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H-Man: A Planar, H-shape Cabled Differential Robotic Manipulandum for Experiments on Human Motor Control

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Abstract

In the last decades more robotic manipulanda have been employed to investigate the effect of haptic environments on motor learning and rehabilitation. However, implementing complex haptic renderings can be challenging from technological and control perspectives. We propose a novel robot (H-Man) characterized by mechanical design based on cabled differential transmission providing advantages over current robotic technology. The H-Man transmission translates to an extremely simplified kinematics and homogenous dynamic properties, offering the possibility to generate haptic channels by passively blocking the mechanics, and eliminating stability concerns. We report results of experiments characterizing the performance of the device (haptic bandwidth, Z-width, and perceived impedance). We also present the results of a study investigating the influence of haptic channel on motor learning in healthy individuals, which highlights the effects of channel variable compliance in enhancing proprioceptive information. The generation of haptic channels to study motor redundancy is not easy for actual robots because of the needs of powerful actuation and complex real-time control implementation. The mechanical design of H-Man affords the possibility to promptly create haptic channels by mechanical stoppers (on one of the motors) without compromising the superior backdriveability and high isotropic manipulability. This paper presents a novel robotic device for motor control study and robotic rehabilitation. The hardware was designed with specific emphasis on the mechanics that result in a system that is easy to control, homogeneous, and is intrinsically safe for use.

Keywords: H-Man, Robotic manipulanda, Human motor control, motor adaptation

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1. Introduction

Traditionally, studies of human motor control were conducted by researchers from the behavior sciences, such as neurophysiology, cognitive science, biomechanics, and psychophysics. More recently, scientists with backgrounds in engineering and robotics have provided their expertise to this area, leading to a proliferation of available human-machine interfaces which provided new means to study the underlying mechanisms by which the Central Nervous System (CNS) modulates interaction strategies with the external environment. A common paradigm to investigate CNS responses to external disturbances is via the use of structured force fields. In these experiments, the participant performs a goal directed movement (e.g., reaching) and a haptic setup provides the user with feedback regarding the dynamic behaviour associated to virtual objects implemented in a simulated environment. The goal of the haptic device is to render mechanical properties of the virtual objects, often expressed as inertia, damping, compliance. Further, these setups are capable of online tuning of the mechanical response as the participant interacts with the system, always with the primary requirement of accuracy in haptic rendering and stability preservation. For example, haptic setups used in robotic rehabilitation allow the physical therapist to increase the stiffness of the assistive action towards a target to be reached, typically implemented as an attractive elastic force. Alternatively, the therapist could set the virtual spring so that it resists movements in specific directions, requiring larger muscular activation to reach a target.

1.1. *Adaptation to Curl Viscous Fields*

Studies on motor learning and adaptation often make use of dynamic perturbations during specific motor tasks like, for example, reaching. Similar to gravity compensation learning mechanisms, the CNS can also learn different types of force fields. Evidence of learning is often found when the new field is suddenly removed. Lackner and DiZio [1] examined rapid adaptations to Coriolis forces by asking participants to sit in a rotating room and perform point-to-point arm reaching movements. When the room was rotating, participants experienced the so-called Coriolis effect, in this case corresponding to a horizontal force proportional to the hand velocity and always perpendicular to it. The initial trajectories of the reaching movements were disturbed by the introduction of the Coriolis force, however with practice participants adapted to it and were able to make straight line reaching movement, as normally expected in non-rotating environments. Similarly, as the room stopped rotating, the reaching movements displayed large lateral errors, opposite in direction to those performed when the room first started rotating.

In fact, in a rotating room, every single atom is subjected to the Coriolis effect, which is more apparent on distal arm segments as these move faster during reaching movements. While experiments in a rotating room might not always be feasible, the Coriolis effect at the hand can be reproduced by means of robotic manipulanda programmed to impose curl viscous fields (i.e. force fields proportional to the hand velocity but perpendicular to it). In the landmark study by

Shadmehr and Mussa-Ivaldi [5], participants were asked to make point-to-point movements while grasping the handle of a planar robotic manipulandum capable of generating a velocity-dependent force fields. When the robot generates no active forces (i.e. null force field), movement trajectories were essentially straight lines to the target, with bell-shaped velocity profiles as expected in planar motions [15]. In contrast, when the robot was turned on, the hand veered off the direction of the target, resulting in skewed trajectories. However, as in the study by Lackner and DiZio [1], hand trajectories became increasingly similar to those in the null field with additional practice. This convergence was gradual but monotonic for all participants, indicating that the CNS learned to compensate for the imposed force. After the participants adapted to the imposed forces and produced nearly straight movements to the target, the force field was randomly turned off (catch trials). In these catch trials, the hand trajectory was skewed mirroring the early force field trials. This after-effect has been interpreted as evidence that the nervous system learns to anticipate and counteract novel forces by building an internal model of the force field dynamics.

1.2. Motor Learning and Adaptation in Virtual Environments

Although several studies have shown that healthy subjects can adapt quite well to different kinematic [17, 16] and dynamic perturbations [5, 20], experiments conducted with impaired subjects have revealed contrasting results [18]. Such findings are generally not comparable due to differences in tasks and subjects' characteristics. Therefore a unifying picture is still lacking [18].

A way to increase the amount of available data would be via the use of simpler and cost-effective platforms which could be deployed in community centres as well as in home environments. In line with this perspective, recent findings [3, 19] concerning adaptation to *virtual tasks* might suggest a paradigm shift to design simpler and low-cost devices.

Some virtual tasks are characterized by a mismatch between visual and proprioceptive feedback. An example is the *isometric reaching* [19] where subjects move a cursor on a screen by applying forces on a static load cell. However, the visually perceived movement of the cursor does not generate the proprioceptive feedback of the hand (which does not move in isometric conditions).

Virtual tasks have been implemented with robotic manipulanda that *channel* subject movements along specific directions by stiffening the robot end-effector in the directions orthogonal to the desired movement direction. In fully isometric conditions adaptation has been investigated for both kinematic (e.g. visuomotor rotations)[19] and dynamic conditions [21] (where subjects learned to balance a virtual inverted pendulum pushing on a static force sensor). Very recently, adaptation to *virtual curl force fields*, in which the controlled cursor is perturbed proportionally to the hand velocity, has been examined by moving the hand along specific channels [3].

In [9], it has been shown that the introduction of a channel, during the washout phase, affects and in particular slows down the re-adaptation to the unperturbed hand condition. In [19], where the handle was completely rigid

(isometric conditions), no learning differences have been reported between subjects experiencing two different cursor dynamic. In our preliminary experiments [6], we showed that adding compliance to an otherwise rigid, mechanical channel does make a difference in motor learning.

From a technological perspective, while haptic attractive/repulsive force fields require relatively low levels of forces, the ability to render realist haptic channels can be very challenging. To render a stiff channel the haptic device should be able to generate very large forces when the handle is pushed against the (virtual) walls of the channel. On the one hand, this requires high feedback gains in the control loop, which is known to induce instability and therefore safety issues. Moreover, the possibility of producing very large force fields necessarily oversizes the actuation system. On the other hand, high-fidelity rendering of the elasticity of the virtual walls also requires extremely accurate position readings. For example, while 1mm handle position sensing resolutions would be perfectly acceptable for purposes of visual feedback (whereby the subject sees a virtual hand on the screen interacting with virtual objects), it can lead to unrealistic rendering of a stiff virtual spring. In fact, rendering a 2000 N/m stiffness (typical value for haptic channels in literature [9]) with a 1mm resolution would cause the virtual elastic force to jump in 2N (200 g) steps rather than vary in a continuous fashion, as expected in a real spring. In this work, we propose a simple planar robot, named H-Man, which combines active haptic rendering of general-purpose, low-level force fields and passive mechanisms to physically implement channels, without any stability issues.

2. H-Man Overview

2.1. Design and Kinematic Model

Previous manipulanda were, for the most part, inspired by planar linkages and parallelograms [10, 11, 12, 13], with the primary requirement being direct drive transmission (and therefore high backdriveability). In these cases, the nonlinear kinematics of four-bar mechanisms must be taken into account for an accurate generation of haptic rendering and compensation of the inertial dynamics. This is especially important in parts of the workspace where the robot is close to one of its configuration of singularity. The main advantage of the H-Man architecture is its lightweight mechanics, characterized by very simplified kinematics and intrinsic high isotropy over the workspace. The ratio between the smallest and the highest eigenvalue of the matrix $J^{-T}J^{-1}$ is called condition number and it is often used as a measure of manipulability, dexterity and isotropy of robotic end-effector [14]. When such index equal one, the robot is said to be isotropic in that configuration. If one considers a multiple bar mechanism, the resulting condition number will be configuration dependent, and the Jacobian matrix, incorporating the geometrical features of the robotic devices will play the major role in dynamics and kinematics transferred from the joint to the end effector. The H-Man system (Figure 1) features a condition number equal to one over the entire workspace. This is achieved by means a

simple kinematic topology in which two actuators in a differential configuration drive two perpendicular linear sliders onto which the end-effector is attached. The force transmission from the actuators to the end-effector is based on an H-shaped cable-driven transmission system. While motors are grounded, each rotor is coupled with a driving pulley. The driving pulleys wound the cable that in turn is wound over four grounded corner idlers which are freely to rotate. The H-shaped transmission is then completed with four additional idlers (depicted in green in Figure 1 B), mounted on top of the carriage, that in turn allow the transmission of the motor torques to the handle.

The Jacobian matrix, which maps the angular velocities of the motors ($[\omega_L \ \omega_R]^T$) into linear velocities of the end-effector ($[\dot{x} \ \dot{y}]^T$) only depends on the radius (r_m) of the driving capstan pulleys coupled to each motor. This mapping is expressed as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix} = \mathbf{J} \begin{bmatrix} \omega_L \\ \omega_R \end{bmatrix} \quad (1)$$

where $\mathbf{J}$ represents the Jacobian matrix mapping motor angular velocities to end-effector linear velocities, and is defined as

$$\mathbf{J} = \frac{r_m}{2} \begin{bmatrix} -1 & -1 \\ -1 & 1 \end{bmatrix} \quad (2)$$

It should be noted that positive rotations of the motor pulleys define the pulling directions ($\mathbf{e}_L$ and $\mathbf{e}_R$):

$$\mathbf{e}_L = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ -1 \end{bmatrix}; \quad \mathbf{e}_R = \frac{1}{\sqrt{2}} \begin{bmatrix} -1 \\ 1 \end{bmatrix} \quad (3)$$

Indeed, if one of the two actuators holds a fixed position while the other is left free to rotate, the end-effector will naturally move along one of the diagonals of the workspace. The Jacobian also relates motor torques to forces at the handle via the following

$$\mathbf{J}^T \begin{bmatrix} F_x \\ F_y \end{bmatrix} = \begin{bmatrix} \tau_L \\ \tau_R \end{bmatrix} \quad (4)$$

[Figure 1 about here.]

In the mechanical assembly and electrical wiring of the H-Man, our convention is that positive currents in the motors induce positive angular velocities with respect to the shaft axis which, in turn, produce positive motions along the directions $\mathbf{e}_L$ and $\mathbf{e}_R$ for the left and right motor, respectively.

2.2. Transmission: Bandwidth and Stability Limits

Two tests were conducted to evaluate the bandwidth and stability limits of the system. The frequency response of the device was ascertained by commanding a sinusoidal current at different frequencies to the motors. The motors are driven by current servos (ELMO Ocarina drivers). The end-effector was blocked

by a custom rigid frame and the force delivered was measured by a force sensor (ATI Mini45). The torque generated by the motors from the sinusoidal current input

$$i_c(t) = I_c \sin(2\pi f_0 t)$$

was then compared with the output force at the handle of the device.

The frequency f_0 range was swept between 1-100 Hz, with incremental steps of 1Hz, while amplitude I_c assumed values of 0.5A, 0.75A, 1A, 1.5A. The system was considered at steady state after an initial period of 1 second from the application of the sinusoidal command. The actual currents at the motors ($i_L^{f_0, I_c}(t)$ and $i_R(f_0, I_c, t)$), as well as the planar force components ($F_x^{f_0, I_c}(t)$, $F_y^{f_0, I_c}(t)$) were acquired at a sampling rate of $f_s = 10kHz$ for a number of N_{cyc} cycles, for each frequency and amplitude. The force components were then combined into a planar force vector

$$\mathbf{F}(t) = \begin{bmatrix} F_x^{f_0, I_c}(t) \\ F_y^{f_0, I_c}(t) \end{bmatrix}$$

and projected in either of the two pulling directions (3) to derive the following components

$$F_L^{f_0, I_c}(t) = \mathbf{F}(t) \cdot \mathbf{e}_L \quad (5)$$

$$F_R^{f_0, I_c}(t) = \mathbf{F}(t) \cdot \mathbf{e}_R \quad (6)$$

where $\cdot$ represents the dot product. For each acquired signal $s(t)$, the n -th complex coefficient of the Fourier series was evaluated as:

$$C_n\{s(t)\} := \frac{f_0}{N_{cyc}} \int_0^{\frac{N_{cyc}}{f_0}} s(t) \exp(-j2\pi n f_0 t) dt \quad (7)$$

where $j = \sqrt{-1}$ is the imaginary constant. It should be noted that

- $C_n\{s(t)\}$ is integrated over $N_{cyc} = 20$ cycles to calculate the average of the measurements obtained over such the extended period of time (i.e., f_0);
- $C_0\{s(t)\}$ returns the mean value of a signal $s(t)$;
- $C_1\{s(t)\}$ is our main interest but we shall use the higher harmonics to also test for nonlinearities in the system (e.g. introduced by the driver).
- We took advantage of the periodicity of the driving inputs to filter out noise. Given the focus on steady-state responses, we considered only the first 5 harmonics of the force. Thus, for a generic signal $s(t)$ in response to a periodic stimulus, we utilized its truncated Fourier series up to the 5th order:

$$\tilde{s}(t) = \sum_{n=-5}^5 C_n\{s(t)\} \exp(j2\pi n f_0 t) \quad (8)$$

For each specific driving frequency and amplitude of the commanded current, we evaluated the response as

$$H_L(f_0, I_c) = \frac{\mathcal{C}_1\{F_L^{f_0, I_c}(t)\}}{\mathcal{C}_1\{i_L^{f_0, I_c}(t)\}} \quad (9)$$

$$H_R(f_0, I_c) = \frac{\mathcal{C}_1\{F_R^{f_0, I_c}(t)\}}{\mathcal{C}_1\{i_R^{f_0, I_c}(t)\}} \quad (10)$$

which can be represented in terms of frequency plots.

Figure 2 shows that the force transmission bandwidth behaves rather linearly with respect to input current amplitude, with a mechanical resonance around $30Hz$.

[Figure 2 about here.]

2.2.1. Haptic Rendering: the Z-Width

The Z-Width of a haptic display can be defined as the dynamic range of impedances that can be rendered during stable interactions, with larger Z-Width generally corresponding to more realistic virtual environments.

In our current implementation, a real-time control platform (dSPACE, Germany) was controlled at $1KHz$ sampling frequency to read the position of the handle via the motor encoders. The actuators were current-controlled via commercial servos (Ocarina current mode servo amplifiers, by Elmo Motion Control).

Rendering large values of the stiffness and/or damping can lead to system instability. To determine the limits of our system we define the zone of stability as the zone below K-B plane in the Z-Width characterization [8, 7], where K and B are the proportional (stiffness) and the derivative (damping) gains of the impedance controller.

The H-Man is controlled by impedance control, where the motion of the subject interacting with the end effector is allowed by the high backdriveability of the system (which was one of the primary design specifications). In our framework, a real-time system is used to read the position $\mathbf{p} = [x \ y]^T$ and derive the velocity $\dot{\mathbf{p}} = [\dot{x} \ \dot{y}]^T$ of the handle in order to command the output torque τ_L and τ_R to the motors transformed into cartesian forces $\mathbf{F} = [F_x \ F_y]^T$.

A Cartesian impedance controller was implemented according to

$$\boldsymbol{\tau} = \mathbf{J}^T \mathbf{F} = \mathbf{J}^T (\mathbf{K}(\mathbf{p}_{des} - \mathbf{p}) - \mathbf{B}\dot{\mathbf{p}}) \quad (11)$$

where the joint torques $\boldsymbol{\tau}$ are the result of a Cartesian elastic force ($\mathbf{K}(\mathbf{p}_{des} - \mathbf{p})$) plus a damping force ($\mathbf{B}\dot{\mathbf{p}}$).

The stability test consisted of a double nested loop used to gradually increment the controller gains and find the combination between the maximum values of K and B for which the system still results in a stable response for a given position input. The incremental limits for the proportional $\mathbf{K}$ were set from $100N/m$ to $4000N/m$. Similarly, for the derivative gains $\mathbf{B}$: from $0Ns/m$

to $5Ns/m$. A given value of stiffness (K) and damping (B) was set for each trial. A target displacement ($\|\mathbf{p}_{des}\| = 2cm$) was set via the controller and the step response of the system was observed. We considered the system to be close to instability (for a given combination of stiffness and damping values) if any of the following phenomena was observed: 1) an end-effector divergent trajectory, 2) highly underdamped oscillations for more than 0.3 seconds, or 3) saturation of the motor drivers. Detection of the instability boundary was performed by initializing the values of B , K and position displacement. The iterative procedure was repeated by gradually incrementing K until instability was observed. Then, the damping coefficient B was incremented and the stiffness K internal loop was reset to the smallest stiffness coefficient ($100N/m$).

In order to investigate the effect of the system's mechanics anisotropy, a Z -width test was set along three different directions: *X-displacement* where motors rotate in phase, *XY-displacement* (or diagonal displacement) where only one motor produces the required displacement, and *Y-displacement* where motors rotate in anti-phase. Stability regions are shown in Fig.3

[Figure 3 about here.]

3. Haptic Fields via Impedance Control

3.1. Visco-Elastic and Curl Force Fields

Our specific interest was to test the capability to generate force fields linearly correlated with the position $\mathbf{p} = [x \ y]^T$ and/or the velocity $\dot{\mathbf{p}} = [\dot{x} \ \dot{y}]^T$ of the handle, as prescribed by the following general equation:

$$\mathbf{F} = -(\mathbf{B}_{sym} + \mathbf{B}_{cor})\dot{\mathbf{p}} - \mathbf{K}(\mathbf{p} - \mathbf{p}_0) \quad (12)$$

where $\mathbf{B}_{sym}$ and $\mathbf{K}$ are symmetric and positive-definite matrices used to generate visco-elastic fields while $\mathbf{B}_{cor}$ is a skew-symmetric matrix used to generate curl force fields. These matrices can be written as

$$\mathbf{K} = \begin{bmatrix} k_{xx} & k_{xy} \\ k_{xy} & k_{yy} \end{bmatrix} \quad (13)$$

$$\mathbf{B}_{sym} = \begin{bmatrix} b_{xx} & b_{xy} \\ b_{xy} & b_{yy} \end{bmatrix} \quad (14)$$

$$\mathbf{B}_{cor} = \begin{bmatrix} 0 & b_{cor} \\ -b_{cor} & 0 \end{bmatrix} \quad (15)$$

Symmetric properties ensure the existence of non-negative eigenvalues (as expected for a damping or a stiffness coefficient of a passive system), and also allow a graphical representation of $\mathbf{B}_{sym}$ and $\mathbf{K}$ in ellipses form [4].

3.2. Active and Passive Haptic Channels

The elastic properties of the stiffness matrix $\mathbf{K}$ can also be described in terms of equipotential lines [4]

$$(\mathbf{p} - \mathbf{p}_0)^T \mathbf{K} (\mathbf{p} - \mathbf{p}_0) = 2\mathcal{E} \quad (16)$$

where $\mathcal{E}$ represents the elastic energy associated with the elastic deformation in a generic direction $(\mathbf{p} - \mathbf{p}_0)$.

The matrix $\mathbf{K}$ can be rewritten as

$$\mathbf{K} = \mathbf{R}_\alpha \begin{bmatrix} k_{min} & 0 \\ 0 & k_{max} \end{bmatrix} \mathbf{R}_\alpha^T \quad (17)$$

where k_{min} and k_{max} are the (necessarily positive) eigenvalues and $\mathbf{R}_\alpha$ is the rotation matrix

$$\mathbf{R}_\alpha = \begin{bmatrix} \cos \alpha & -\sin \alpha \\ \sin \alpha & \cos \alpha \end{bmatrix} \quad (18)$$

where the orientation angle α determines the orientation of the major axis of the ellipse. By modulating the ratio of eigenvalues k_{max}/k_{min} , it is possible to modulate the anisotropy of ellipses, as shown in Fig.4.

[Figure 4 about here.]

A particular application in motor learning using robotic devices, which relies on the generation of high anisotropic elastic fields, is the *haptic channel effect*. A haptic channel can be thought of as a slot-like elastic force field described by a stiffness ellipse with a high ratio between the eigenvalues ($k_{max}/k_{min} \gg 1$). Such fields provide a negligible resistance to motion along the major axis of the ellipse, as defined in (16), while constraining the motion of the end effector in the orthogonal direction by generating a stiff virtual wall. As an example, Fig.4 shows how the force field isolines point towards the channel (at least within the boundaries of the workspace of interest) when $k_{max}/k_{min} = 100$.

A unique feature of the proposed H-Man design is the possibility to generate haptic channels in the vertical, horizontal and $\pm 45^\circ$ directions without actively controlling the actuators. Preventing the horizontal rail from sliding along the vertical rail (with mechanical stoppers) allows only horizontal movements of the handle, and thus, the horizontal channel. Alternatively, blocking the handle on the horizontal rail (again, with mechanical stoppers) allows only vertical motions of the horizontal rail, and therefore of the handle as well, along the vertical rail. Oblique channels along the $\pm 45^\circ$ directions can be achieved by blocking one of the motors and allowing the other motor to freely rotate. This design feature makes the H-Man device suitable to motor learning experiments focusing on constrained induced movements.

As previously mentioned, mechanical rigid channels can be easily implemented through mechanical stoppers, that in turn constrain a particular movement direction or reduce the degree of freedom of the end-effector. Rigid channels are a distinctive feature of the H-Man that cannot be implemented by means

of motors due to Z-width limit that defines the maximum level of compliance that can be generated by the electromechanical system. The H-Man kinematic design, on the other hand, enables the possibility of passively implementing haptic channels in the vertical, horizontal, and $\pm 45^\circ$ oblique directions. This design feature provides a higher level of safety while a subject is interacting with the device.

In a previous work (see sec. 5) we implemented a horizontal elastic channel using elastic bands connected to the H-Man’s end-effector. Here, we designed an elastic joint that generates an oblique channel producing elastic forces parallel to the direction $\mathbf{e}_L$. The elastic joint (Fig.5(a)) is made of a cylindrical nylon shaft 15mm long with a 2.5mm diameter section. As shown in Fig.5 (b) one end of the cylinder was fixed to the H-Man frame and hence could not rotate. The other end was connected to the left driving pulley, and therefore acting as a torsion spring that reacts to any rotation from pulley (or any end-effector displacement away from the $\mathbf{e}_R$ direction).

Figure 6 shows the Cartesian force field due to the channel implemented by the nylon joint when the operator pushes the handle forward and backward and both handle trajectory and operator forces are recorded.

[Figure 5 about here.]

[Figure 6 about here.]

4. Performance Evaluation and Perceived Mechanical Impedance

Perceived mechanical impedance at the end effector determines the level of backdriveability of the system when the system is not actively controlled. Robots developed for motor rehabilitation and/or motor adaptation studies should present transparent mechanical behavior in order minimize interference with subject-specific strategies and to avoid uneasiness and discomfort or change in natural motor strategies [22]. Furthermore, a highly backdriveable system prevents complex controller implementations, which would otherwise have to compensate the manipulator dynamics.

Most of the platforms previously developed present an inertial tensor that is highly configuration-dependent and introduces non-isotropic mechanical behavior to the robot’s end-effector workspace. In this section, we provide details of an important feature of the H-Man: an inertia tensor that does not depend on the joints configuration.

4.1. Estimation of the inertia tensor from CAD parameters

The inertial tensor can be derived from the kinetic energy of the system. Moving masses, pulleys, and rotors’ inertia contribute to the kinetic energy of the H-Man. Before entering into mathematical details we shall first highlight some considerations and introduce the nomenclature that will be used in the mathematical model. As shown in Figure 1 the H-Man is a mechanically symmetric platform in which the inertia is equally distributed between the *left*

actuation (LA) and *right actuation* (RA), due to the action of the left and right motors, respectively. We distribute the effect of the moving masses M_x and M_y , along x and y , respectively.

The rotor and the shaft of each motor are coupled to a driving pulley, all of which rotate at the same angular velocity. Accordingly, we consider the rotor, connecting shaft and driving pulley as a single system with inertia I_{lm} and I_{rm} for the left and right motor, respectively.

The motor torques are transmitted to the handle through the cable wound on eight identical (i.e., same radius and weight) pulleys. Four of these pulleys are fixed to the corners of the frame (see Figure 1) and therefore introduce rotational inertia into the system, but do not contribute as Cartesian moving masses. Out of these four corner pulleys, the ones on the left rotate only when the left motor rotates and similarly for the right ones. We refer to these inertial contributions as I_{lp} and I_{rp} for the left and right couple, respectively.

The remaining four pulleys only rotate when the handle moves along the y axis. Therefore, their angular velocity is proportional to $\omega_L + \omega_R$. The equivalent inertia of these pulleys is denoted as I_{mp} , where mp stands for moving pulley, and highlight the fact that these pulleys rigidly move in the y direction together with the handle. Finally note that the eight pulleys have a smaller radius compared to the driving pulleys, and therefore their angular velocities must be scaled by the transmission ratio γ .

Regarding the moving masses, the inertia due to movement in x is affected only by the handle, the load-cell and the connector to the slider. In contrast, inertia due to translations along the y direction is affected not only by these masses, but also by the four moving pulleys and the horizontal slider/rail system.

With these considerations, we derive the inertial tensor starting from the calculation of the kinetic energy T :

$$T = \frac{1}{2}(I_{lm}\omega_L^2 + I_{rm}\omega_R^2 + I_{lp}\gamma^2\omega_L^2 + I_{rp}\gamma^2\omega_R^2 + I_{mp}(\omega_R + \omega_L)^2 + M_x\dot{x}^2 + M_y\dot{y}^2) \quad (19)$$

By grouping the terms depending upon ω_L and ω_R together, the above expression is rewritten as:

$$T = \frac{1}{2}(I_{LA}\omega_L^2 + I_{RA}\omega_R^2 + 2I_{mp}\omega_L\omega_R + M_x\dot{x}^2 + M_y\dot{y}^2) \quad (20)$$

where $I_{LA} = I_{lm} + I_{lp}\gamma^2 + I_{mp}$ is the contribution due the left actuation system and $I_{RA} = I_{rm} + I_{rp}\gamma^2 + I_{mp}$ is the contribution due the right actuation system.

The angular velocities are then converted into linear velocities along x and y using (1) and the generalized inertia tensor $\mathbf{H}(\mathbf{p})$ can be computed from (19) by applying the Hessian operator:

$$\mathbf{H}(\mathbf{p}) = \frac{\partial^2 T}{\partial^2 \dot{\mathbf{p}}} \quad (21)$$

We obtain

$$\mathbf{H} = \begin{bmatrix} M_x + (I_{LA} + I_{RA} + 2I_{mp}\gamma^2)/r_m^2 & (I_{LA} - I_{RA})/r_m^2 \\ (I_{LA} - I_{RA})/r_m^2 & M_y + (I_{LA} + I_{RA} - 2I_{mp}\gamma^2)/r_m^2 \end{bmatrix} \quad (22)$$

which does not depend on the robot configuration (and is therefore homogeneous) and leads to a diagonal matrix, which corresponds to the desired case of perfect mechanical symmetry (i.e. $I_{LA} = I_{RA}$). With the aid of the *SolidWorks* CAD modeler we estimated the values of the matrix diagonal elements (see Table 2).

4.2. Experimental estimation of friction and inertia tensors

Assuming the driving cable is completely rigid and does not deform during interaction, the perceived mechanical impedance can be modeled using the following second order linear differential equation:

$$\mathbf{F} = \mathbf{B}\dot{\mathbf{p}} + \mathbf{H}\ddot{\mathbf{p}} \quad (23)$$

where $\mathbf{F}$ is the bi-dimensional vector of forces (F_x and F_y) acting at the robots' end-effector and $\dot{\mathbf{p}}$ and $\ddot{\mathbf{p}}$ are its velocities and accelerations, respectively.

To estimate the matrix components b_{ij} and h_{ij} (respectively for $\mathbf{B}$ and $\mathbf{H}$ with imposed symmetry, i.e. $b_{12} = b_{21}$ and $h_{12} = h_{21}$) data was collected for five different end-effector positions (Center, North-East, North-West, South-East and South-West) according to the following procedure: for each of the five positions, the robot's handle was manually moved for 10 seconds using clockwise and counter-clockwise circular displacements¹ (both clock-wise and counter-clock wise). Hand-handle interaction forces $\mathbf{F}_i$ and displacements $\mathbf{p}_i$ were recorded at 1000Hz. Motors were electrically disconnected during the experiment to avoid additional perceived damping due to the resistance and added mechanical friction.

Figure 7 shows the power density spectra of the perturbing forces and the resulting displacements.

[Figure 7 about here.]

Velocities and accelerations were obtained by numerical differentiation of the displacement vector. However, due to the finite resolution (500 counts/revolution)

¹A perfectly circular motion pattern performed at uniform speed would generate tangential velocities and centripetal accelerations both of constant amplitudes, i.e. uniformly rotating vectors describing perfect circles.

of the encoders, prior to the backward differentiation, both forces and displacements were forward and backward filtered (*filtfilt* Matlab function) with a low-pass 2nd order Butterworth filter with a $10Hz$ cutoff frequency.

The filtered forces together with the estimated velocities and accelerations were used for the regression (*mvregress* Matlab algorithm). Figures 8 (a) and (c) show the comparison between the measured raw force components with the filtered version. A qualitative goodness of fitting (for a 2 second data segment) is shown in Figure 8 (b) and (d), where the filtered force used for regression is compared with the estimated one.

[Figure 8 about here.]

The quantitative goodness-of-fitting ($\%VAF$) for all five positions is shown in Table 1.

[Table 1 about here.]

The end-effector trajectory (relative to the center position of the workspace), in terms of positions, velocity and acceleration resulting from the applied force (Figure 9 (a)) are shown in Figure 9 (b),(c) and (d) respectively. Due to anisotropy of the system a force with y-component twice as high as a x-component is necessary to produce almost circular motions.

[Figure 9 about here.]

The estimated tensors for the central position of the workspace are shown in Table 2.

[Table 2 about here.]

Figure 10 shows the damping and inertia ellipses for the five different positions, computed with the method proposed in [4]. Again, the results confirm an inertia tensor that does not depend upon specific positions of the workspace, although, friction behavior is slightly affected by the robot configuration.

[Figure 10 about here.]

Although these last plots provide useful visual information regarding the anisotropy and homogeneity of the tensors, they do not convey which is the main factor (i.e. inertial or friction forces) perceived at the end-effector. To do so, we superimposed the contribution of frictional and inertial forces. Figure 11 illustrates the relationship between the x and y components of these forces and highlight that the inertia is the main force component experienced at the end-effector.

[Figure 11 about here.]

5. Motor Adaptation in Response to Channel Stiffness

Prior work showed that motor adaptation to virtual tasks (characterized by a mismatch between visual and proprioceptive feedback) is affected by channel stiffness. For example, participants in [9] made targeted reaching movements in the horizontal plane while holding the handle of a two-joint robotic manipulandum. After adaptation to the novel viscous force field, the force field was removed, and kinematic errors were either allowed or prevented by imposing a simulated mechanical channel on the movements. Results showed that the introduction of a channel during the washout phase resulted in slower re-adaptation compared to the case in which kinematic aftereffects were allowed. Moreover, participants generated larger forces than necessary for goal attainment when kinematic errors were prevented. On the basis of these results, the authors argued that motor adaptation is influenced by both kinematic and dynamic criteria, whereas kinematic-dependent criteria are a dominant constraint in re-adaptation.

Building on this work, we used the H-Man device to evaluate the extent to which motor adaptation is influenced by lateral channel stiffness. Specifically, a stiff channel (SC) was implemented by locking the horizontal degree of freedom, which constrained participants to forward-backward movements. A passively compliant channel (CC) was implemented by constraining the lateral motion to 2000 N/m via elastic bands. Thus, when participants applied lateral forces to the handle, the hand was allowed to move along the lateral direction, generating proprioceptive feedback.

Participants ($n = 5$ in each group) were randomly assigned to either the stiffness channel (mean age = 24.3, SD = 5.4, 2 men and 3 women) or the compliant channel group (mean age = 23.6, SD = 4.8, 3 men and 2 women). Participants were seated in front of the H-Man device and performed outbound reaching movements from a starting position to a target position (15cm center-to-center) displayed on a 43 cm flat screen monitor placed vertically 10 cm behind the H-Man. Subjects were instructed to move within a certain time frame (i.e., 500-700 ms) and paying attention to movement accuracy. Participants were also informed that visual feedback would be displayed if movements were made in less than 500 ms ('TOO FAST') or more than 700 ms ('TOO SLOW').

The experimental session was comprised of three blocks: 50 baseline trials (virtual force field deactivated), 100 adaptation trials (virtual force field activated), and 25 washout trials (virtual force field deactivated).

During trials in which the force field was activated, there was a 1:1 mapping of the y coordinate of the cursor and the y coordinate of the participant hand on the platform. In contrast, the displacement of the cursor along x was the result of the actual lateral force (F_s) of the subject (sensed via the force sensor) and a virtual Coriolis-force (F_{cor}):

$$F_{cor} = b_{cor} \cdot \dot{y} \quad (24)$$

with $b_{cor} = 14.1Ns/m$.

Specific information regarding cursor dynamics and parameter setting can be found in [6].

The acquired data was processed off-line using custom written Matlab script (The MathWorks, Version R2010a). Data was first filtered using a window length 20 moving average filter. Subsequently, movement onset and offset were determined separately for each trial. Movement onset was determined as the time at which the cursor left the starting position ($y > 0.5\text{cm}$), whereas movement offset was determined as the time point at which the center of the cursor was closer than 1 cm to the center of the target and v_y was less than 0.2 m/s.

Motor adaptation was quantified using cursor-path error and peak force error. Cursor-path error

$$e_p = \sum_{i=1}^{N-1} x_i \cdot (y_{i+1} - y_i) \quad (25)$$

was used to assess the evolution of the lateral deviations x across trials; where N is the number of samples acquired in a trial, x_i is the lateral deviation at the sample i and y_i is the coordinate of the handle at the sample i .

Peak force error

$$e_f = F_{cor_i} + F_{s_i} \quad (26)$$

was used to examine the applied force modulation (i.e., the force exerted at the peak velocity) over different trials; where i represents the sample number relative to the peak velocity of trial t . Note that subjects must apply a negative force in order to counteract the Coriolis-force.

Trends in adaptation for both performance measures (e_p and e_f) were assessed using (27), a trial-dependent exponential function $f(t)$ with bias β , amplitude A and time constant τ .

$$f(t) = \beta + Ae^{(-\frac{t}{\tau})} \quad (27)$$

Figure 12 illustrates typical cursor path trajectories for each group during the different phases of the experiment. Cursor path and peak force errors for each subject, together with the average performance, are shown in Figure 13.

[Figure 12 about here.]

These results show that participants executed straight line cursor paths with minimal peak force errors during the Baseline phase. However, the introduction of the force field at trial 51 resulted in strong rightward curvatures for both groups.

The fitted adaptation trend (27) showed a decreasing error trend for both groups and a cursor-path error reaching a plateau after the first 20 trials of adaptation. Comparison of the adaptation phase data to the washout phase also shows strong adaptation. As demonstrated in Figure 12, the adaptive movement patterns (developed when the force field was activated) were maintained when the force field was deactivated and lasted over several trials. These after-effects

were more prominent for participants in the compliant channel group relative to the stiff channel group.

[Figure 13 about here.]

Despite the evident motor adaptation observed, cursor paths are still slightly curved towards the end of the adaptation phase, especially for participants in the compliant channel group. Closer inspection of the force data revealed that there was a large delay in exerted force when the virtual force field was suddenly introduced, indicating that participants relied on a feedback control strategy and that the movement pattern did not correspond to the required pattern. Although participants were not fully able to anticipate the virtual force, a reduction in the force delay was observed towards the end of the adaptation phase, which indicates the use of feedforward strategies. The observed curved cursor paths might result from the viscous environment dynamics. In such case, the applied forces produce cursor changes that are damped and delayed by the viscosity factor.

We tested the statistical significance of our findings using a mixed effects Analysis of Variance (RM ANOVA) with Group (CC, SC) as the between-subjects factor and time (early baseline [trials 1-25], late baseline [trials 26-50], 1st quarter adaptation [trials 51-75], 2nd quarter adaptation [trials 76-100], 3rd quarter adaptation [trials 101-125], 4th quarter adaptation [trials 126-150], washout [trials 151-175]) as the within subjects factor, separately for cursor-path error and peak force error. The results showed a significant effect of Group ($F = 6.878$, $p = 0.031$) on cursor-path error, with larger values reported for the SC (14.20) compared to the CC group (6.02). Time was also a significant factor in the ANOVA ($F = 33.802$, $p < 0.001$). Post-hoc analysis showed that, as expected, cursor-path error values were higher for all adaptation phases (1st quarter = 24.68, 2nd quarter = 21.03, 3rd quarter = 18.07, 4th quarter = 20.91) compared to both baseline phases (early = -3.17, late = -1.85) and the washout phase (-8.91), all p 's < 0.01 . In contrast, cursor-path error values were similar between baseline phases ($p = 1.0$), between both baseline phases and the washout phase (both p 's > 0.5), and between all four adaptation phases (all p 's = 1.0).

Analysis of peak force error showed a significant main effect of time ($F = 17.614$, $p < 0.001$) and a significant interaction between time and group ($F = 11.306$, $p < 0.001$). Peak force error values were similar for both groups during the baseline and 1st quarter of the adaptation phase. However, there were significant group differences through the remaining phases of adaptation; peak force error was constant for the CC group, whereas error values decreased over time for the SC group. This resulted in similar peak force error values for both groups in the 4th quarter of the adaptation phase. Peak force error values were also significantly higher for the CC group (1.67) relative to the SC group (-2.036) during the washout phase.

In summary, the results of this study indicate that channel stiffness plays an important role in motor adaptation in viscous environments. Specifically, a

more compliant channel tends to result in better motor adaptation, as indicated by lower cursor-path errors and longer after-effect retention. Nevertheless, participants in the compliant channel group were still not able to fully anticipate the force field at the end of the adaptation phase. We hypothesize that this is due to the dynamics associated with the viscous environment.

6. Conclusions

This paper presented a novel 2D planar robot for use in the rehabilitation of upper limb extremity dysfunctions. The device was designed to be inherently transparent, featuring not only low, but also homogeneous, dynamic properties perceivable at the handle such as impedance (inertia and damping). This was achieved with an H-shaped cable-driven differential mechanism which merges the advantages of Cartesian (XY) mechanisms, (i.e. direct transmission and ease of control), with those of semi-parallel mechanisms (i.e., low impedance achieved via mechanically grounded motors). The H-Man prototype was experimentally characterized, with results indicating that the H-shaped cabled-transmission led to a very responsive system, in terms of bandwidth of force transmission (>10 Hz). The perceived inertia and damping were also found to be not only low (approximately 700 gr perceived inertia and about 16 N.s/m damping coefficient) but also homogeneous throughout the workspace.

The most novel aspect of the proposed H-shaped differential is the possibility of constraining movements along straight channels without the use of active control. Due to the nonlinearity of the transmission, semi-parallel mechanisms can impose linear constraints on the motions only via active control, and as such, rendering a stiff channel can be challenging from a stability perspective due to high gains. Furthermore, properly rendering the haptic walls of the channels requires generation of large forces, which translates to the need of more powerful actuators. This, in turn, induces larger perceived inertias and raises safety concerns in case of a malfunction. On the other hand, Cartesian (XY) mechanisms can simply use passive stoppers to induce motion either along the X or Y directions.

Our H-shaped cabled-transmission also allows for the generation of oblique (45 degrees) channels by passively blocking either one of the motors. This produces a very stiff channel which is limited only by the stiffness of the steel cables. Whenever a more compliant channel is needed, the passive stoppers can be simply replaced by more or less stiff springs, and these passive mechanisms, raise no concerns in terms of stability.

To understand the role of lateral channel stiffness on motor learning we used the current H-Man prototype in a passive modality (i.e. without the use of motors) to generate two types of passive channels: laterally compliant or rigid. Tests conducted on healthy individuals ($n = 5$ in each group) revealed that motor adaptation is favoured by a compliant channel compared to a rigid channel. We posit that more compliant channels enhance the amount of proprioceptive information with benefits in terms of learning dynamics.

In the near future, the H-Man device will be used to examine upper extremity motor control in physically and neurologically healthy individuals over a wide range of functionally relevant conditions, and will also be used in the development and improvement of rehabilitation techniques for upper extremity disabilities.

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(b)

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(a)

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	C	N-E	N-W	S-E	S-W
VAF%	96.6	98.1	97.8	98.2	98.4

Table 1: Goodness-of-fit (VAF) for the five workspace positions: Central, North-East(N-E), North-West(N-W), South-East(S-E) and South-West(S-W) .

	$\mathbf{B}(Nm/s)$		$\mathbf{H}(Kg)$	
Estimation Type	B_{xx}	B_{xy}	I_{xx}	I_{xy}
	B_{yx}	B_{yy}	I_{yx}	I_{yy}
CAD			0.5808	0
			0	0.9295
MLR	11.5446	-0.0953	0.3422	-0.0016
	-0.0953	16.0855	-0.0016	0.7176

Table 2: Regressed coefficients for the friction and inertial tensors relative to the center of the workspace. Comparison is relative to the CAD model and the Multiple Linear Regression (MLR).