Combined use of DMP and real objects in robot-aided rehabilitation

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***Abstract*—Robot-aided rehabilitation enables to assist the patient in executing task-oriented exercises and typically takes advantage of virtual environments in which motor tasks are performed. However, a mismatch between the visual and the proprioceptive stimuli can occurr. The use of real tools to perform rehabilitation tasks could overcome this drawback. Nevertheless, several issues arise, such as the estimation of the pose of the real objects in the workspace and the planning of the trajectories the robot has to execute to guide the patient's limb to reach the objects. In this paper, a robot-aided upper-limb rehabilitation system able to recognize the objects the patient has to interact with and to dynamically plan the robot trajectories is presented. The performance of the DMP-based Motion Planner is assessed to evaluate its capability i) to reproduce the motion style of an healthy subject and ii) to reach the target position with small residual errors.**

***Index Terms*—Robot-aided Rehabilitation, Vision-based Pose Estimation, Dynamical Movement Primitives**

I. Introduction

Robot-aided rehabilitation platforms have been developed in the last decades to guide the patient's affected limb in executing controlled and assisted movements with a task-oriented approach [1]. It is particularly useful in occupational therapy contexts.

Robot-aided rehabilitation is often supported by virtual reality: the interaction of the patient with virtual objects promotes his/her involvement during the therapy. Despite the widespread use of virtual environments, a misalignment between visual and proprioceptive stimuli can occurr with this approach. In fact, the haptic feedback that a robotic system can return to the patient may mismatch what happens in the virtual environment [2]. To overcome this drawback, real tools can be used during the exercises to guarantee the involvement of the subjects and avoid the sensory misalignment.

The desired motion of the robot in guiding the patient's arm should guarantee a human limb motion as natural as possible to re-educate the patient to move. The Motion Planner module plans the movements to be executed. The trajectories that are currently adopted in robot-aided rehabilitation are minimum-jerk displacements [3]. However, complex Activities of Daily Living (ADLs) cannot be modeled with these methods. Learning from demonstration techniques, like the Dynamical Movement Primitives (DMPs) [4], enable to plan complex and generalizable trajectories taking as a reference movements previously recorded on healthy subjects [5].

Currently, only a few rehabilitation robotic systems exploit real tools during the therapy [6]. Those systems imply the adoption of: i) object recognition and pose estimation algorithms; ii) robot motion planners that allow the robot to assist patients in reaching the recognized objects. To date, the high computational burden of such algorithms, in particular in presence of occlusions [6], has limited the use of the proposed state-of-the-art systems in a real clinical scenario.

This paper introduces an intelligent robot-aided upper-limb rehabilitation system used to perform occupational therapy tasks with real objects. The robotic architecture is able to recognize, with limited computational burden, the objects the subject has to interact with, and to online generate the Cartesian trajectories to be followed exploiting a DMP-based Motion Planner.

II. Materials and Methods

The overall architecture of the proposed system is reported in Fig. 1A. It is composed of: i) a pose estimation pipeline based on an RGB-D camera that estimates the pose of the objects in the rehabilitation scenario, ii) a DMP-based Motion Planner that computes the trajectories the end-effector of the robot has to perform to reach the recognized objects.

The vision system used in this work is the Kinect v2, an RGB-D camera that captures images and PointClouds at 30 Hz. The objects to be recognized must be single-coloured to be correctly identified by the proposed pipeline. The estimation pipeline segments the tool from the workspace and computes its geometrical features, i.e. the centroid. The position of the object, retrieved from the RGB-D camera, is given as input to the DMP-based Motion Planner.

The proposed Motion Planner is based on the DMPs equations. This non linear second order system used to model motor behaviours can be described as

$$\tau \ddot{y} = \alpha_z \left(\beta_z \left(g - y \right) - \dot{y} \right) + f(\omega) \tag{1}$$

where τ is a time constant, α_z and β_z are positive constants, g is the goal position, ω are the DMP parameters obtained by using a Locally Weight Regression algorithm, and $f(\omega)$ is a

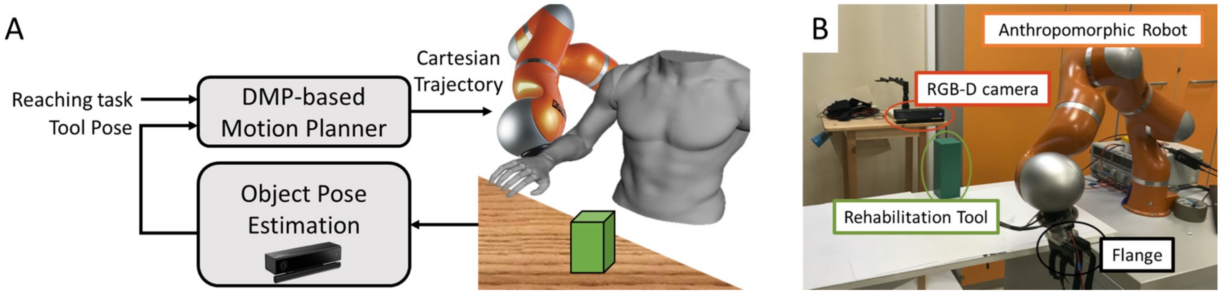

Fig. 1. A. Block scheme of the proposed approach. B. Real rehabilitation scenario composed of: a real tool, the RGB-D camera, the anthropomorphic robot and the flange connected to the subject's wrist.

forcing term creating the landscape attractor of the system to reproduce reaching trajectories.

The experimental setup used to record the reaching demonstration is shown in Fig. 1B. The subject's wrist was attached to the robot end-effector by using an ad-hoc developed flange. One subject was asked to reach the green box, placed on a table in front of him. Five repetitions of the reaching task were recorded, moving the box position. To compute the capability of the proposed DMP-based Motion Planner to accurately reproduce the user's personal motion style, the motion style index (MSI) is used. It can be computed as

$$MSI_j = \sqrt{\frac{1}{N}\sum_{t=0}^{N}\left(a_j^r(t) - a_j^c(t)\right)^2} \tag{2}$$

where N is the number of time instants and $a_j^r(t)$ and $a_j^c(t)$ are the accelerations of the recorded and computed Cartesian trajectories (obtained by integrating the DMPs equation), evaluated at the time instant t, along the j-th Cartesian axis. Lower values are expected when a high degree of similarity between the trajectories is reached.

The DMP-Based Motion Planner is validated in simulation. Starting from a fixed starting point (i.e. $p_0 = [0, 0, 0]^T$ m), the DMP-based Motion Planner is asked to generate Cartesian trajectories to reach six target positions estimated by the RGB-D camera. The accuracy of the reaching is evaluated by measuring the Target Error at the end of the planned movement as

$$TE = \|p_c(t_f) - g\| \tag{3}$$

where p_c and g are the computed Cartesian trajectory and the target position, respectively, and t_f is the last time step used to compute the reaching DMP.

III. Results and Discussion

The MSIs of the computed DMP reaching Cartesian trajectories, starting from the demonstrated ones, are 7 ± 0.6 cm/s^2, 6$\pm$0.5 cm/s^2 and 0.7 ± 0.6 cm/s^2 for MSI_x, MSI_y and MSI_z respectively. These results suggest that the DMP computed reaching task is reproduced with a high degree of similarity with respect to the recorded one, in particular along the z axis. Along the xy plane the DMP numerical integration produces a smoother Cartesian profile with respect to the demonstrated reaching movements. The mean and standard deviation of the TE obtained with the DMP-based Motion Planner is 9.1 ± 2.6 mm, which is acceptable for the proposed application.

IV. Conclusions

In this work, a robot-aided rehabilitation system capable of recognizing the pose of the objects and planning Cartesian reaching trajectories is proposed. The DMP-based Motion Planner shows promising results, therefore enabling the application of the system in a real rehabilitation scenario. It generates reaching Cartesian trajectories with a small TE and a high degree of similarity with respect to the recorded ones. Future work will be devoted to geometrically calibrate the two systems, i.e. the RGB-D camera and the robot, and implement different tasks according to the detected tool, thus extending the system capabilities.

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