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Methods

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Hybrid path controller enables haptic guidance along self-crossing paths

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Abstract: Until today, in the field of motor learning and rehabilitation, haptic controllers were mostly limited to teach simple tasks such as movements along straight lines, curves, or circles. However, commonly, real-life tasks consist of more complex movements such as in writing, rehabilitation, or surgery. In this paper, a novel haptic controller for robot-assisted learning is introduced. This hybrid path controller can cope with interfering path sections, while it also incorporates the common requirements of effective motor learning: it allows freedom for making spatial errors, free timing to explore the task dynamics, and adaptation to the current skill level of the user. In a practicability study with two different robots, results confirmed the full functionality of the controller and its applicability for a broad range of complex movements.

Keywords: user-cooperative control; arbitrary reference path; potential field; shortcuts prevented; passive control; preventing shortcuts

Zusammenfassung: Bis heute waren im Bereich des motorischen Lernens und der Rehabilitation haptische Regler meist darauf beschränkt einfache Aufgaben wie Bewegungen entlang gerader Linien, Kurven oder Kreise zu vermitteln. In der Praxis bestehen reale Aufgaben jedoch häufig aus komplexeren Bewegungsabläufen, wie sie beispielsweise beim Schreiben, in der Rehabilitation oder in der Chirurgie vorkommen. In dieser Arbeit wird ein neuartiger haptischer Regler für das robotergestützte Lernen vorgestellt. Dieser hybride Pfadregler kann mit sich selbst überlappenden Pfadabschnitten umgehen und berücksichtigt zugleich die wesentlichen Anforderungen an effektives motorisches Lernen: Er erlaubt dem Nutzer räumliche Fehler zu machen, bietet die Möglichkeit sich zeitlich frei zu bewegen, um die Dynamik der Aufgabe zu erfühlen und ermöglicht es die Unterstützung an das aktuelle Können des Nutzers anzupassen. In einer Machbarkeitsstudie mit zwei verschiedenen Robotern bestätigten die Ergebnisse sowohl die volle Funktionalität des Reglers sowie seine Anwendbarkeit für eine breite Palette komplexer Bewegungen.

Schlagwörter: benutzerkooperative Regler; beliebiger Referenzpfad; Potenzialfeld; Abkürzungen verhindern; passive Regler; Verhindern von Abkürzungen

1 Introduction

Haptics is the human's only sense that allows exploration and manipulation of the environment at the same time [1]. For human newborns, haptics is even the first impetus to explore and learn to manipulate the world [2]. In basic research on motor learning, haptic control strategies applied by various robots have been demonstrated to enhance learning of a large variety of motor tasks [3]–[13]. In robot-assisted rehabilitation of stroke patients, different haptic control strategies mainly in upper limb rehabilitation were shown to promote motor relearning [12], [14]–[22], while results in lower limb rehabilitation remain less clear [23]–[25]. However, most studies on the effectiveness of haptic control strategies so far have focused on enhancing motor learning on simple tasks [26]. According to Wulf and Shea, tasks are simple "…if they have only one degree of freedom, can be mastered in a single practice

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session, and appear to be artificial" [27]. Consequently, in real-life situations, such as in rehabilitation, surgery, writing, or sports, most tasks to be learned are complex, i.e. "they generally cannot be mastered in a single session, have several degrees of freedom, and perhaps tend to be ecologically valid" [27]. Initially less skilled participants seem to benefit from performance-enhancing haptic methods to learn the spatial aspects of the task, probably because the conditional task difficulty is reduced, and learners are optimally challenged [28]. Accordingly, in one study, participants who initially performed poorly benefited from haptic control strategies that reduce errors, while they benefited from error-amplifying force fields once they improved [29]. This finding is in line with literature stating that there is an important difference between different forms of haptic feedback and that researchers should be specific about which type of haptic control strategy they apply [26]. Also, motor learning principles are not guaranteed to generalize from simple to complex tasks [27]. Therefore, haptic control strategies, which are known to enhance learning of simple tasks have to be reevaluated and possibly redesigned to also facilitate learning of complex tasks [26]. Accordingly, in this paper, we introduce a control strategy, which is intended to provide haptic guidance for enhancing motor learning during arbitrarily complex movements.

This haptic control strategy should fulfill three main requirements: First, the haptic controller should include principles that are known to be crucial for human motor learning. Second, the haptic controller should be passive to avoid instability. Third, the haptic controller should provide haptic guidance along arbitrarily complex movements (i.e. movements along an arbitrarily complex predefined path) for which potential self-crossings can be hidden.

To fulfill the first requirement, it was found that robots must provide freedom for humans during motor learning. Freedom allows making spatial and temporal errors, since making errors was found to be crucial for motor learning [30]–[34]. Thus, haptic strategies that provide compliance and therefore do not completely restrict the human's movements (as requested also by the third requirement) have been shown to be effective [26]. In this context, participants in a study on a complex tracking task with a wheelchair could freely choose the traveling speed, while a PD-look ahead force controller for a joystick helped them to stay on the desired path. In this experiment, the PD-look-ahead force controller significantly improved the steering ability of healthy children more than without haptic guidance [11]. In another experiment investigating piano playing on an instrumented keyboard, the effectiveness of compliant haptic guidance was also demonstrated. There, compliant haptic guidance through magnetic forces in addition to auditory feedback demonstrated to be more effective than auditory feedback alone [35]. Besides spatial freedom, also temporal freedom is important to enable motor learning and therefore contributes to the first requirement. Having sufficient spatiotemporal freedom is important to explore the dynamics of a task through its inherent interaction forces. Such interaction forces can be inertial forces, impacts, or velocity-dependent resistances. Learning of dynamic interactions may even be accelerated if dynamics of a task is exaggerated. For instance, in a writing task, school-aged children increased their handwriting quality through increased inertia and viscosity of a robot-guided pen [36]. This writing study also confirmed previous results that reported an increased learning rate caused by an augmentation of performance errors [31], [37]–[39]. Another important aspect that contributes to the first requirement targeting successful motor learning is described by the "Challenge Point Theory" [40]. The Challenge Point Theory states, that users profit most from training when they are supported or challenged optimally according to their individual skill level, which was confirmed experimentally in [10] and has been applied in hundreds of studies over the years [41]. One such study focused on correct timing to start a complex forward tennis stroke, where the authors showed that the effectiveness of a haptic control strategy depends on the subject's initial skill level [42]. In another study, multimodal feedback based on position control for instruction and path control for learning spatial aspects of the task while rendering the dynamics of the environment, allowed even accelerating motor learning. Accelerated learning was achieved in the intervention group thanks to automated, personalized feedback selection depending on the biggest error of the participants compared to a reference group that received the same feedback as the participants in the intervention group, but not in a personalized form. In both groups, the different forms of feedback led to significant learning effects, but the intervention group learned aspects related to speed even faster because the individual largest issues were correctly addressed by the respective feedback strategy and modality [43]. Therefore, also path control applied in the right moment during learning allowed to optimally challenge the participants as requested by the Challenge Point Theory [40], newer paradigms based on the Challenge Point Theory that also take transfer learning to other tasks into account [44], and the first requirement for our haptic controller design. Results also from a recent study in teleoperated surgery observed that participants who had high initial path errors benefited more from haptic guidance. Hereby, error-amplifying and error-reducing

haptic training for robot-assisted telesurgery benefited trainees of different abilities differently, indicating that participants with high initial combined error-time benefited more from guidance and error-amplifying force field training [29]. To summarize, from a motor learning point of view, a haptic controller is expected to be effective, if it incorporates the following three concepts: (i) provision of freedom to allow errors, (ii) enabling free exploration of the task dynamics, and (iii) skill-dependent support or challenge for the user.

According to the second requirement, the haptic controller should be passive since passivity of a haptic controller inherently guarantees the controller's stability [45]. Moreover, when one passive system is combined with another passive system, the overall system remains passive [45]. Therefore, the overall system's stability is maintained if a passive controller is appended to a stable control system. Only a few control principles fulfill the requirement of passivity by concept. One group of such passive controllers are those based on conservative potential fields such as "virtual fixtures" [46]–[49] and "path controllers" [47], [50]–[54]. Both, the virtual fixtures and path controllers are used for haptic rendering of elastic walls. The difference in the nomenclature of these two groups of passive controllers mainly originates from their applications. Virtual fixtures are used to haptically render the border of virtual objects by elastic walls, e.g. in robot-aided surgery to prevent surgeons from injuring vital body parts with the scalpel [47]–[49]. In contrast, path controllers are mainly used to render a tunnel with elastic walls guiding users compliantly along a desired path without enforcing timing [51]–[53]. In addition to guiding the user on a desired path while remaining passive, path controllers based on conservative potential fields also fulfill the previously mentioned properties for enabling motor learning: they provide freedom for the user to make errors, allow free exploration of the task dynamics, and in some cases even allow continuous adaptation from a supportive to a challenging behavior [53]. If such an adaptation is performed, passivity of the idealized controller might not be guaranteed anymore in dependence of the adaptation speed. However, if the adaptation of the support is performed slowly, friction and other physical effects in the real robotic setup will dissipate the energy created by the adaptation of the support and the system will remain stable. Also, recent work shows that it is possible to obtain improved haptic performance while maintaining ultimate passivity [55] or adapting stiffness of a dynamic control system while maintaining stability [56].

The third requirement asks for a controller that allows learning of arbitrarily complex tasks. Until today, path

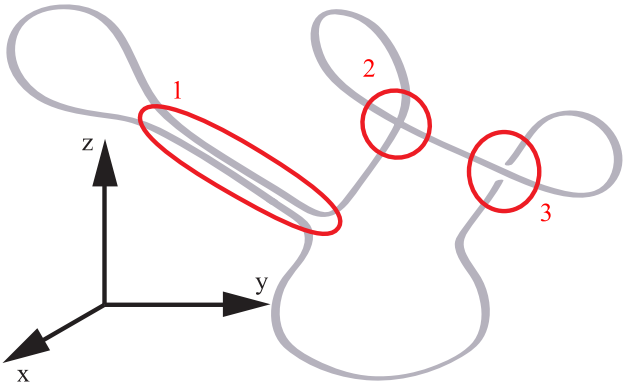


Figure 1: Regions in paths that may lead to instabilities in control or may give users the possibility for undesired shortcuts: (1) parallel paths in close vicinity to each other, (2) paths with crossings, or (3) paths that are close to each other and skew.

controllers are mainly used to guide users along rather simple paths, e.g. straight lines or circles. The reason for the limitation to simple paths are that in complex movements, single path sections may interfere when they (i) are parallel to each other in close vicinity, (ii) have crossings, or (iii) are close to each other and skew (see Figure 1). These interfering path sections result in unwanted path crossings or thin path walls. In consequence, the user may take shortcuts in interfering path sections and, therefore, perform wrong movements. Commonly, such unwanted crossings are observed in planar movements, e.g. in slings of letters during hand writing, and in three dimensional movements, e.g. in stitching movements when suturing a wound. Thus, hiding path sections that interfere with each other would be the key to extend path controllers based on conservative potential fields from simple movements to arbitrarily complex movements.

In conclusion, path controllers based on conservative potential fields have important properties that can enhance human motor learning (first requirement) while providing a passive and stable environment (second requirement). The remaining challenges to be solved are interfering path sections that limit the application of current path controllers to complex movements (third requirement). This paper presents a new path controller that can hide interfering path sections from the user, which is the key to extend the application of path controllers to arbitrarily complex paths. Interfering path sections are hidden from each other by dividing a complex path into a finite number of sub paths without such interfering path sections, i.e. "layers". When the user reaches the end of one layer, the path controller switches to the corresponding next layer. In this way, arbitrarily complex paths can be rendered, while path crossings are hidden from the user. Systems that combine continuous

control and discrete states (the switching between layers) are called “hybrid systems”. Therefore, we call the new control concept “Hybrid Path Controller” (HPC).

In the first part of this paper, the principle of the HPC is explained. In the second part, the functionality of the HPC is demonstrated by simulations. In the third part, the practicability of the HPC for application of complex movements is demonstrated on two different robotic concepts, i.e. on a large parallel robot (custom made tendon-based robot, Experiment 1), which is described in detail in previous publications also in different applications [43], [51], [53], [57], [58], and on a small serial robot (*PHANTOM Omni*® haptic device, Experiment 2).

2 Principle of the hybrid path control

The HPC is based on our previous work with path controllers. Namely, a path controller called “from path control to error augmentation” (PCEA) [53]. Before explaining in detail how the PCEA is extended to the HPC to allow its application for arbitrarily complex movements, the basic principle of the PCEA needs to be explained.

2.1 Previous work on path control

The PCEA is based on a C^2 positive semi definite potential field ϕ that surrounds a predefined reference path $\boldsymbol{q}_{\text{ref}}$. Here, C^2 refers to the PCEA’s mathematical property allowing to differentiate the potential field function $\phi(\boldsymbol{q})$ twice with respect to the position $\boldsymbol{q}$ and still obtain a continuous function as a result. This potential field is similar to a landscape consisting of hills and valleys. Hereby, the lowest potential is attributed to the reference path $\boldsymbol{q}_{\text{ref}}$ lying on an equipotential line. So, the reference path represents the valley in the landscape. Around the reference path, the potential increases as a function of the distance to the closest point on the reference path. In this way, the hills in the landscape are created. Points of equal distance to the reference path lie on equipotential lines. When the negative gradient of the potential field (gradient field) is calculated, a unique assignment of elastic forces $\boldsymbol{f}_{\text{elast}}$/torques $\boldsymbol{\tau}_{\text{elast}}$ to each position $\boldsymbol{q}$ of the robot in the chosen workspace is obtained. These forces/torques correspond to downhill-slope forces/torques in the landscape representation of the potential field:

$$\left[\boldsymbol{f}_{\text{elast}}(\boldsymbol{q})\ \boldsymbol{\tau}_{\text{elast}}(\boldsymbol{q})\right]^T = -\nabla_{\boldsymbol{q}}\phi(\boldsymbol{q}). \tag{1}$$

The description of the path controller through a gradient field enables the user to move freely around in the landscape without time constraints, i.e. the user is not pushed in tangential direction along the reference path, but experiences compliant elastic interaction forces/torques normal to the reference path.

To create continuous gradient fields with a limited amount n of discrete points at positions $\boldsymbol{q}_j$ with j as the index for the current layer, we have chosen to approximate the underlying potential field for the gradient field by compactly supported normalized radial basis functions $\boldsymbol{g}_j$ (NRBFs) of Wendland type [59] with radius r_{NRBF} and weight $\boldsymbol{w}_j$. The advantage of compactly supported NRBFs over analytic functions is that they have finite extension and low complexity. Therefore, only a limited amount k of simple basis functions $\boldsymbol{g}_j$ around the current position $q(t)$ at the current time point t needs to be evaluated in real-time.

Due to the approximation of the potential field by NRBFs, equation (1) can be rewritten as a linear combination of the matrix $\boldsymbol{A}$ and the weights $\boldsymbol{w}_j$, where $\boldsymbol{A}$ approximates the negative gradient of the potential field $-\nabla_{\boldsymbol{q}}$ at position $\boldsymbol{q}$ by the compactly supported NRBFs:

$$\boldsymbol{\tau}_{\text{elast}}(\boldsymbol{q}) = \mathbf{A}(\boldsymbol{q})\boldsymbol{w}. \tag{2}$$

More details to the transformation from equation (1) to equation (2) can be found in [50].

An important property of the previously introduced formulation of the path controller by an underlying conservative potential is passivity. Due to the formulation of the PCEA as a force field resulting from the negative gradient of a passive potential field, conservation of energy is guaranteed. Therefore, the PCEA does not introduce energy into the system (i.e. each points in space remains at the same energy level over time) and therefore instability of the controller can be avoided. Moreover, the PCEA can be combined with other passive controllers and the overall system still remains passive and stable.

During the learning process, it is important to optimally support those users that are less skilled, while more skilled users should be challenged to further strengthen the already established neuronal pathways [10]. To adapt the amount of support provided by the PCEA and even to challenge the user, it is enough to introduce the scalar factor λ in equation (2):

$$\boldsymbol{\tau}_{\text{elast}}(\boldsymbol{q}) = \lambda\mathbf{A}(\boldsymbol{q})\boldsymbol{w}. \tag{3}$$

Thanks to its linearity, multiplying of equation (2) by the scalar factor λ does not have an influence on the shape of the potential field around the reference path. Only the gradient of the potential field is changed linearly. So when λ is changed e.g. from 1 to -1, the path controller inverts its behavior and pushes the user away from the reference path. This behavior is also known as error augmentation or error

amplification [60]. The parameter λ can be changed continuously during training in order to support or challenge a user according to their performance. Note at this point that the behavior of the HPC will no longer remain passive as soon as λ is changed online. So, readapting λ before each training can be a viable solution to guarantee passivity while the user obtains the individually optimal support or challenge. At the same time, changing the parameter λ slowly enough over time will usually not result in stability issues in the real physical system since friction will dissipate the energy that might be introduced through the controller when λ is adapted.

2.2 Hybrid path control

Until today, path controllers remain limited to applications with rather simple path forms such as straight lines or circles. Applying existing path controllers such as the PCEA to complex paths with interfering path sections such as (1) parallel paths in close vicinity, (2) paths with crossings, or (3) paths that are close to each other and skew will lead the user to take shortcuts (see Figure 1). Therefore, the user may learn wrong movements or the wrong sequence of sub movements. To prevent users from taking shortcuts, we propose a new path control strategy that hides interfering path sections such as the crossing in the middle of a lemniscate used as a reference path (Figure 2).

To hide crossings with the HPC, the reference path is first divided into path segments without interferences. Hereby, an interference is automatically detected if one path section gets closer than $2 * r_{\mathrm{NRBF}}$ to another path section. The segmentation of the paths is semiautomatic. Semiautomatic segmentation means that the operator has to confirm the proposed segmentation or can choose a different segmentation manually, since sharp edges or curves can lead to undesired segmentation. Each of the resulting path segments is placed in one layer and obtains its own potential field. In case of the "lemniscate", two segments are generated (Figure 3). When a user reaches the end of a path fragment in one layer, the layers are switched. In this way, the movement can be continued on the next layer. So, layer by layer, the entire path can be explored in the correct sequence of the path fragments. The areas where one layer can be switched to another layer are called "portals". These circular portals are automatically placed on the reference path fragment $2 * r_{\mathrm{NRBF}}$ away from the beginning and the end of the respective path fragment in each layer. Layers are only switched when the user moves through a portal of the currently active layer. Furthermore, layers are only switched, if the active part of a portal is crossed in direction towards the closer end of the current path segment. Due to the augmentation of continuous control by a finite number of different layers, which are switched from one

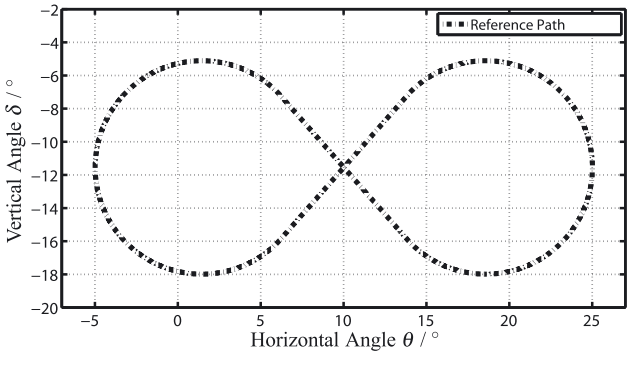


Figure 2: Reference path with a crossing: a "lemniscate". Hereby, the horizontal angle θ represents the horizontal oar angle and the vertical angle δ represents the vertical oar angle of the oar motion in the rowing simulator used for Experiment 1 later in the paper (see also Figure 5).

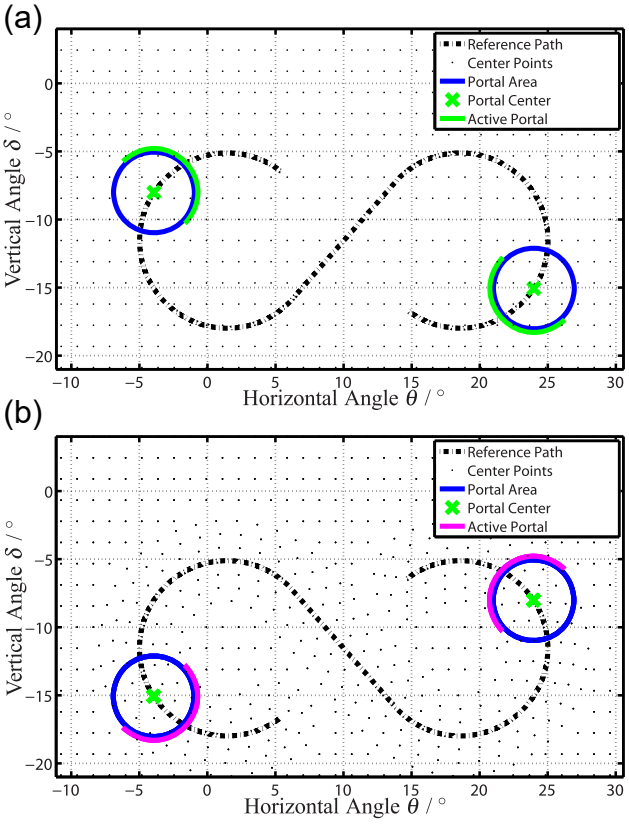


Figure 3: The HPC for the lemniscate consists of two potential fields. Each potential field is assigned to one layer. Reference paths should be divided in a way that no critical areas, such as crossings, remain in the path fragments (Figure 1). Hereby, the horizontal angle θ represents the horizontal oar angle and the vertical angle δ represents the vertical oar angle of the oar motion in the rowing simulator used for Experiment 1 later in the paper (see also Figure 5).

to another at discrete time points (i.e. discrete states), the herein described path controller belongs to the field of hybrid control.

To guarantee stability of the HPC, the condition for passive systems should be guaranteed. This is the case, when the controller fulfills the condition for passive systems:

$$V(\boldsymbol{q},t) = \phi(\boldsymbol{q}_0) + \int_0^t \boldsymbol{y}(\xi)^T \boldsymbol{u}(\xi)\mathrm{d}\xi - \int_0^t m(\boldsymbol{q},\xi)\mathrm{d}\xi$$

$$\begin{gathered} \text{with} \\ \boldsymbol{q} \in \Omega, \\ t \in \mathbb{R}_0^+, \\ V(\boldsymbol{q},t) \text{ has a lower bound,} \\ V(\boldsymbol{q},t) \text{ is continuous,} \\ \dot{V}(\boldsymbol{q},t) \text{ exists and is continuous,} \\ m(\boldsymbol{q},t) \geq 0, \forall t \in \mathbb{R}_0^+. \end{gathered} \tag{4}$$

Hereby, $V(\boldsymbol{q},t)$ corresponds to the energy stored in the system at position $\boldsymbol{q}$ and time point t. Note that the position $\boldsymbol{q}$ can represent the pose (i.e. the position and orientation) of a robot's end-effector (i.e. the device at the end of a robotic arm that allows it to perform tasks in the physical world, essentially acting as the robot's "hand" or "tool"), the joint coordinates of the robot, or a combination of both [61]. The term $\phi(\boldsymbol{q}_0)$ represents the system's potential in the initial position $\boldsymbol{q}_0$. The variable $\boldsymbol{y}(\xi)$ is the system's response at time ξ, which corresponds to the elastic force $\boldsymbol{f}_{\text{elast}}$/torque $\boldsymbol{\tau}_{\text{elast}}$ for the HPC at the current position $\boldsymbol{q}$. Hereby, the current position $\boldsymbol{q}$ is defined in the workspace Ω for the robot. Since the HPC might consist of several layers, the current position $\boldsymbol{q}$ also contains the information about the current number of the current layer, e.g. $\boldsymbol{q} = \boldsymbol{q}(\theta, \delta, \text{Layer})$. In this example, the variable θ represents the horizontal oar angle and the variable δ represents the vertical oar angle of the oar motion in the rowing simulator used for Experiment 1 later in the paper (see also Figure 5). The term $\boldsymbol{u}(\xi)$ represents the user's input at time ξ, i.e. the joint or end-effector velocity. $m(\boldsymbol{q},\xi)$ corresponds to the power consumed by the system in dependence of position $\boldsymbol{q}$ and time ξ. In the current version of the HPC, $m = 0$.

When equation (4) holds globally, then passivity of the HPC is maintained. In particular, this requires that there are no discontinuous changes in the equation when the layers are switched, i.e. there are no discontinuities between the potential fields at the location $\boldsymbol{q}$, when one layer is switched to another. To avoid force peaks and discontinuities during switching between layers, the potential fields in the region of the portals have to be identical in both layers that are involved in the switching process. This can be reached, when the path sections in the region of the portals are identical in both layers. Consequently, paths are always segmented in a way that the last $4 * r_{\text{NRBF}}$ of the path segment in one layer is identical to the first $4 * r_{\text{NRBF}}$ of the path segment in the following layer. So, when layers are switched, the end-effector will be located in a locally identical potential field also on the new layer. Thus, the user will not remark the layer change and passivity of the HPC can be conserved.

The here proposed HPC incorporates another advantage compared to previous path controllers based on conservative potential fields. In previous path controllers, the potential field had always to be precalculated, i.e. the weights of the compactly supported NRBFs had to be calculated prior to application of the path controller. Precalculation was either based on optimization algorithms [50] or on direct shaping of the potential field by adjusting the NRBFs in dependence of their distance to the nearest point on the reference path [51], [53], [61]. Moreover, the entire potential field had to be uploaded to the robot control for application of the path controller. The HPC in contrast can directly use the desired reference path, without precalculating the potential field. To do so, two NRBFs are placed in fixed distance Δ_{NRBF} left and right from the actual robot position $\boldsymbol{q}$ for each degree of freedom (DOF), i.e. the NRBFs move together with the robot's position $\boldsymbol{q}$ at constant distance. The distance of the NRBFs' center points is chosen according to the following formula:

$$r_{\text{NRBF}} > \Delta_{\text{NRBF}} > \frac{r_{\text{NRBF}}}{2}. \tag{5}$$

In our chase, we chose $\Delta_{\text{NRBF}} = \frac{3r_{\text{NRBF}}}{4}$. So, the NRBFs span a small potential field around the end-effector. The two parameters that influence the shape of the potential field are the radius r_{NRBF} and the weight $\boldsymbol{w}_j$ of the NRBFs. The radius r_{NRBF} determines the degree of detail at which a reference path can be rendered, i.e. the larger the radius, the less detail. When the radius of the NRBFs is large, the NRBFs cannot represent high details of the reference path such as sharp curves since a large radius acts like a spatial low pass filter. The final shape of the small potential field is obtained through adjustment of the NRBFs' weights $\boldsymbol{w}_j$ in real-time. In our case, the weights $\boldsymbol{w}_j$ increase linearly in dependence of the distance to the closest point on the reference path.

The proposed approach of using two NRBFs per DOF is independent of the workspace. This means that the potential field approach allows to control the position $\boldsymbol{q}$ of the robot in joint space, in Cartesian space, or in both spaces at the same time. When the number of DOFs needs to be increased, only the dimensionality of the NRBFs has to be adapted.

To conclude, the HPC is a path controller that can be used on arbitrarily complex paths in joint and Cartesian space at the same time. The HPC prevents the user from taking shortcuts, while providing temporal freedom during task and dynamics exploration as well as allowing to make spatial errors. At the same time, the HPC is inherently passive and requires little lead time for the operator, i.e. the HPC only requires the desired reference path as input instead of a precomputed potential field.

3 Simulation

3.1 Simulation preparation

Before testing the HPC on a real robot, we want to demonstrate its functionality in a simulation, i.e. the automatic switching between layers. As a reference path, a lemniscate is used (Figure 2), which is divided into two layers (Figure 3). For this simulation, an end-effector trajectory is generated by linear interpolation of 15 waypoints (Table 1). The end-effector movement starts at point 1 on layer 1, ends at point 15, and takes 10s overall (Figure 4). A sampling frequency of 1 kHz is used, which is common in real-time control of robots. The simulation is performed with *MATLAB/Simulink*® 2011b, 32 bit on a laptop with an *Intel*® i7 prozessor (1.73 GHz), 8 GB-RAM, on the operating system *Windows*® 7.

3.2 Simulation results and discussion

The simulation shows the automatic switching behavior of the HPC between layers, when portals are crossed in the correct direction, i.e. the end-effector has to move from inside the circular portal across the active part of the portal to the outside of the portal. So, layer switches result as expected

Table 1: Indices and according simulation times of the simulated end-effector trajectory. Trajectory starts at point 1 (=index 1) on layer 1. The variable θ represents the horizontal oar angle and the variable δ represents the vertical oar angle of the oar motion in the rowing simulator used for Experiment 1 later in the paper (see also Figure 5).

Index	θ°	δ°	time s	Index	θ°	δ°	time s
1	24	−8	0	9	4	−16.5	6
2	25	−13	0.5	10	11	−10.5	7
3	20	−18	1	11	5	−20	7.5
4	16	−17.5	2	12	−3	−18	8
5	4	−6	2.5	13	−7	−12.5	9
6	−2	−6	3	14	−5	−6.5	9.5
7	−3	−16	4	15	4.2	−4	10
8	0	−17	5				

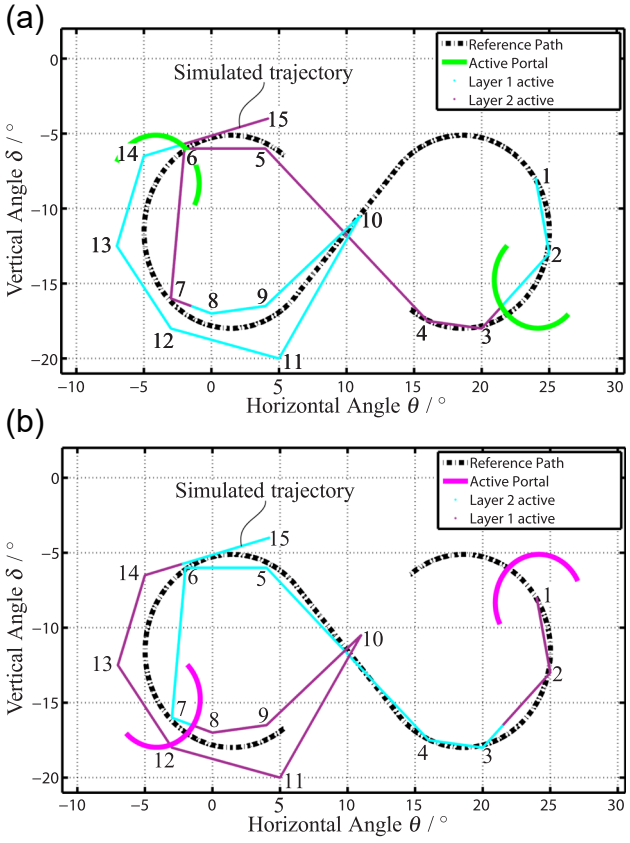


Figure 4: Behaviour of the hybrid path controller during a simulated motion along a lemniscate reference path that is divided into 2 layers with overlapping parts. (4a) and (4b) show the two layers of a HPC. In both layers, the same trajectory for the simulation is depicted. A change in the trajectory color indicates an automatic switching between layers. The horizontal angle θ represents the horizontal oar angle and the vertical angle δ represents the vertical oar angle of the oar motion in the rowing simulator used for Experiment 1 later in the paper (see also Figure 5).

between trajectory points 2 — 3 from layer 1 to layer 2 and back from layer 2 to layer 1 between trajectory points 14 — 15 (Figure 4). Since the reference paths in the regions around the active portals are identical and therefore also the local potential fields are identical, switching between layers cannot be noticed by the user. Now, the HPC is ready for testing in experiments with human users on real robots.

4 Experiments

To prove the functionality of the HPC not only by simulations, but also in real applications with human users and robots, two experiments were performed. The goal of both experiments was to demonstrate that the HPC is fully functional for applications with complex movements on any kind of haptic device (parallel, serial, large, small),

in different workspaces (joint space, Cartesian space), and different number of DOFs similar to previous work with a path controller that could not switch paths [61]. Newly, in this paper, we intend to demonstrate that the HPC allows a human user to explore an *a priori* unknown complex movement, while providing the user the freedom to make errors, and allowing continuous adaptation of the provided support from a supportive to a challenging behavior. Therefore, in a first experiment, the HPC based on the 2D reference path of the lemniscate in joint space (Figure 2) was implemented on a large custom-made tendon-based parallel robot. In a second experiment, a more complicated reference path in 3D Cartesian space was implemented and tested on a second haptic device, a small commercial serial robot, a *PHANTOM Omni*® haptic device (Geomagic, Sensable group, Wilmington, MA, USA).

4.1 Hybrid path control on a tendon-based parallel robot

For the first experiment, the HPC was implemented on a large, versatile, custom-made tendon-based parallel robot. Usually, this robot is applied in research on robot-assisted human motor learning and sleep research [43], [51], [53], [57], [58], [61]–[65]. For the current study, the tendon-based parallel robot was set up as a scull rowing simulator (Figure 5). From this scull rowing simulator, we used the right-hand oar as a simple lever arm mechanism with two actuated degrees of freedom (DOFs) in spherical coordinates (joint coordinates). These two DOFs were the horizontal oar angle θ and the vertical oar angle δ. The oar/lever arm could be rotated around its fixation point (oar lock). On one side of the end-effector, i.e. a shortened oar, a human user could grasp a handle. On the other side, five drive trains of the robot were connected in parallel. The third degree of freedom, i.e. the rotation of the oar around its longitudinal axis, remained unactuated. For the experiment with a human subject, the HPC was based on the lemniscate reference path as the previous simulation (Figure 2).

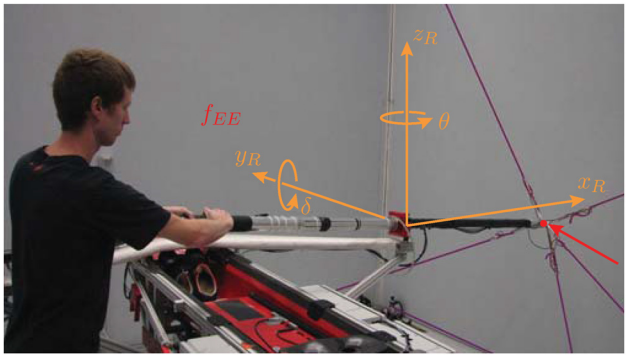


Figure 5: A human volunteer was operating the right-hand oar of the rowing simulator/lever arm mechanism in spherical space. The five drive trains of the tendon-based parallel robot were attached to the opposite side of the shortened oar. Here, the robot applied a force at the end-effector $\boldsymbol{f}_{\text{EE}}$ that is transformed to a torque around the fixation point of the oar (oar lock).

The implementation of the HPC for the experiment on the tendon-based parallel robot was realized using a *MATLAB/Simulink*® model running at 1 kHz on an xPC-target. Hereby, xPC-target is a real-time software environment from MathWorks that uses standard PC hardware as a target machine for real-time simulations, connected to a host PC for development and control. In this setting, the HPC was embedded in the robot's control structure together with a force controller that took over the compensation of friction forces by model-based, closed-loop force control due to force measurement in all drive trains close to the end-effector ($\boldsymbol{f}_{R,\text{meas}}$). Furthermore, the force controller transformed the desired elastic torques $\boldsymbol{\tau}_{\text{elast}}(\boldsymbol{q})$ that were provided by the HPC to the desired rope forces $\boldsymbol{f}_R$ for the five drive trains. This transformation needed to know the length of all five tendons $\boldsymbol{l}_{R,\text{meas}}$ and was based on a real-time optimization using active set algorithms [66], [67]. More detailed information on the force controller can be found in the reference [53]. For the experiment with a human user, a time-dependent (t_{CPU}) adaptation of the amount of support/challenge provided by the HPC was chosen. This time-dependent adaptation was realized through online-adaptation of the scaling factor λ (Figures 6 and 7). At this point it needs to be mentioned that an online adaptation of the scaling factor λ violates the passivity condition. However, for the experiment we were more interested in demonstrating the possibility to adapt the amount of support online and even to challenge users along a complex path. Moreover, instabilities in the performance of the robot were not observed during the experiments despite online adaptations of the scaling factor λ, which was very likely thanks to friction in the system of the robot.

To test the implementation of the HPC on the tendon-based parallel robot, an experiment involving one human volunteer was conducted. The experiment was approved by the ethics commission of ETH Zurich (EK_2010-N-53). For the experiment, a healthy human volunteer without prior knowledge of the reference path was recruited. In total, the volunteer performed three trials of 100 s each with breaks of 1 min in between. From the first to the last trial, the amount of support was linearly decreased in a predefined way by changing the scaling factor λ of the HPC from 1 to −0.1 (Figure 7). During the third trial, λ changed from positive to negative values. This indicated that the participant was not

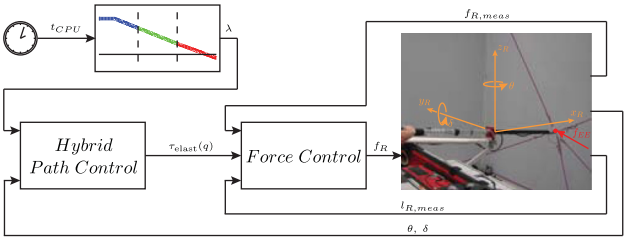


Figure 6: For Experiment 1, a large tendon-based parallel robot was used. The HPC was implemented in connection with a Force Control block that compensated for undesired effects in the system and realized a desired pretension in the ropes while transforming the elastic torque $\boldsymbol{\tau}_{\text{elast}}(\boldsymbol{q})$ from the HPC to the five desired rope forces $\boldsymbol{f}_R$. The robot provides measurements of the oar angles θ and δ as a feedback for the HPC. In addition, the robot also measures the resulting forces in the ropes $f_{R,\text{meas}}$ as a consequence of the interaction forces f_{EE} resulting from the oar movement induced by the user. To provide the measurement of rope forces for the Force Control, unidirectional force sensors in the ropes close to the end-effector are implemented. Additionally, also the lengths of the ropes $l_{R,\text{meas}}$ that are required for the forward kinematics inside the Force Control is measured by the robot.

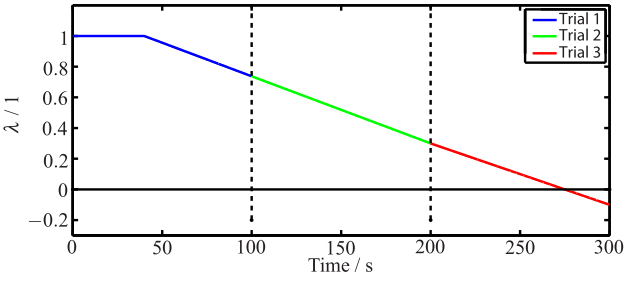


Figure 7: Development of the parameter λ of the HPC during the three measurement trials with a volunteer. For positive values of λ, the HPC pushed the volunteer back onto the reference path, whereas for negative values of λ, the volunteer was pushed away from the reference path.

supported but challenged, i.e. the end-effector was pushed away from the reference path. The human volunteer was instructed to explore the closed-form reference path at a self-selected speed and to keep repeating the discovered movement, even if the support was decreasing over time. No information was provided about the movement shape, direction of movement, or the way the human volunteer should remember the reference path.

To assess the effect of the HPC on the human volunteer, the following performance measures were applied:

1. T_{cycle}: the duration to complete an entire path cycle
2. n_{cycle}: the number of entirely completed cycles per trial
3. $\epsilon(A, B)$: the figural distance between the reference path (A) and the trajectory performed by the human volunteer during each trial (B) according to the following formula that was first proposed by Conditt et al. [68] and also used in other tracking experiments, e.g. [69]:

$$\epsilon(A,B) = \frac{\sum_{i=1}^{n} d_{A-B}(i) + \sum_{j=1}^{m} d_{B-A}(j)}{m+n}. \tag{6}$$

Here, n denotes the number of data points with the according index i for the reference path A, m is the number of data points with the according index j for the trajectory performed by the human volunteer B, $d_{A-B}(i)$ is the shortest distance from the point i on reference path A to the volunteer's trajectory B, and $d_{B-A}(j)$ is the shortest distance from the point j on the volunteer's trajectory B to the reference path A.

4.2 Results from Experiment 1 on a tendon-based parallel robot

The resulting movement of the end-effector that was performed by the human volunteer while the support provided by the HPC was constantly decreased as shown in Figure 8. The analysis of the three performance measures revealed an increase in the number of cycles n_{cycle} from the first to the second trial, while the mean duration to complete one cycle T_{cycle} decreased. From the first to the third trial, a constant decrease in standard deviation of the cycle durations was found. As a result of the constantly decreasing support and the applied disturbance during last part of the third trial, the values in figural distance $\epsilon(A, B)$ increase constantly across the three trials (Figure 9 and Table 2).

4.3 Discussion of Experiment 1

First, the HPC allowed the human volunteer to successfully explore and repeatedly complete entire cycles of the

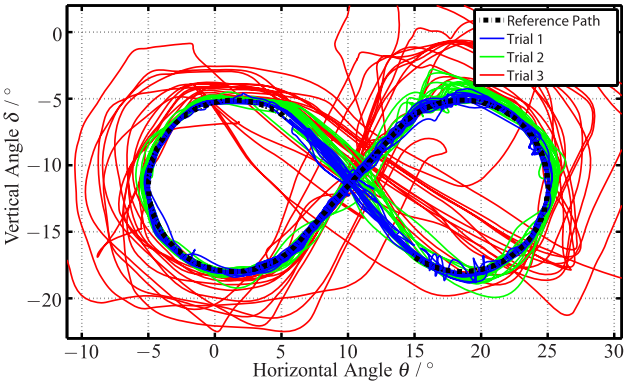


Figure 8: Trajectories of the human volunteer for the three measurement parts with changing amount of support (Figure 7). The horizontal angle θ represents the horizontal oar angle and the vertical angle δ represents the vertical oar angle of the oar motion in the rowing simulator used for Experiment 1 later in the paper (see also Figure 5).

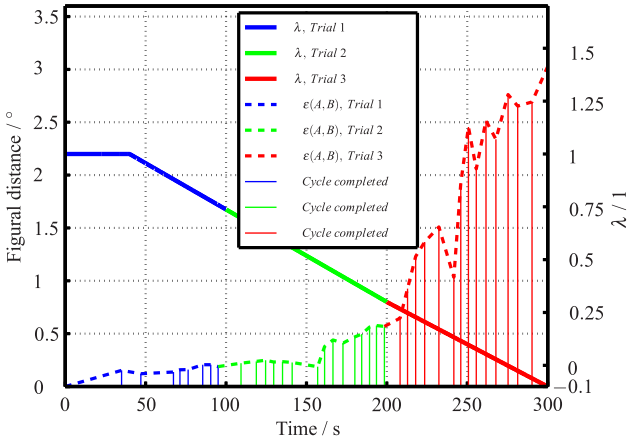


Figure 9: Development of the figural distance $\epsilon(A, B)$ over time while the amount of support λ is constantly decreased across the three trials.

Table 2: Results Experiment 1.

Performance measure	Trial 1	Trial 2	Trial 3
$n_{cycle}/1$	8	15	15
T_{cycle}/s	11.9(10.8)	6.6(3.0)	6.7(1.9)
$\epsilon(A, B)/°$	0.2(0.03)	0.4(0.15)	1.9(0.77)

lemniscate without prior knowledge of the path shape. This was shown by the number of successfully completed cycles n_{cycle} greater than zero for each trial. Thus, the human volunteer was prevented from taking shortcuts and was successfully guided through the entire path. Second, the variation in the duration to complete a cycle indicates that the volunteer was free in timing. Third, the increasing values in the figural distance and the recorded trace of the three trials (Figure 8) over time and trials indicates that the continuous adaptation of the HPC from a supportive to a challenging behavior was successful. Moreover, the human volunteer was able to make errors. Additionally, the volunteer must have remembered the learnt path since entire cycles could be accomplished even under the challenging condition during trial three. In conclusion, the HPC behaved as expected and proved its practicability in the experiment with a human volunteer and a large tendon-based parallel robot. The HPC could successfully hide the path crossing of the lemniscate path in 2D spherical space, provided freedom to explore the task, make errors, and to adapt the amount of support.

4.4 Hybrid path control on a serial robot (Experiment 2)

In a second experiment with another human volunteer, we wanted to demonstrate that the HPC is generalizable

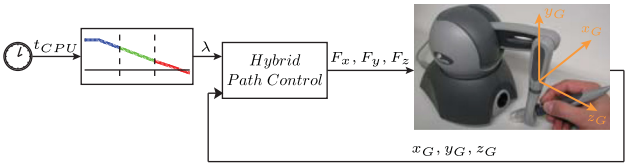


Figure 10: For the second experiment, a small serial robot, a *PHANTOM Omni*® haptic device was used. The hybrid path controller was implemented for the gimbal positions x_G, y_G, and z_G. The hybrid path controller directly rendered the forces F_x, F_y, F_z based on the potential field that is scaled by adapting the parameter λ over time in order to adapt the support from assistance to challenge.

to other robots, different workspaces, and more DOFs. Therefore, in this second experiment, the HPC was tested in three dimensional Cartesian space on a small, commercial serial robot, a *PHANTOM Omni*® haptic device (Figure 10). The *PHANTOM Omni*® was connected via "Firewire 400" (*IEEE* 1394a) to a laptop with an *Intel*® i7 prozessor (1.73 GHz), 8 GB-RAM, on the operating system *Windows*® 7. The control application for the robot was realized with *MATLAB/Simulink*® 2009b, 32 bit together with the "Phansim" toolbox [70]. The control algorithm was run under "Accelerator" mode using a "Fixed-step" solver of "ode3 (Bogacki-Shampine)" type with an automatically defined step size. Furthermore, the *MATLAB/Simulink*® application was executed using "high priority" task execution settings under *Windows*®.

The *PHANTOM Omni*® haptic device was controlled in 3D Cartesian space using coordinates x_G, y_G, and z_G (Figure 10). These three coordinates were used to close the control loop through the HPC that provided the forces F_x, F_y, and F_z. Also for this experiment, a time-dependent (t_{CPU}) adaptation of the amount of support/challenge provided by the HPC was reached through online-adaptation of the scaling factor λ (Figure 10) exactly like in Experiment 1 (see Figure 7).

For this second experiment, a different reference path was used compared to the lemniscate in 2D joint space of the first experiment. The reference path in 3D Cartesian space consisted of a rectangle combined with an ellipse, with an intersection in the point [−30mm, 0mm, −20mm]. Similar to the lemniscate, the reference path was divided into two reference paths that overlapped at their ends. Each of the two reference segments was used to create the potential field for one of two layers. Through switching between these layers, the human user could explore the entire path without remarking crossings or paths in close vicinity to each other (Figure 11). For the current potential field, the height of the NRBFs' weights $\boldsymbol{w}_j$ increased with the square of the minimal distance to the reference path.

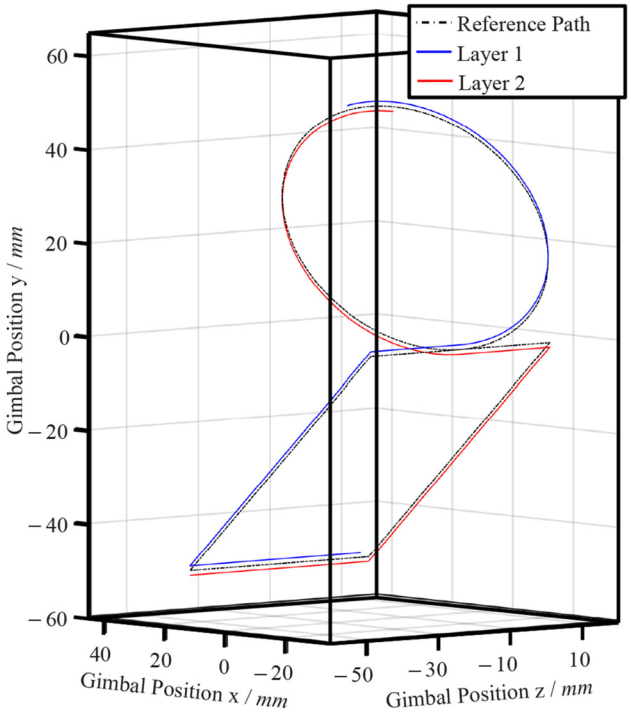


Figure 11: The reference path for the second experiment consisted of a rectangle and an ellipse that had to be explored sequentially. For the implementation in the HPC, the reference path was divided into two reference paths that overlap at their ends (blue and red path). The blue/red reference path was used to generate layer one/two for the HPC. Through switching between the two layers, the entire path could be explored without intersections. Note that the blue and the red reference path are illustrated with a slight offset for visualization purposes.

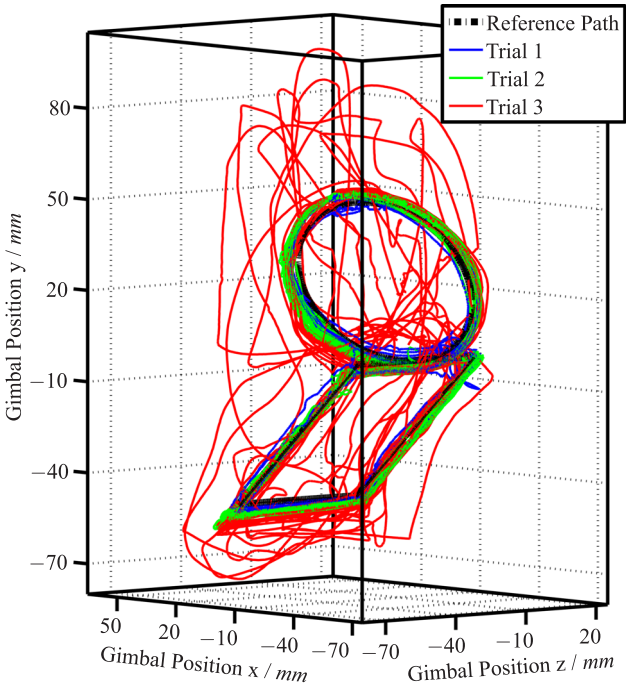


Figure 12: Trajectories of the human volunteer for the three measurement trials with changing level of support (Figure 7).

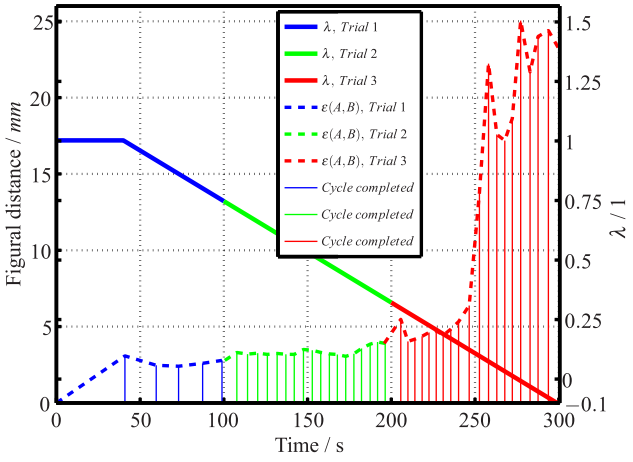


Figure 13: Development of the figural distance $\epsilon(A, B)$ over time while the amount of support λ was constantly decreased across the three trials.

The implementation of the reference path was tested on the serial robotic device with another human volunteer. The protocol and performance measures were the same as in the first experiment: The human volunteer was instructed to explore the closed-form reference path at a self-selected speed and to keep repeating the discovered movement even when the support was decreased over time. No information was provided about the movement shape (no visual feedback), direction of movement, or the way the human volunteer should remember the reference path.

4.5 Results from Experiment 2 on a serial robot

During the three trials with the serial robot, the end-effector movement performed by the human volunteer was recorded (Figure 12). The analysis of the three performance measures revealed an increase in the number of cycles n_{cycle} from the first to the last trial, while the mean and the standard deviation of the duration to complete one cycle T_{cycle} decreased constantly. The constantly decreasing amount of support over the three trials resulted in increasing values of the figural distance $\epsilon(A, B)$ across the trials (Figure 13 and Table 3).

4.6 Discussion of Experiment 2

Results of the second experiment were similar to those from the first, even though another robot and a different and more complex reference path were used. First, the HPC allowed the human volunteer to successfully explore and repeatedly complete entire cycles of the 3D path without

Table 3: Results Experiment 2.

Performance measure	Trial 1	Trial 2	Trial 3
n_{cycle}/1	5	18	20
T_{cycle}/s	19.8(12.1)	5.4(0.8)	5.0(0.8)
$\epsilon(A, B)$/mm	2.7(0.3)	3.4(0.3)	12.8(8.6)

prior knowledge of the path shape. This was shown by the number of successfully completed cycles n_{cycle} greater than zero for each trial. Thus, the human volunteer was prevented from taking shortcuts and was successfully guided through the entire 3D path. This result and the result of the first experiment seem to indicate that the HPC can be used as an instruction to learn even complex movements without imposing timing constraints. Second the variation in the duration to complete a cycle indicates that the volunteer was free in timing. Third, the increasing values in the figural distance and the recorded trace of the three trials (Figure 12) over time and trials indicates that the continuous adaptation of the HPC from a supportive to a challenging behavior was successful. Moreover, the human volunteer was able to make errors. Additionally, the volunteer must have remembered the learnt path since entire cycles could be accomplished even under the challenging condition during trial three. In conclusion, the HPC behaved as expected and proved its practicability in the experiment with a human volunteer and a small serial robot. The HPC could successfully hide the path crossing of the complex 3D reference path, provided freedom to explore the task, make errors, and to adapt the amount of support.

5 Conclusions

Robot-aided training of real-life tasks such as in sports or robot-aided rehabilitation with multiple degrees of freedom require controllers that fulfill three main requirements: First, the haptic controller should include principles that are known to be crucial for human motor learning. Second, the haptic controller should be passive to avoid instability. Third, the haptic controller should provide haptic guidance along arbitrarily complex movements (i.e. movements along an arbitrarily complex predefined path) for which potential self-crossings can be hidden. However, until today, there is no controller that combines all these requirements in one concept. Therefore, we introduced a hybrid path controller (HPC) that can overcome the limitations of existing controllers. Additionally, the controller is passive, which guarantees its stability.

Exemplarily, for applications on any robotic device, the hybrid path controller could prove its full functionality on a large custom-made parallel robot and on a small commercially available serial robot. Hereby, complex reference paths with varying degrees of freedom and workspaces (spherical joint coordinates, Cartesian coordinates) could be successfully implemented and explored by naïve human volunteers. As an additional result, the hybrid path controller could successfully adapt the amount of support from an assisting to a challenging behavior along complex paths with crossings. The human volunteers were able to explore the *a priori* unknown complex paths during assistive mode and they even continued performing the correct movement under challenging mode. These first results with human volunteers do not only confirm the full functionality of the hybrid path controller as intended, but seem also to support the applicability of the controller for motor learning. As a consequence, we plan to investigate the hybrid path controller's potential in future motor learning studies.

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Research ethics: The experiment was approved by the ethics commission of ETH Zurich (EK_2010-N-53).

Informed consent: Informed consent was obtained from all individuals included in this study, or their legal guardians or wards.

Author contributions: All authors have accepted responsibility for the entire content of this manuscript and approved its submission.

Use of Large Language Models, AI and Machine Learning Tools: None declared.

Conflict of interest: All other authors state no conflict of interest.

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Data availability: The raw data can be obtained on request from the corresponding author.

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