokomat. Therefore, tests with patients who have real difficulties to carry their own body weight during walking have to be performed. Nevertheless, the obtained results for the estimated level of activity were consistent despite the high variability.

Currently, the algorithm is mainly limited by the very simple measure for gait quality defined in (16). If the Lokomat legs are controlled rigidly (position control or impedance control with high stiffness), the elastic coupling between the Lokomat leg and the human leg causes model inaccuracies. In such cases, the assumption that the angles of Lokomat and human legs were identical, is violated. Particularly, excess knee flexion of the human leg during stance phase does not translate to the Lokomat leg. A more sophisticated measure of gait quality taking also interaction forces between Lokomat and human subject into account would allow the combination of the aBWS algorithm with other controllers for the Lokomat legs than the impedance controller used in the evaluation for this paper.

Furthermore, the assumption that no vertical forces are exerted by the human subject using the parallel bars may be difficult to fulfill in a clinical setting. Even though subjects would not need to rely on the parallel bars as they are safely supported by the BWS system, they feel generally more comfortable if they can also partially support themselves with their arms. Additional force sensors in the parallel bars could compensate for model errors introduced by arm forces.

The proposed algorithm is intended as the basis for a training mode for active weight bearing. After estimating the subject's maximal level of activity $\tilde{A}_{\text{max}}$, subjects could be trained at a given percentage of $\tilde{A}_{\text{max}}$ to keep them constantly challenged. Graphical feedback of their current activity in relation to the desired activity may increase the motivation of the subjects in this training mode.

V. CONCLUSION

In this paper, we have implemented a bio-cooperative system by means of an algorithm that controls active participation of human subjects during robot-aided gait rehabilitation. The algorithm adapts the amount of body weight support in such way that the subject reaches a desired level of activity. If the subject is not able to participate as much as desired, the desired level of activity is automatically reduced to an achievable level. Based-on the presented algorithm, a special training mode for active weight bearing will be developed, which may help to train patients with neurological gait impairments in a more engaging and, thus, hopefully more effective way.

The next most important step will be the evaluation of the algorithm in a trial with impaired subjects.

VI. ACKNOWLEDGMENTS

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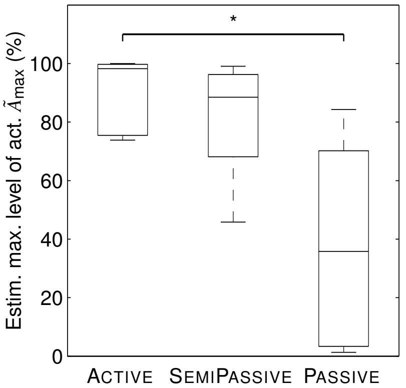

Fig. 7. Estimated maximal level of activity $\tilde{A}_{\max}$ of all subjects ($n = 8$) walking actively, with medium activity, and passively

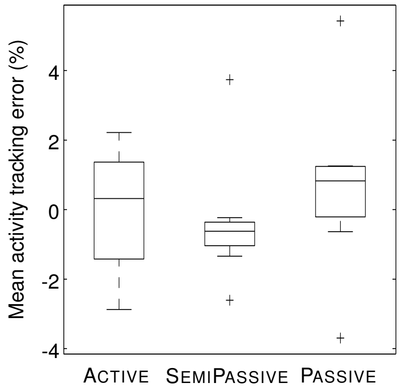

Fig. 8. Mean activity tracking error at steady state of all subjects ($n = 8$) walking actively, with medium activity, and passively

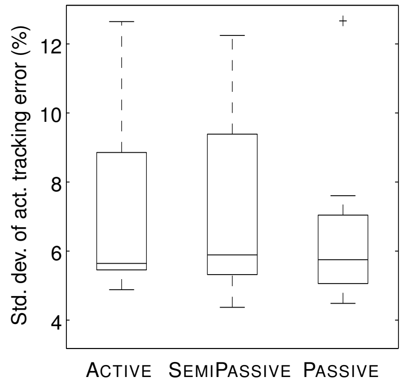

Fig. 9. Standard deviation of activity tracking error at steady state of all subjects ($n = 8$) walking actively, with medium activity, and passively

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