A Dataset of DMPs for robot motion planning

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***Abstract*—Collaborative robots, working autonomously or in cooperation with humans, are used in industrial scenarios to help workers during the execution of repetitive and tiring activities that may lead to the onset of musculoskeletal disorders.**

This paper introduces a publicly available dataset of distinctive motion parameters (i.e. Dynamic Movement Primitives, DMPs) to be used for planning the motion of cooperative robots.

Learning by Demonstration methods were adopted to compute DMP parameters for common working activities, i.e. handling good, hammering and screwing, executed by human demonstrators. The computed DMP parameters were then stored inside the dataset. Once known the task to be performed and the target to be reached, the most appropriate set of DMP parameters is extracted from the dataset and the numerical integration of the DMP equation returns the robot desired Cartesian reference.

The dataset-based motion planner was tested in simulation: for each sub-task, several target points were used to plan trajectories. The obtained results, in terms of generalization capability of the motion planner, confirmed that the proposed approach is able to plan Cartesian trajectory for working activities with a mean Success Rate of 85% for the handling good, 67% for the hammering and 61% for the screwing tasks.

***Keywords*—Dataset, Working Activities, Dynamical Movement Primitives, Human-robot interaction**

I. INTRODUCTION

The study of human motion can have important applications in several research areas, such as imitation learning, action recognition and motion generation for robotic platforms.

For these reasons, several motion capture datasets containing information about human movements have been built up and made available to the research community at the site https://francescacordella.com/ in the Dataset section. One of the largest motion capture dataset is the CMU Graphics Lab Motion Capture dataset [11]. It contains data about different kind of actions such as locomotion, sports and pantomime. The HDM05 dataset [16] includes 70 different motion classes. It was created for motion generation in computer animation. The Carnegie Mellon University built up two multimodal datasets [4] about food preparation while TUM Kitchen dataset [6] includes motion capture data of subjects setting the table. Another remarkable work is the KIT dataset [15] addressing the robot motion generation using imitation learning. From the literature analysis, two crucial aspects can be pointed out: datasets focusing on working activities are missing and all the available datasets need further elaboration in order to be used.

The advent of Industry 4.0 is strongly contributing to promote the use of collaborative robotics in industry to improve working conditions and reduce workload of industrial workers. A winning approach seems to be providing robotic systems with the capabilities of reproducing the human motion behaviour [1]. This could increase the safety of interaction since the human user can somehow predict robot motion. Several solutions have been proposed in the literature to teach robots to move as humans. A valid approach has been found in motion planning based on dynamic motion primitives. As demonstrated in [2], the main advantages of these motion planning techniques are i) the generalization capabilities with respect to the environment variability, ii) the high level of anthropomorphism of the computed motion.

A dataset containing DMP parameters ready to be used for generating reference motion for robotic platforms in working environments can represent a contribution to the research community. Therefore, this paper proposes a dataset of working gestures created through a Learning by Demonstration approach, containing a set of distinctive motion parameters (i.e. Dynamic Movement Primitives parameters, DMPs), that can be used to plan the motion of robotic manipulators acting autonomously or in cooperation with humans. Such a trajectory planner is able to reproduce working actions through the modular composition of motor primitives.

II. MATERIALS AND METHODS

Setup and Experimental Protocol

The adopted experimental setup is shown in Fig. 1. Motion capture data were collected by using the eigth cameras of the BTS Smart-DX optoelectronic system [10] with a frame rate of 60 Hz. The placement of retroreflective markers on anatomical landmarks followed the Rab protocol [5]. This way, it was possible to compute the trajectory of the wrist with respect to the shoulder frame.

Eight healthy subjects, 7 males and 1 female (mean age 27± 4), were asked to perform three common working activities, i.e. handling goods, hammering and screwing. The attention has been focused on these gestures since they represent the working tasks with the highest incidence of musculoskeletal disorders (MSDs) [14]. Worker safety may be improved with robotic assistance when these tasks have to be performed. A shelf unit, composed of three different levels, was positioned in front of the subject. The lower level was placed at the subject's shoulder height while the other shelves were placed at 0.19 m and 0.38 m above the first one. In order to investigate lateral load maneuvering, the shelf covered a circular sector of $\pi/3$ rad for 0.2 m of radius. The shelves were dimensioned following the directions of the International Organization of Standardizations ISO 11228-3 establishing ergonomic recommendations for repetitive working tasks involving the manual handling of low loads at high frequency.

Fig. 1: Experimental setup for the acquisition sessions.

Different conditions were assessed in this study: the target position (i.e. the load final position, the nail or the screw) was moved, from one recording to another, in 9 different points. In the first acquisition, the target was in front of the subject, 0.20 m distant. In the following recordings, it was moved at $\pi/6$ rad and $-\pi/6$ rad with respect to its initial position. This procedure was repeated at all the available heights. Two repetitions of each task and target position were collected.

Data Analysis

Tracked raw data were filtered with a 4th order low-pass Butterworth filter, with a cutoff frequency f_{cut} of 3 Hz. Such a value was chosen because noise and motion artifacts can be found at higher frequencies. It was confirmed by the results of a residual analysis performed on the collected data [18]. The f_{cut} of 3 Hz led to a residual RMS of $(5.9 \pm 1.6) \cdot 10^{-4}$ m for the hammering, i.e. the most impulsive task. Such a small residual confirmed that the chosen value of f_{cut} is suitable for the application.

All the working activities analyzed in this work were composed of different phases, each having its goal and motion features. In particular, the handling goods task is composed of three different sub-tasks: 1) to reach the load, 2) to "pick and place" the load at the proper position and 3) to return to the rest condition, also called homing. In the same way, the other two working gestures consist in: 1) reaching the working tool (i.e. the hammer or the screwdriver), 2) reaching the target, 3) performing the working activity, 4) releasing the working tool and 5) homing.

Dynamical Movement Primitives

The collected motion capture data was used to implement a trajectory planner for a robotic manipulator. A compact way to reproduce human complex motor behaviour consists in the non-linear dynamical system, called Dynamical Movement Primitives, proposed in [13, 3]. To be thorough, the fundamental equations of the DMP are reported in the following. A DMP is a non-linear second order system used to model motor behaviours, expressed as

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

where τ is a time constant, α_z and β_z are positive constants, g is the goal position and f is a forcing term that creates the landscape attractor of the system.

For discrete movements, the forcing term can be written as a weighed sum of a Gaussian Kernel basis functions Ψ, as follows

$$f(x) = \frac{\sum_{i=1}^{N} \Psi_i(x) \omega_i}{\sum_{i=1}^{N} \Psi_i(x)} x(g - y_0) \tag{2}$$

The Gaussian functions Ψ_i are described as

$$\Psi_i(x) = \exp\left(\frac{1}{2\sigma_z^2} \left(c_i - x \right)^2 \right) \tag{3}$$

where σ_z and c_i are the width and the centre of the Gaussian, respectively. The c_i centres are equally distributed over x. The state variable x is defined by $\tau \dot{x} = -\alpha_x x$, where α_x is a positive constant. By using a different formulation of the forcing term, it is possible to generate periodic pattern referred to as rhythmic DMPs

$$f(x) = \frac{\sum_{i=1}^{N} \Psi_i(x) \omega_i}{\sum_{i=1}^{N} \Psi_i(x)} r \tag{4}$$

where the periodic function $\Psi_i(x)$ is given by

$$\Psi_i(x) = \exp\left(\frac{1}{2\sigma_z^2} \left(\cos(\phi - c_i) - 1 \right) \right) \tag{5}$$

where $\phi \in [0, 2\pi]$ is the phase angle of the oscillator in polar coordinates while r is the amplitude of the oscillation. A locally weighted regression (LWR) [8] can be exploited to identify the ω parameters from human demonstrations. The discrete formulation of the DMP were used for the reaching, moving and homing tasks. Conversely, rhythmic DMPs were conveniently adopted for the hammering and screwing tasks, since they can be seen as periodic movements.

Looking at the acquired kinematic data, it is important to outline that the wrist of the subjects does not rotate during the execution of the reaching, moving and homing tasks. Accordingly, DMP parameters that account for these tasks were referred only to the translations along the three axes. For the same reason, the parameters of the screwing sub-task are referred only to the rotations. The DMP parameters, in this case, were computed by using the Euler angle representation (i.e. Roll, Pitch and Yaw).

The DMP meta-parameters, i.e. α_z, β_z, α_x, σ_z and r, were experimentally retrieved and set as follows: $\alpha = 20$, $\beta_z = \alpha_z/4$, $\alpha_x = \alpha_z/3$, $\sigma_z = 0.0128$ and $r = 1$.

Motion Planner

The block scheme of the proposed DMP-based trajectory planner for a robot is shown in Fig. 2. Human motion trajectories are firstly recorded during the execution of the specific working activities. They are performed by healthy subjects and distinctive features (i.e. DMP parameters) are subsequently computed by using a LWR algorithm. Hence, a dataset of DMP parameters was built up (i.e. Off-line dataset building).

After the dataset is offline built, it can be used online: the user choose the working activity to perform with the robot assistance and the target position, then the most appropriate DMP parameters are extracted online from the dataset (DMP parameters selection). The nearest set of parameters used to compute the DMP equation and plan the motion for the desired task (DMP computation) is selected by means of a lookup table.

The dataset is made of M point clouds, where M represents the number of sub-tasks ($M = 13$), as evident from Table I.

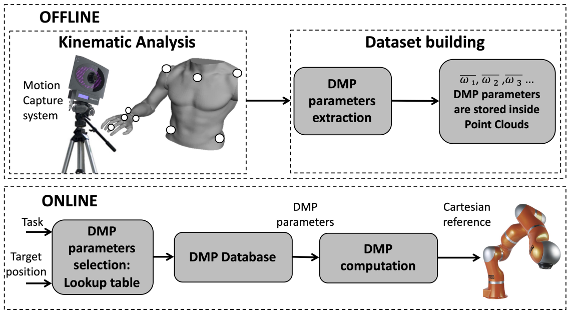

Fig. 2: Block scheme of the proposed motion planning system.

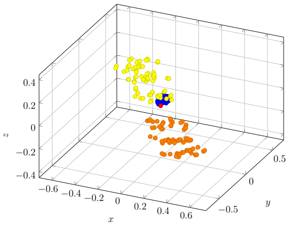

Fig. 3: Dataset of the handling good task. The red dot represents the initial position $\mathbf{p_0}$. The other points are those used to build up the DMP-dataset for an instance of *reaching*, *moving* or *homing*, respectively in blue, yellow and orange.

The points used to build up the dataset related to the handling goods task are reported in Fig. 3.

Evaluation Metrics

The proposed motion planner was validated in simulation. In particular, the simulated robot workspace was defined as follows: $x \in [-0.7, -0.45]$ m, $y \in [-0.35, 0.35]$ m and $z \in [0, 0.5]$ m. The targets used to test the planner for each sub-task have been placed in 990 different positions of the human-robot workspace. The initial position was $\mathbf{p_0} = [-0.5, 0.2, 0.15]^T$ m. These positions were obtained by dividing the entire workspace into cubic cells of 0.05 m side. The rhythmic DMPs of the hammering tasks were assessed by using each of the simulated point as initial and target position. The simulation workspace is reported in Fig. 4. For each simulated trajectory two conditions were checked:

1st Criterion: the trajectory is entirely contained within the workspace;

$$\boldsymbol{p}(t) \subset workspace \; \forall t \in [0, t_f]$$

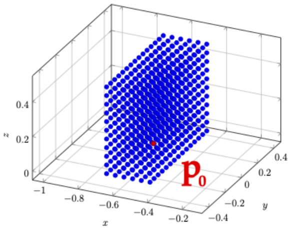

Fig. 4: Workspace used for the test in simulation. Blue points were used as a target positions while the red point represent the initial position $\mathbf{p_0}$

2nd Criterion: the target point $\mathbf{g}$ is reached with a small residual error;

$$\|\boldsymbol{p}(t_f) - \boldsymbol{g}\| < 0.015\, m$$

The performance of the motion planner was evaluated at the end of the simulation by means of the success rate index

$$Success\, rate = (N_{succ}/N_{tot}) \cdot 100 \tag{6}$$

where N_{succ} is the number of completed trajectories (i.e. the trajectories that satisfy both the previously listed criteria) and N_{tot} is the total number of simulated motions.

III. RESULTS

Fig. 5 shows a graphical representation of the trajectories that can be obtained by computing the DMP equations with the extracted parameters. In particular, Fig. 5A shows an example of a discrete DMP, computed for the reaching task. The Cartesian trajectories are very similar to the ones modeled by means of the Minimum Jerk theory [9]. 3D reaching tasks are naturally performed as quasi-monotonic trajectories with bell-shaped velocity profile [7]. Figure 5B reports the moving task. This differs from the previous one only for the z-axis (Fig. 1): which presents a sopra-elevation before reaching the goal. Additionally, in Fig. 5C-D both the Cartesian position and the Euler angles obtained by computing the DMP with the rhythmic formulation for the hammering task is shown. The Cartesian displacement highlights that the hammering task is condensed along the z-axis while some oscillations are visible in the other axes. At the same time, the prominent rotation during the hammering execution is around the y-axis. Finally, an example of rhythmic DMP computed for the screwing task is shown in Fig. 5E. It is worth observing that this task is performed as a pure rotation around the screwdriver axis, as observed during the acquisitions on human subjects.

The success rates obtained in simulation for each sub-tasks of the analyzed working gesture are reported in Table I. For the handling goods task, the trajectories that had a target point on the edge of the workspace did not meet the first criterion since they go out the workspace for a short period of time. Hammering task obtained the worst results. The hammering trajectory, reported in Fig. 5(a), is characterized by the peak along the z-axis. This motion features brings the trajectories out of the defined boundaries for some target points. This goes against the first criterion and leads to a success rate of 55.86% for the pure hammering gesture. The success rate of the screwing sub-task was not computed as this gesture was considered as a pure rotation around the screwdriver axis. The other sub-tasks of the screwing obtained low success rates. This could be related to the orientation of the tool to be reached. In fact, the reaching performances are impacted by the way the user approaches to the object before the grasping [12].

IV. CONCLUSION

This work presents a working gesture dataset, created through a Learning by demonstration approach, containing a set of distinctive motion parameters (i.e. Dynamic Movement Primitives, DMPs), that can be used to plan the motion of

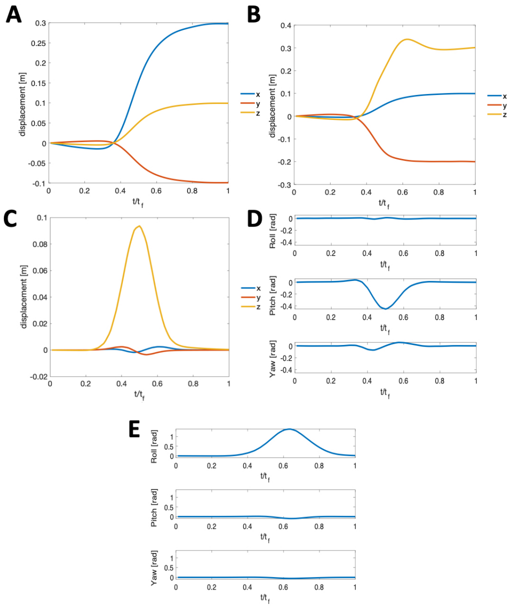

Fig. 5: Trajectories obtained by integrating the DMP parameters stored inside the proposed dataset. In A is reported a reaching, in B a pick and place, in C and D the Cartesian trajectory and the Euler angles for the hammering respectively while in E is shown the Euler angles for the screwing.

TABLE I: Success rates obtained in the simulation environment for the proposed motion planner.

Working gesture	sub-task	*Success rate*
Handling Goods	Reaching	81.81%
	Moving	82.42%
	Homing	90.90%
Hammering	Reaching of the hammer	78.79%
	Reaching of the nail	62.37%
	Hammering	55.86%
	Releasing of the hammer	75.75%
	Homing	62.22%
Screwing	Reaching of the screwdriver	56.24%
	Reaching of the screw	65.35%
	Screwing	—
	Releasing of the screwdriver	63.33%
	Homing	58.78%

robotic manipulators to perform such gestures, autonomously or in cooperation with a human. This learning method allows generalizing the trajectories with respect to target positions and robot kinematics and reproducing complex movements. Starting from the study of the kinematics of healthy subjects, the dataset was built up and used to generate Cartesian references for a manipulator. The DMP-based motion planner was validated in simulation. The generated trajectories have to meet specified criteria: i.e. the Cartesian reference contained within a predetermined workspace and a residual error less than 0.015 m. In particular, all the handling goods sub-tasks achieved success rates greater than 80%. The working sub-task that has achieved lower success rates in simulation is the hammering: the oscillation performed by the subject's wrist during the hammering does not satisfy the first criterion for some target positions.

Future work will be devoted to add information about the interaction forces [17] and to validate the proposed motion planner on a robotic platform in an experimental scenario of human-robot interaction during the execution of working activities.

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