

Generalized Elasticities Improve Patient-Cooperative Control of Rehabilitation Robots

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Abstract—In the effort to make rehabilitation robots patient-cooperative, two prerequisites have to be met: One is providing the necessary amount of guidance and safety for the patient. Just as important is transparency, i.e. minimum interaction between robot and human when it is not needed. Recently, we suggested the method of Generalized Elasticities, which reduce undesired interaction forces due to robot dynamics by shaping optimal conservative force fields to compensate these dynamics. We now show that these conservative force fields can not only be used to minimize undesired interaction, but that they can also support and guide the patient during therapy when needed. Thus, the patient is given maximum freedom within a safe training environment, with the aim to maximize training efficacy.

I. INTRODUCTION

To promote effective rehabilitation after brain injury, a key element is intensive training [1], [2]. The strenuous labor of physiotherapists associated with conventional therapy can be alleviated by rehabilitation robots such as the commercial devices Lokomat [3] or the Gait Trainer [4]. The first versions used position control along a fixed reference trajectory. However, recent multicenter controlled trials showed that subacute and chronic stroke patients still profit more from conventional manual physiotherapy than from position-controlled gait training with the Lokomat [5], [6]. New results on motor learning and neural plasticity help explain this by the fact that position control does not allow the subjects to make errors, which is necessary for learning and the formation of an internal task representation [7], [8]. Furthermore, the robot induces motion and does not require active participation of patients. However, active participation is considered a key element for recovery [9]–[12]. These results encourage patient-cooperative control of rehabilitation robots, which allow the human to make errors. Nevertheless, the robot must also provide a safe training environment or frame. To achieve these two goals, two prerequisites are necessary: Transparent behavior when the human moves in an acceptable way, and support and guidance when needed.

To achieve transparency, one of the best means is to minimize the robot's mass. Then, its dynamics cause only small interaction forces between human subject and robot. However, mass reduction is limited when a certain force and

power are needed. Inertial forces generated by the actuators can be reduced by suitable actuation concepts, e.g. using Series Elastic Actuators [13]. However, it is difficult to avoid additional inertia after the actuators, e.g. due to an end effector or exoskeleton. Furthermore, compliant concepts compromise maximum achievable stiffness [14], which the robot might need for other tasks (like stiff guidance for severely affected patients). Closed-loop force control improves transparency by reducing reflected inertia of robot and actuators [15]–[17]. However, this reduction is limited, i.e. there will always be inertial forces remaining [16], and the control scheme requires force sensors.

As reduction of inertia is limited, a common attempt is to compensate “at least” robot gravity (and possibly Coriolis, centrifugal, and friction forces). Though this seems intuitive, it is based on the implicit supposition that the interaction force magnitude depends on the *sum of absolute values* of inertial and gravitational terms. This is true for some scenarios, e.g. when moving perpendicular to the direction of gravity, or very slowly, such that inertia is negligible. However, many rehabilitation tasks require dynamic motion instead of quasi-static behavior. Kao et al. [18] even advocate the paradigm “faster is better in rehabilitation”, because muscle activation amplitude increases with movement frequency. During dynamic movements such as walking, robot gravity compensation can even *increase* undesired interaction forces. The LOPES gait rehabilitation robot [19] was reported to be more transparent without gravity compensation, due to similar eigenfrequencies of robotic and human legs. With the help of gravity, human and robot legs swing in parallel while exchanging hardly any forces.

The example shows that it can be beneficial to shape passive dynamics of haptic devices, which are in this case similar to the human passive dynamics. Another example are elastic elements for exoskeletons, which store and release energy to reduce human energy expenditure [20], [21].

Recently, we presented a control scheme that explicitly optimizes passive dynamics of haptic devices with regard to interaction forces, using the concept of *Generalized Elasticities* [22]. Given that the user's preferred movements are approximately known in advance, optimal conservative force fields are derived. The algorithm does not need a model of the human, and the robot's kinematics does not have to resemble that of the human limbs. With conservative force fields, the robot is stable when coupled to any passive system [23], which is important for safe human-robot interaction.

Generalized Elasticities have been implemented on the Lokomat gait rehabilitation robot, and first results have

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been published in [22]. The approach reduced interaction torques compared to closed-loop force control only and to gravity compensation, and the gait pattern was more natural regarding cadence (step frequency).

Besides free walking, a rehabilitation robot needs to provide also support and guidance. In principle, the conservative force fields can act jointly with other controllers, like our previously developed Nearest-Neighbor Path Control with Gravity Cancellation [24]. Due to the passive nature of the Generalized Elasticities, no stability problems should occur when interacting with other passive concepts. However, the potential of the conservative force fields might be higher, which means that they can take over additional guiding functions as well. By finding a conservative force field that optimally approximates an arbitrary assistive strategy, complex controllers can be realized without tedious stability analysis. The fitted force field is intrinsically passive, and it preserves the originally desired assistance in an optimal way.

In the work presented in this paper, we investigate this additional potential, i.e. whether conservative force fields can provide the same patient-cooperative support and guidance as nearest-neighbor Path Control / Force Field Tunnel approaches. Furthermore, we want to test the hypothesis that this added functionality does not compromise unhindered free walking, verified by cadence and interaction forces between the subject's legs and the exoskeleton. After a first overview of Generalized Elasticities and how they can encode spatial motion constraints, practical experiments with a group of healthy subjects walking both normally and with a simulated deficiency in weight bearing will be presented.

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 in the sagittal plane. In each joint, force sensors are integrated between actuators and exoskeleton.

B. Nearest-Neighbor Path Control with Gravity Cancellation

Existing control algorithms of the Lokomat [25] are based on a template or reference trajectory $\mathbf{q}_{\text{ref}}(S)$ for each leg. Here, the vector contains two elements, namely reference trajectories for hip and knee angles. This reference trajectory is derived from gait patterns of healthy subjects [26]. The scalar S denotes the relative position in the gait cycle, which is normalized to the interval $[0, 1)$. Two subsequent heel strikes of the same foot define the beginning ($S = 0$) and end ($S = 1$) of a step.

In the Lokomat's conventional impedance control, S is simply calculated as a function of time and the desired replay speed in cycles/second. This replay speed is synchronized



Fig. 1. Human subject walking in the Lokomat gait rehabilitation robot (Photo courtesy of Hocoma AG, Switzerland)

with the treadmill speed, which is chosen by the therapist. This synchronization can either be done manually, or automatically by an iterative learning algorithm [27].

For the path control algorithm, S is not calculated as a function of time, but as a function of the actual joint angles \mathbf{q} . There, S is determined by searching for the nearest neighbor to the actual position \mathbf{q} on the reference trajectory $\mathbf{q}_{\text{ref}}(S)$:

$$S : \|\mathbf{q}_{\text{ref}}(S) - \mathbf{q}\|^2 \stackrel{!}{=} \min \quad (1)$$

An adjustable deadband of variable width $w_{\text{db}}(S)$ creates a virtual tunnel around the reference trajectory. Leg postures outside the tunnel are corrected by the impedance controller, which uses the nearest neighbor on the desired path $\mathbf{q}_{\text{ref}}(S)$ as set point. Within the tunnel, motion should be unhindered, which in this version of the path controller is realized using the conventional so-called “free-run” mode of the Lokomat, where gravity and friction torques of the robot are compensated. This kind of control is denoted as “Nearest-Neighbor Path Control with Gravity Cancellation” in the following. The concept is described in detail in [24].

C. Generalized Elasticities

1) *Idea and Concept:* We consider an arbitrary robot that is to be moved by a human operator, whereby interaction forces/torques¹ are to be minimized via control. We assume that the motion of the robot can be described in terms of the coordinates \mathbf{q} , which can be translations or angles. The inertia of the robotic manipulator and its actuators are subsumed in a common mass matrix $\mathbf{M}_r(\mathbf{q})$. Gravitational, damping, and Coriolis torques are subsumed in $\mathbf{n}_r(\mathbf{q}, \dot{\mathbf{q}})$. With these conventions, the robot's equations of motion are:

$$\boldsymbol{\tau}_{\text{need}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \mathbf{M}_r(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{n}_r(\mathbf{q}, \dot{\mathbf{q}}). \quad (2)$$

The needed torques $\boldsymbol{\tau}_{\text{need}}$ to move the robot can be generated by the robot's actuators or by the human. Forces from the

¹Without loss of generality, only the term torques is used in this section.

human acting on the robot are the interaction torques τ_{int} , and actuator torques are written as τ_{act} :

$$\tau_{\text{need}} = \tau_{\text{int}} + \tau_{\text{act}}. \quad (3)$$

The question is how we can find a control law for the robot's actuators such that they take over the main part, and that the torques that need to be generated by the human are minimal.

If the robot is equipped with force sensors to measure τ_{int} on-line, we assume that closed-loop force control is applied. However, there will always be a certain minimum inertia remaining [16]. Therefore, in addition to feedback (fb) terms depending on force, also feedforward (ff) terms depending on time or position can be beneficial to make τ_{act} match the needed torques closely:

$$\tau_{\text{act}} = \tau_{\text{fb}} + \tau_{\text{ff}}. \quad (4)$$

We assume that τ_{fb} reduces the mass matrix $\mathbf{M}_r(\mathbf{q})$ to the minimum achievable value (and possibly $\mathbf{n}_r(\mathbf{q}, \dot{\mathbf{q}})$ is also modified, for example to compensate friction). Then, the equations of motion (2) are changed to:

$$\tau_{\text{need}'}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \tau_{\text{need}} - \tau_{\text{fb}} = \mathbf{M}_{r'}\ddot{\mathbf{q}} + \mathbf{n}_{r'}(\mathbf{q}, \dot{\mathbf{q}}). \quad (5)$$

With (3) and (4), the residual needed torques are

$$\tau_{\text{need}'} = \tau_{\text{int}} + \tau_{\text{ff}}. \quad (6)$$

This representation includes the special case without closed-loop force control ($\tau_{\text{fb}} = 0$), such that $\mathbf{M}_{r'} = \mathbf{M}_r$, and also the case where $\mathbf{n}_{r'} = \mathbf{n}_r$. A standard procedure is to use τ_{ff} as a function of \mathbf{q} for gravity cancellation. As outlined earlier, this is only optimal for certain movements, for example for very slow ones. In the following, we describe the optimal design of feed-forward components τ_{ff} that are tailored for arbitrary preferred user movements. No force sensors and no biomechanical model of the user is necessary, the only input needed for the optimization is a model of the robot and one or more movements the user prefers to perform. The robot's kinematic structure and mass distribution does not need to resemble that of the human body, which means that the approach can be used for exoskeletons and end-effector-based systems alike. The method uses conservative force fields, such that the robot emulates the behavior of passive components. Thus, no net energy is provided to the user, who has to initiate and control any motion.

In order for τ_{ff} to describe a conservative force field, its work must be zero for any closed trajectory. This implies that the torques in the vector τ_{ff} can be interpreted as "elastic" functions of the joint variables \mathbf{q} , and as the negative gradient of a potential field $\phi(\mathbf{q})$ with respect to \mathbf{q} :

$$\tau_{\text{ff}} = \tau_{\text{elast}}(\mathbf{q}) = -\nabla_{\mathbf{q}}\phi(\mathbf{q}). \quad (7)$$

Apart from the required conservativeness, this representation is very open, such that it can e.g. represent elastic belts, and it also includes gravity cancellation as a special case.

The optimization procedure shapes the potential ϕ and, thus, τ_{elast} as functions of \mathbf{q} in such a way that interaction torques needed to move the robot along given trajectories are

minimal. Using (6) and (7), these residual interaction torques required to move the compensated robot are given by

$$\tau_{\text{int}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) = \tau_{\text{need}'}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) - \tau_{\text{elast}}(\mathbf{q}). \quad (8)$$

If a set of trajectories is given with n samples for \mathbf{q} and the corresponding velocities $\dot{\mathbf{q}}$ and accelerations $\ddot{\mathbf{q}}$, the goal is to minimize the quadratic cost function J with

$$J = \left\| \left(\begin{array}{c} \tau_{\text{need}'}(\mathbf{q}_1, \dot{\mathbf{q}}_1, \ddot{\mathbf{q}}_1) \\ \dots \\ \tau_{\text{need}'}(\mathbf{q}_k, \dot{\mathbf{q}}_k, \ddot{\mathbf{q}}_k) \\ \dots \\ \tau_{\text{need}'}(\mathbf{q}_n, \dot{\mathbf{q}}_n, \ddot{\mathbf{q}}_n) \end{array} \right) - \left(\begin{array}{c} \tau_{\text{elast}}(\mathbf{q}_1) \\ \dots \\ \tau_{\text{elast}}(\mathbf{q}_k) \\ \dots \\ \tau_{\text{elast}}(\mathbf{q}_n) \end{array} \right) \right\|_{\mathbf{Q}}^2, \quad (9)$$

whereby the symmetric positive definite matrix \mathbf{Q} contains weights that stress the importance of certain joints (Extreme weights might even increase interaction torques at one joint to transfer energy to others) and of certain instances k of the movement. Following (6), the needed torques are calculated using the robot model and expected trajectories with given positions, velocities and accelerations. The aim of the optimization is to find the optimal torques $\tau_{\text{elast}}(\mathbf{q})$ that compensate $\tau_{\text{need}'}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})$ for the expected motions and fulfill the constraint of conservativeness (7). It should be noted that it is *not* the aim to urge the human to perform the expected movement, like in impedance control. Nevertheless, when the movement differs strongly from the expected movement types, compensation is not optimal anymore, and interaction torques might increase.

For trivial problems, the optimal passive dynamics can be deduced intuitively. For example, we consider a one-dimensional robot represented by a floating point mass (no gravity acting), which a user moves in a sinusoidal oscillation. Here, the optimal passive position-dependent element to be added is a linear spring (with appropriate stiffness to achieve the desired eigenfrequency). Thus, the passive force field linearly depends on position, and it reduces necessary user interaction torques to maintain the oscillation to zero.

If the problem is not trivial, a suitable parameterization of the conservative force field $\tau_{\text{elast}}(\mathbf{q})$ can be set up, and the parameters need to be optimized. Such a parameterization can be done either in terms of the potential, or directly in terms of the force field. In the first place, an arbitrary C^1 -continuous scalar function of \mathbf{q} can be used. In the second case, the constraint of conservativeness must be considered, such that a possible strategy would be to build the force field by superimposing several passive elements. There is an almost infinite number of possible parameterizations, also depending on the dimensionality of the problem. A frequent choice are polynomials or Radial Basis Functions (RBFs, see e.g. [28]). In [22], we employed a parameterization in the force field space, based on polynomials. In the following, we apply an RBF approach in the potential field space.

2) *Optimization Using Normalized Radial Basis Functions:* Here, the parameterization is performed in terms of the potential ϕ as a function of the position coordinates in the vector \mathbf{q} . Furthermore, ϕ is a function of various centerpoints

c_i and of weighting parameters w_i that define normalized radial basis functions of the type

$$\phi(\mathbf{q}) = \frac{\sum_{i=1}^N (w_i f_i[r_i(\mathbf{q})])}{\sum_{j=1}^N f_j[r_j(\mathbf{q})]}. \quad (10)$$

The radius functions r_i are scalar functions of the distance vector δ_i between a point \mathbf{q}_k and the i -th centerpoint c_i :

$$\delta_i(\mathbf{q}_k) := \mathbf{q}_k - c_i, \quad r_i(\mathbf{q}_k) := \sqrt{\delta_i^T(\mathbf{q}_k) \mathbf{D}_i \delta_i(\mathbf{q}_k)}, \quad (11)$$

with symmetric positive definite weighting matrix \mathbf{D}_i for each centerpoint. The choice of the N centerpoints is free, for example they can be placed on the nodes of a grid, or they can be points on the trajectories to be facilitated.

As the potential in (10) is linear in the parameters, it can be written as a scalar product of a vector function $\mathbf{g}(\mathbf{q})$ and a vector of weights $\mathbf{w} = (w_1 \ w_2 \ \dots \ w_N)^T$:

$$\phi(\mathbf{q}) = \mathbf{g}(\mathbf{q})^T \mathbf{w} \quad (12)$$

The gradient of the potential is given by the transposed Jacobian of \mathbf{g} multiplied with the weight vector, which gives the feed-forward control vector of (7):

$$\boldsymbol{\tau}_{\text{elast}}(\mathbf{q}_k) = -\nabla_{\mathbf{q}} \phi = -\left(\frac{d\mathbf{g}(\mathbf{q})}{d\mathbf{q}} \right)^T \mathbf{w} \quad (13)$$

When the negative transposed Jacobians for all n samples of the preferred trajectories are concatenated to the matrix \mathbf{A} with

$$\mathbf{A} := -\left(\left. \frac{d\mathbf{g}(\mathbf{q})}{d\mathbf{q}} \right|_{\mathbf{q}=\mathbf{q}_1} \quad \dots \quad \left. \frac{d\mathbf{g}(\mathbf{q})}{d\mathbf{q}} \right|_{\mathbf{q}=\mathbf{q}_n} \right)^T \quad (14)$$

and the vectors $\boldsymbol{\tau}_{\text{need}}(\mathbf{q}_k, \dot{\mathbf{q}}_k, \ddot{\mathbf{q}}_k)$ are concatenated to a vector \mathbf{b} for all samples, the cost function of (9) is:

$$J = \|\mathbf{b} - \mathbf{A}\mathbf{w}\|_{\mathbf{Q}}^2 \quad (15)$$

This is a linear Least Squares (LS) problem and the parameter vector \mathbf{w} can be found recursively or by use of the pseudoinverse. The equation system has a rank deficiency of 1, such that an additional equation is necessary to avoid numerical problems. This can e.g. be the constraint that

$$\sum_{i=1}^N w_i \stackrel{!}{=} N. \quad (16)$$

There is a wide variety of Radial Basis Functions (RBFs) that can be used for the f_i in (10). Frequently, exponential forms are used. In the application here, the force field is calculated off-line and then used on-line to look up corresponding forces. In this case, exponential functions are not ideal, because all center points c_i influence the force field at a certain position of the robot. This requires high computational resources during operation. Therefore, another class of functions is advantageous, which are compactly supported RBFs. With this kind of RBFs, it is sufficient to calculate the function value depending on a limited number of points c_i in the neighborhood of the robot's position.

In our implementation for the Lokomat, we used compactly supported RBFs of minimal degree for the f_i , as

proposed by Wendland [29]. In our application, the vector \mathbf{q} contains four elements: Hip and knee angles for the left leg, and hip and knee angles for the right leg in the sagittal plane. To simplify the problem, we chose to make all radius functions in (11) spherical and of equal size using a scalar distance parameter d :

$$\mathbf{D}_i = d^2, \quad i = 1, \dots, N \quad (17)$$

In order to make the force field versatile and independent of a single template gait, a multitude of physiological gait trajectories² are concatenated and used as training points. Along these trajectories, the field then minimizes forces needed by the human to move the robot.

3) *Generalized Elastic Path Control*: In the last section, the Generalized Elasticities were used to render the robot transparent for a certain range of allowed or safe movements, which are defined by the training trajectories within this allowed range. In order to assist impaired subjects, additional training points are now added that define the robot behavior when the subject leaves this domain of safe motions. One example would be deficient weight bearing, where the stance leg gives way. Then, transparent behavior is not beneficial, instead assistive forces of the robot are necessary to avoid falling. This assistance is realized by additional training points for the force field that lie outside the allowed region. For the Lokomat, the allowed region is defined to be equivalent to the deadband or "tunnel" described by $w_{\text{db}}(S)$ in section II-B. Training points are obtained using a simulated impedance with the nearest-neighbor approach and the reference trajectory \mathbf{q}_{ref} . Thereby, the controller has been modified compared to its description in section II-B, where it was based on two separate nearest-neighbor searches for the two legs. Now, the reference trajectory \mathbf{q}_{ref} contains four elements, hip and knee angles for the left leg, and hip and knee angles for the right leg. A four-dimensional grid is constructed in joint space, the distance of each grid point \mathbf{q} to its nearest neighbor $\mathbf{q}_{\text{ref}}(S)$ according to (1) on the path is calculated, and the corresponding impedance torques are obtained depending on the deadband and the desired stiffness (no velocity-dependent impedance is used). In (15), the matrix \mathbf{A} is extended in function of the grid points, and the corresponding torques given by the path controller are concatenated and appended to the vector \mathbf{b} . Because of the large number of training points (generated by the four-dimensional grid), we use recursive optimization. This "Generalized Elastic Path Control" describes both the unhindered motion within the "tunnel" and the assistive forces outside of it by a unified mathematical concept, and a single controller results that ensures passivity.

D. Experimental Evaluation

1) *Protocol*: Nine healthy subjects participated in the evaluation. The subjects walked once freely on the treadmill (condition FREE), and with four different Lokomat conditions, at a treadmill speed of 3 km/h for 90 seconds each:

²The trajectories have been taken from the Carnegie Mellon database, which was supported by NSF Grant #0196217 (<http://mocap.cs.cmu.edu>).

- 1) Under condition NNACT, the Lokomat was controlled by Nearest-Neighbor Path Control with Gravity Cancellation. The subjects were instructed to walk actively and autonomously.
- 2) Under condition ELACT, the Lokomat was controlled by Generalized Elastic Path Control. The subjects were instructed to walk actively and autonomously.
- 3) Under condition NNPASS, the Lokomat was controlled by Nearest-Neighbor Path Control with Gravity Cancellation. The subjects were instructed to walk passively, i.e. to simulate difficulties in stabilizing their legs in stance phase, and to rely on the support of the Lokomat to help them carry their own body weight.
- 4) Under condition ELPASS, the Lokomat was controlled by Generalized Elastic Path Control. The subjects were instructed to walk passively, i.e. to simulate difficulties in stabilizing their legs in stance phase, and to rely on the support of the Lokomat to help them carry their own body weight.

The order of the Lokomat conditions was randomized and—apart from the instruction to walk actively or passively—not revealed to the subjects. During walking with the Lokomat, hip and knee joint angles were recorded by the potentiometers located at the exoskeleton joints, and hip and knee joint torques were recorded by the force sensors located at the Lokomat drives; sampling rate was 1 kHz. The last 60 seconds of walking under each condition were video-taped.

2) *Data analysis*: A direct criterion to evaluate the performance of the controllers are interaction torques. The robot's force sensors are located between drives and exoskeleton and not directly at the interaction points with the human, such that a model of the exoskeleton's dynamics has to be used. This model allows for an acceptable reconstruction. Given the trajectory recorded during gait and smoothed numerical derivatives thereof, the interaction torques that the human had to provide to move the robot are calculated:

$$\tau_{\text{int}} = \mathbf{M}_{\text{exo}}(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{n}_{\text{exo}}(\mathbf{q}, \dot{\mathbf{q}}) - \tau_{\text{sensors}}. \quad (18)$$

In contrast to \mathbf{M}_r in (5), only the inertia \mathbf{M}_{exo} of the *exoskeleton* needs to be used here and inertia of the drives is excluded due to the force sensor location.

Afterwards, all recorded data is cut into single strides. Each stride is normalized in time to 0–100% of the gait cycle ($S \in [0, 1)$). Next, joint angles and interaction torques of all strides are averaged to one average stride trajectory $\tilde{\mathbf{q}}(S)$ and $\tilde{\tau}_{\text{int}}(S)$, respectively.

To quantify the overall interaction torques, the root mean square of the the interaction torques during the average stride is calculated for each joint m of the four joints (hip and knee of both legs), and the average value

$$\bar{\tau}_{\text{int}} = \frac{1}{4} \sum_{m=1}^4 \sqrt{\int_0^1 [\tilde{\tau}_{\text{int},m}(S)]^2 dS} \quad (19)$$

is used as a measure of the interaction between robot and human under a particular condition.

As a parameter to describe the resulting gait pattern in comparison to free treadmill walking without the robot, the subjects' walking cadences under the different conditions are determined manually from the videos by counting the strides in the last 30 seconds and division by the elapsed time.

To quantify the assistance of the controller under the conditions NNPASS and ELPASS, the maximal knee flexion angle $q_{\text{max}}^{(\text{flex})}$ and the maximal knee extension torque $\tau_{\text{max}}^{(\text{ext})}$ during initial loading and mid stance phase (defined according to [30] as 0%–30% of the gait cycle) are determined.

The conditions are compared by a Kruskal-Wallis nonparametric ANOVA at the 5% significance level [31]. The Tukey-Kramer adjustment accounts for multiple comparisons.

III. RESULTS

There is a trend towards lower interaction torques $\bar{\tau}_{\text{int}}$ under condition ELACT than under condition NNACT (Fig. 2), although the difference between these two is not significant.

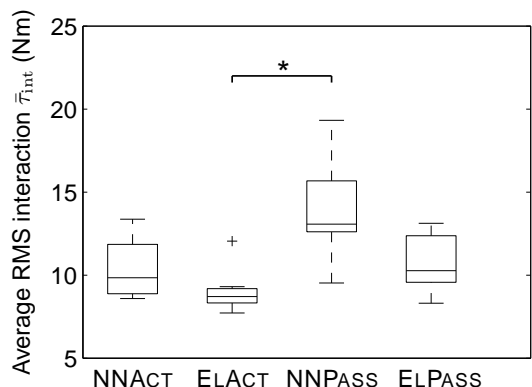


Fig. 2. Average RMS joint interaction torque $\bar{\tau}_{\text{int}}$ of all subjects ($n = 9$) for the different Lokomat conditions.

When walking with Nearest-Neighbor Path Control with Gravity Cancellation, both actively and passively, the subjects covered an increased hip range of motion compared to Generalized Elastic Path Control, i.e. they were making longer steps (Fig. 3). Increased step length (at constant speed) is reflected in the cadence: With Nearest-Neighbor Path Control with Gravity Cancellation, subjects significantly reduced their walking cadences compared to free treadmill walking (Fig. 4). With Generalized Elastic Path Control, a trend to lower cadences is also visible, but not significant.

Under the conditions where subjects were instructed to behave passively during stance phase, both controllers lim-

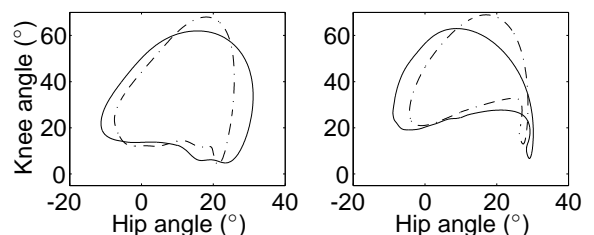


Fig. 3. Active (left) and passive (right) walking trajectories for an exemplary subject (solid line: NNACT, dash-dotted line: ELACT).

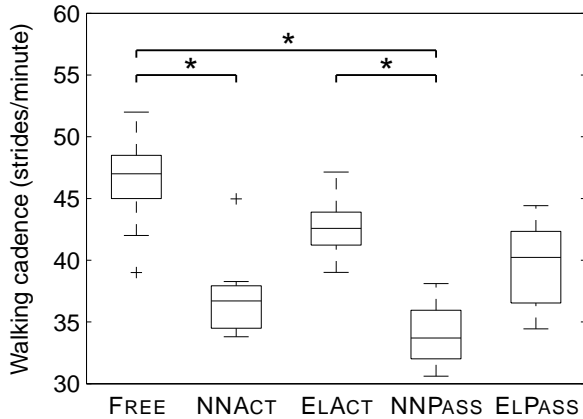


Fig. 4. Walking cadences of all subjects ($n = 9$) for free walking and the different Lokomat conditions.

ited the maximum knee flexion during initial loading and mid stance phase (Fig. 3 right). The maximal knee flexion angles $q_{\max}^{(\text{flex})}$ in a passive stance phase (Fig. 5, left) are not significantly different for the two different controllers ($p = 0.17$), but the maximal knee extension torques $\tau_{\max}^{(\text{ext})}$ generated by Nearest-Neighbor Path Control with Gravity Cancellation are significantly higher than those generated by Generalized Elastic Path Control (Fig. 5, right).

IV. DISCUSSION

Lower cadences and increased step length with Nearest-Neighbor Path Control with Gravity Cancellation are in congruence with theoretical expectations. Gravity of the exoskeleton helps compensate inertia of the robot's swinging legs. When these forces are missing and only inertia acts, the heavy robot legs tend to continue the swing motion. In order to stop swing phase, the human has to decelerate the robot legs without the help of gravity. The human does this slowly and smoothly and makes longer steps, finding a new optimal gait adapted to the new dynamic environment. Another way to explain the phenomenon is by regarding the compound of human and exoskeleton as a person with heavier legs. Gravity compensation of the Lokomat legs is then equivalent to a lower gravitational field, and the resulting gait resembles that of a person walking on the moon. This kind of adaptation is not desirable for patient training, because training needs

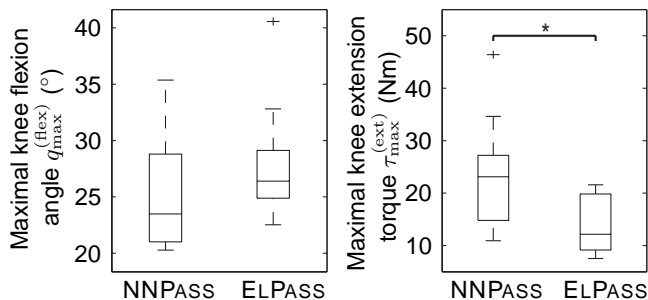


Fig. 5. Maximal knee flexion angle $q_{\max}^{(\text{flex})}$ (left) and maximal knee extension torque $\tau_{\max}^{(\text{ext})}$ (right) during load response and initial loading under both passive walking conditions.

to be task-specific in order to transfer to real life [32]. With Generalized Elastic Path Control, the adjustments the subjects need to make to walk in the robot are much lower, and the dynamics come closer to free walking.

It should be noted that the Generalized Elasticities favor certain motions by reducing human-robot interaction forces for these motions. Although the concept is much more open to different types of walking than e.g. impedance control, the robot is not optimally compensated anymore when a subject's pathological gait leaves the range of favored motions, and interaction forces may increase. There is an ongoing discussion in rehabilitation science whether more emphasis should be put on physiological or on functional movements. To find the ideal compensation of robot dynamics for a pathological motion, individual preferred gait trajectories would have to be tailored for each patient. A compromise would be to include various healthy gait patterns and typical pathological ones during the force field optimization. However, increasing the number of different, but overlapping trajectories may compromise the fit for each individual one.

Concerning the second demand for support and guidance in case the subject lacks force or coordination, both controllers are effective. The knee angle is limited, and buckling is prevented. However, there is a difference in the forces that are generated. One explanation may be that Nearest-Neighbor Path Control with Gravity Cancellation has a component that is not present in Generalized Elastic Path Control, which is velocity-dependent impedance. This leads to higher forces during the dynamic descent of the center of mass with passive knees. Adding such a component to Generalized Elastic Path Control would contradict the basic idea of a conservative force field that depends only on absolute position. Furthermore, such damping counteracts downward motion, but it also counteracts subsequent recovery and ascent. The elastic force field, on the contrary, helps during recovery by pushing the center of mass up again. Nevertheless, it is possible that the forces are not sufficient for severely impaired subjects. However, the exoskeleton control is not the only way of coping with deficient weight bearing, the complementary body weight support system also contributes to limit downward motion of the center of mass.

Based on these positive findings, we have tested Generalized Elastic Path Control with a patient who had suffered a spinal stroke. The patient is mildly impaired on his left side and tends to a stiff-knee gait. With (19), we found an average RMS interaction torque of 12.5 Nm, which is in the upper range of the healthy subject's values in ELPASS, and in the lower range of NNPASS. Instead of during the stance phase, the patient needs selective support during initial swing, to help flex the left knee. Indeed, there is a significant difference in controller action between the two legs, with a median initial swing knee interaction torque of 3.1 Nm on the right, and 5.7 Nm on the left side, both in flexing direction. This selective support was possible although the patient had full control of movement timing, apart from the fixed treadmill velocity, because controller actions are based on purely spatial constraints.

V. CONCLUSION

In this paper, we presented a novel patient-cooperative control strategy for rehabilitation robots, Generalized Elastic Path Control. This strategy reduces interaction between robot and human to a minimum, and still provides the necessary support when the subject needs it. Using optimal robot dynamics encoded in a conservative force field, the eigendynamics of the robot come very close to physiological human gait. This means that the exoskeleton moves in parallel to the human legs, hardly exchanging any forces. When the human leaves the range of allowed gait patterns, a second mechanism is encoded in the conservative force field, which are corrective forces that ensure safe training and functional gait. Practical experiments with healthy subjects and a simulated impairment have shown the effectiveness of the approach: Compared to our previous Nearest-Neighbor Path Control with Gravity Cancellation, interaction forces are significantly reduced. The subject has full control of gait timing, but crucial gait features can still be supported, in particular weight bearing during stance. This shows that Generalized Elastic Path Control is a viable method to realize patient-cooperative training.

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