"Assistive" Forces for the Acquisition of a Motor Skill: Do they assist or disturb motor learning?

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***Abstract*—A number of rehabilitation robots were developed and used to promote the recovery of motor functions in the upper extremities of stroke patients. Current clinical evidence suggests that the robotic rehabilitation is much more effective in acute than in chronic patients. One important difference between the two groups is the amount of the baseline skills with which they start the training. The goal of our research was to get a further insight into this issue by conducting an experiment in healthy subjects. As a model of motor learning, simulating the process of robotic rehabilitation, we developed a methodology for the transfer of a motor skill from an expert to a novice subject by using a haptic interface integrated with the virtual environment. A motor skill was implemented in the form of a challenging computer game, and the haptic interface provided the assistive forces during playing. To assess if and how a level of prior skills affects the motor learning assisted by the robot, the game was played by both novice and partially trained players. The results showed that the assistance was effective only in the novice players, while the trained players experienced the assistive forces as a disturbance. In the context of neurorehabilitation, this finding implies that the existing experience of chronic patients, i.e., the established motor patterns (e.g., compensatory strategies), has to be considered when designing the assistance that would actually promote (instead of disturbing) the learning process.**

***Keywords*–haptics, robotic rehabilitation, assistive forces, motor learning, stroke.**

I. Introduction

HEMIPLEGIA caused by a stroke is a motor disability characterized by the paralysis of the side of the body contralateral to the injury. It is a debilitating condition that dramatically decreases the quality of life.

The term neurorehabilitation refers to a set of techniques and technologies that are designed to promote the recovery of patients with paralysis [1]. The basic instrument of modern neurorehabilitation is an intensive training comprised of repetitive, task-oriented, and challenging exercises [2,3]. It is believed that such training provides a rich substrate for motor relearning and reorganization of neural structures [4].

In this context, robotic devices can be very useful tools for rehabilitation. Present-day rehabilitation robots are highly sophisticated systems that can monitor ongoing movements and generate forces which assist, resist or perturb the subject while he/she is doing a motor task [5]. They have the capacity to deliver high dosage and high intensity training through a massed practice of functional movements under the strictly controlled conditions. A number of devices has been constructed and tested for the rehabilitation of the upper extremities of stroke patients [6]: MIT-Manus, MIME robot, Bi-Manu-Track, T-WREX, Pneu-WREX etc.

In general, the available systems can be classified into two broad categories: exoskeletons (e.g., T-WREX and Pneu-WREX), enclosing a patient limb, and end-effector devices (e.g., MIT-Manus), contacting the patient only at the end point.

One particularly interesting class of end-effector devices are the so called haptic robots [7,8]. These systems are integrated into a virtual environment, where the role of a haptic robot is to be an active interface through which the user can interact with the virtual scene. Namely, when the user comes into contact with a virtual object, the haptic device renders interaction forces reflecting the object physical properties. In addition to providing haptic and visual feedback, these systems can also generate active forces assisting the patient in completing a motor task. Importantly, the rich multimodal feedback, characteristic for haptic interfaces, can be used to create a feeling of immersion and to provide strong incentives for the practicing patient.

From the motor learning perspective [9], the goal of robotic rehabilitation is to provide the assistance helping the patient to re-master a skill lost due to the injury of the central nervous system. The assistance is designed to guide the patient towards a predefined desired solution, and this solution is typically selected so as to clone the performance of a healthy human. In this context, a healthy human is essentially used as a model of an expert performance, which the patient should learn to reproduce.

The clinical practice suggests that robotic rehabilitation [10,11] as well as rehabilitation in general [12] is more

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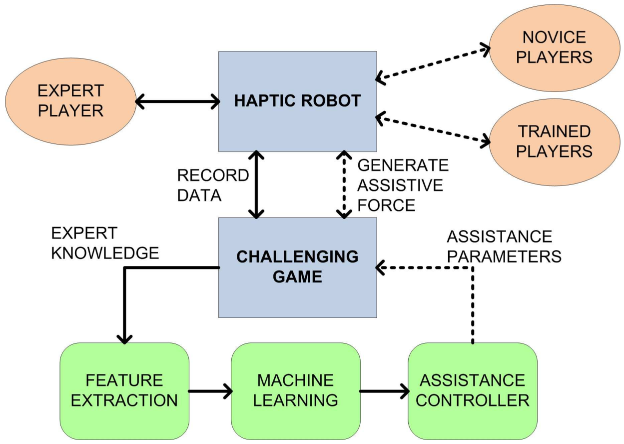

Fig. 1. Transfer of a motor skill from an expert by using a haptic system. First, an expert user plays a game while the system records the data to capture the expert knowledge. A model of the expert performance is then used to guide the assistance. The game is played by both novice and partially trained players to assess the effects of assistance on motor learning in subjects with and without baseline skills.

effective in acute then in chronic stroke patients. One important difference between the two patient populations is the amount of previous experience with which these two groups enter the training. While acute patients start the learning process effectively from zero, the chronic patients already had some time to practice various motor tasks, usually developing an extensive set of compensatory strategies [13,14]. It is with this, well rooted and often unconscious bias, that the chronic population starts the training process.

The goal of our research was to get a further insight into this issue indirectly, by conducting a pilot study with healthy subjects. To simulate the aforementioned conditions, we carried out several steps (Fig. 1). First, we designed a game implementing a redundant motor task that was challenging enough for the healthy population. In order to play the game successfully, a novice player had to master a novel and non-trivial motor skill. Secondly, we developed a method based on machine learning to capture the performance of an expert player to serve as a model for designing a scheme of assistance. In other words, the haptic robot provided the assistance that would stimulate and help the novice player to adopt and/or achieve the playing style of an expert, i.e., the recorded expert kinematics was a target model that should be reproduced by a novice player. Finally, to test how a different level of previous experience and skills affects the motor learning when the assistance is provided, we conducted an experiment in which the game was played by both novice and partially trained players.

II. Methods

A. *Implementation*

1) *Game*

The motor task was to throw a ball into a goal frame (Fig. 2[right]). The game was developed by using a Phantom Omni haptic robot (SensAble, US) and H3DAPI development environment (www.h3d.org, SenseGraphics, SE). The subject interacts with the game by holding a stylus of the device (Fig. 2[left]). The movement of the stylus translates into the movement of the virtual stylus that is visible on the screen. A virtual ball is connected to the tip of the stylus via a spring. Both the mass of the ball and the stiffness of the spring are settable parameters. The haptic interface simulates the dynamics of the ball-spring system, and exerts the interaction forces at the player's hand. At the beginning of the game, the player moves the stylus into initial position, and then generates a throwing movement. The game implements an auto-release function, which means that the ball is automatically disconnected from the stylus, when the stylus leaves a predefined bounding box.

2) *Capturing expert performance*

A randomly selected subject was playing the game until he became an expert. A success rate of 70% was adopted as a threshold that defines an expert player. The expert performance was captured by recording the position and velocity of the stylus during throwing movements at a sample rate of 32 Hz. Eighteen different positions of the goal frame were selected, sampling evenly the game workspace, and for each of these goal positions six throws were recorded. A subset of recorded expert trajectories is shown in Fig. 3.

As can be seen in Fig. 3, the trajectories are roughly straight and, for the same goal position, tend to cluster close

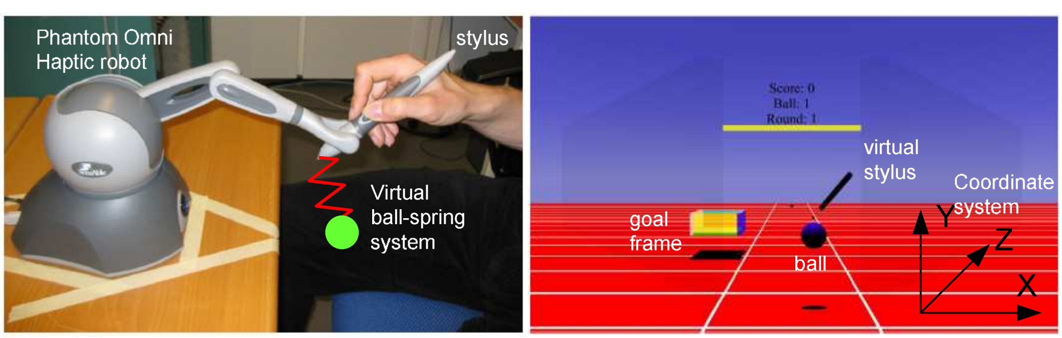

Fig. 2. "Throw the ball" game. Haptic robot (left) that is used to interact with the virtual world (right). A virtual ball is connected to the stylus via a spring. The goal of the game is to throw the ball into a goal frame.

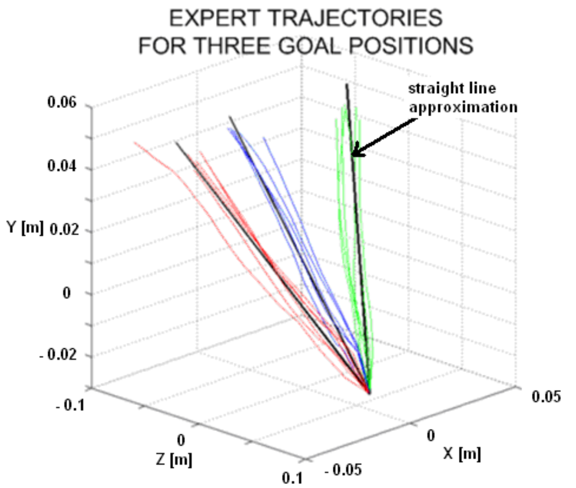

Fig. 3. Expert trajectories recorded during successful throws at the three representative goal positions. Note that for the same goal position the trajectories cluster tightly. Black lines approximate the trajectories and represent straight lines connecting the initial position of the stylus with the average point of release for the respective goal position.

to each other. Therefore, we assumed that the recorded trajectories could be approximated as straight lines connecting the initial position with the point of release. Consequently, the expert performance was modeled as a simple mapping from G_i to (P_i, V_i), i = 1, 2, … 18, where G_i represents the ith position of the goal frame, while P_i and V_i are the average point and velocity of release for the goal position G_i, respectively. The P_i and V_i were obtained by averaging the release points and velocities of the trajectories recorded for the position G_i.

To establish this mapping we have used feedforward back-propagation artificial neural networks (ANNs). A separate network was trained to estimate each of the release point coordinates, and the magnitude of the release velocity (see Fig. 4). The data were divided into training (70%), validation (15%) and testing data sets (15 %). The ANNs were trained so that they smoothly interpolate between the points comprising the training data set, covering the whole workspace of interest.

3) Assistance

By using the captured expert knowledge, we implemented a simple scheme of assistance. We used a form of the so called haptic guidance, in which the robotic device guides the subject towards a predefined desired trajectory. The current position of the goal frame in the game was presented at the inputs of the ANNs to estimate the coordinates of the release point and magnitude of the release velocity. An attractive force was then generated towards this release point, while the desired release velocity was used to adjust the assistive force during successive trials at the same goal position. Namely, the force in the next trial (F_{n+1}) was increased if the achieved velocity in the previous trial (V_n) was smaller then the desired one (V_{EXPERT}), or otherwise decreased:

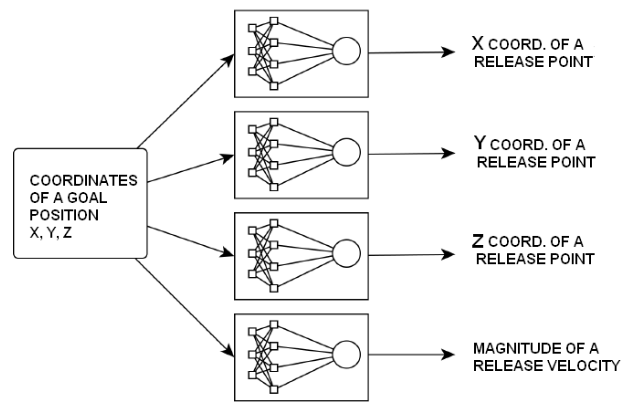

Fig. 4. A set of four artificial neural networks (3 input, 4 hidden and 1 output neuron) was used to estimate the important features of the expert performance (i.e., release point and velocity) given a goal position. The inputs are the coordinates of a goal position and the outputs are the coordinates of a release point and the magnitude of a release velocity.

$$F_{n+1} = F_n + K \cdot \frac{V_{EXPERT} - V_n}{V_{EXPERT}} \tag{1}$$

where F_n is the force in the previous trial and K is the gain. The initial value F_1 for the assistive force in the first trial and the value for the gain K were preset heuristically for each subject during a set of initial trials in which the subject familiarized himself/herself with the system.

B. Experiment

Six subjects participated in the pilot experiment. They were split into two groups of three subjects each. The subjects from the first group ("group with baseline skill", GBS) received a short training before the experiment. They were instructed on how to play the game and then let to practice for half an hour. The assistance was off during practicing. The subjects from the second group ("group with no baseline skill", GNoBS) were only instructed on how to play the game.

The experiment itself consisted of the three phases: baseline assessment (five throws at each of five randomly selected target positions), training session (15 throws at each of the five target positions) and final assessment (five throws at each of the five target positions). During the training session the subjects were assisted by the haptic robot. The performance was assessed by recording the trajectories of the stylus, counting the number of successful throws, and by calculating, for each trial, the closest distance between the trajectory of the ball and the center of the goal frame.

III. Results

When comparing the performances between the baseline and final assessments, we discovered that all the subjects from GNoBS and only one subject from GBS improved the performance. The average improvement was around 30% for the subjects from GNoBS and only 10% for the one subject from GBS, respectively. The performance of the other two

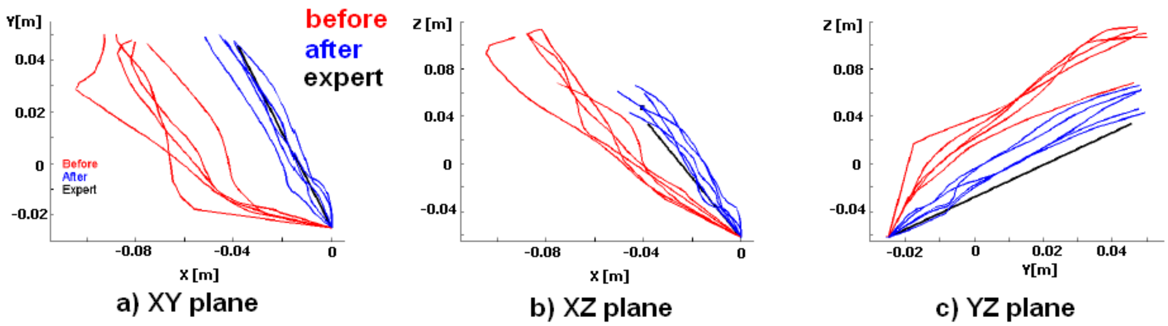

Fig. 5. Trajectories recorded while throwing the ball at the same goal position during the baseline (red) and final (blue) assessments from a subject (GNoBS group) that improved the performance after the training. The estimated expert trajectory is depicted by a black straight line. Note that the subject generated trajectories converged towards the expert one.

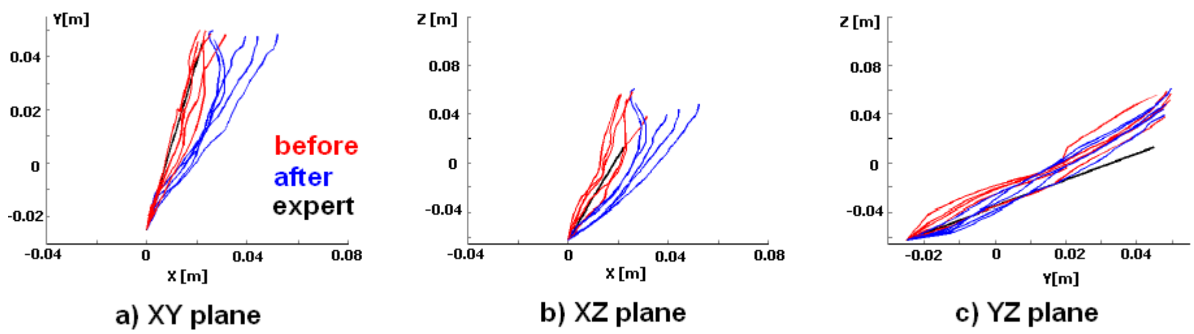

Fig. 6. Trajectories recorded while throwing the ball at the same goal position during the baseline (red) and final (blue) assessments from a subject that became worse after the training (GBS group). The estimated expert trajectory is depicted by a black straight line. Note that the subject generated trajectories were initially close to the expert path but that at the end they eventually diverged from it.

subjects from GBS actually deteriorated.

To reveal the possible reasons for the apparent detrimental effect of the assistance in the subjects that entered the experiment with a basic level of skill already acquired, we analyzed the recorded trajectories of both groups. A typical result for a subject (GNoBS group) that improved the performance with the training is shown in Fig. 5. Note that the baseline trajectories are variable, relatively spread and quite off the straight line depicting the estimated expert performance. At the final assessment however, the trajectories became straight and tightly clustered around the expert path. Moreover, during the training, we noticed that the assistance immediately improved the subject movements, making them closer to the desired one.

Fig. 6 shows the recorded data for the subject (GBS group) that became worse after the training. We can see exactly the opposite trend to the one that was observed in Fig. 5. The subject started by generating the trajectories that were already quite close to the one that would be generated by the expert. However, after the training, the trajectories became more curved, scattered and in fact drifted off the desired direction. In fact, we noticed that when the subject started the training, the assistance had an immediate negative influence on the subject movements.

IV. DISCUSSION

The experiment demonstrated that the assistance was effective only in the subjects that had no previous experience (novice players). On the contrary, in the subjects that already partially acquired the motor skill, even at the very basic level, the implemented assistance operated effectively as a disturbance. This is also what the subjects reported when asked about how they experienced the assistive force. The assistance suddenly changed the dynamics of the motor task, interfering with the already adopted strategies and confusing the subject. This effectively invalidated what was previously learnt and also interfered with further learning.

Several studies [15,16] that employed haptic guidance to assist motor learning investigated the influence of initial skill level on the effectiveness of the training. They also found that training with haptic guidance was more useful for the subjects with less initial skill. One reason for this could be the fact that guidance makes the task easier. According to a challenge point theory [17], in order to have optimal learning, the difficulty of the task should be adapted (scaled up/down) so that it is appropriate for the individual subject's level of expertise. In more skilled subjects, other training modalities (e.g., error-amplification approach) showed to be more effective, likely due to the similar reasons (i.e., reaching a proper level of challenge).

The results in this preliminary study (see Fig. 6) suggests that for the subjects entering the training already with a level of baseline skill, not only the "assistance" might be less effective (due to, for example, a lack of challenge), but it can actually have a more potent, directly disruptive effect. Namely, the "assistive" force can interfere actively with the already established motor strategy, acting essentially as a disturbance, and being experienced as such by the subject. The subjects reported that they felt as they were playing a different game when the assistance was activated.

This is an important observation, with the potential implications in neurorehabilitation, pointing to one possible reason for the decreased effectiveness of robotic driven rehabilitation in chronic patients. Namely, the similar conflict might be taking place: the assistance actually forcing the patient to go against the already well established and deeply rooted motor strategies. This implies that the compensatory patterns of chronic patients should be taken into account when designing an effective robotic rehabilitation program. In other words, it might not be enough to simply guide the patient towards a global optimum (healthy-like patterns); he/she should be carefully but actively stimulated to "break out" from the "comfortable" local optima, as suggested in [9], "giving away" previously adopted suboptimal (compensatory) movement strategies, and then slowly guided along a carefully planned path towards a new and better solution.

The previous conclusion fits very well within the more general idea of designing truly individualized haptic training algorithms, as suggested recently [15]. For the most effective learning, the assistance modality as well as the other training parameters should be designed by taking into account initial motor skills, the level of impairment [18], as well as existing, suboptimal motor strategies of a specific trainee.

The current study also addresses one more general question in robotic rehabilitation: given a motor task, how to determine a desired solution that will be used to guide the assistance? In this study, the desired solution was determined by capturing the performance of an expert human. This in itself is not a novel idea. Pre-recorded trajectories from healthy subjects are used routinely in many robotic rehabilitation devices (see [5,9] for a review). However, this study describes a general method that can be used to develop a model of normative behavior (i.e., a desired solution) for a motor task that is more complex then the training of relatively simple (e.g., point-to-point reaching) and/or stereotyped (e.g., walking) movements. The performance is acquired by observing an expert under a number of conditions (i.e., goal positions), and the collected knowledge is represented compactly as a set of trained artificial neural networks. This is a general approach that can be applied to a number of different redundant motor tasks (e.g., bowling, dart throwing etc.) to establish the mapping from the current task parameters (inputs) to the estimated expert performances (outputs). In this study, the expert performance was captured from only one subject. However, several "experts", possibly at different levels of expertise, could be used in order to obtain a more versatile model that can be customized for a specific trainee and/or adapted as the trainee improves his skills during the training. The next step in this research is to recruit more subjects to verify if these preliminary results also hold in a larger experimental group.

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