Intention-based motion-adaptation using dynamical systems with human in the loop

Mahdi Khoramshahi* and Aude Billard

***Abstract*— The goal of this work is to enable robots to intelligently and compliantly adapt their motions to the intention of a human during physical Human-Robot Interaction (pHRI) in a multi-task setting. We employ a class of parameterized dynamical systems that allows for smooth and adaptive transitions across encoded tasks. To comply with human intention, we propose a mechanism that adapts generated motions (i.e., the desired velocity) to those intended by the human user (i.e., the real velocity) thereby switching to the most similar task. We investigate our method through experimental evaluations for different robotic scenarios.**

I. INTRODUCTION

The applications of pHRI are multifarious: carrying and installing heavy objects, hand-over, cooperative manipulation and manufacturing, and assistive tele-operation. As the field of pHRI is rapidly expanding, the demand for adaptive robotic behavior toward human intention is increasing. It is of particular interest to design algorithms and controllers that recognize the human intention and enable the robot to adapt its motion accordingly. As humans, we achieve such capabilities through our compliant behavior. Complying with partners' motions allows us to recognize their intention and consequently predict their actions [1]. Conversely, due to the same compliant behavior, others are able to communicate their intentions through interaction forces [2] and movements [3]. Such prediction capabilities enable us to better coordinate our actions and provide assistance in the task; e.g., being a pro-active rather than a passive follower.

The amount of previous efforts addressing intention-recognition and motion-adaptation in pHRI is sparse. Oftentimes, the adaptation is addressed at the force-level by adapting the impedance parameters w.r.t. human interaction-force [4], [5], [6] or at the motion-level by relying on the local anticipation of human motions [7], [8], [9]. As examples for addressing the problem at the task-level, [10] employs a velocity threshold resulting abrupt switching across tasks and [11] proposes a framework where the task is switched if it is pushed by its human-user to a specific area of its workspace limiting the versatility of the robot. In this short paper, we report on our recent efforts toward an task-adaptation framework using dynamical systems. This framework allows for efficient human-intention recognition and adaptive motion-generation. Our experimental results confirm the efficacy of our approach in terms of human-intention recognition, stable and smooth motion generation, safety, human-effort reduction, and execution of the task.

All authors are with Learning Algorithm and Systems Laboratory, EPFL
*Corresponding author `mahdi.khoramshahi@epfl.ch`

II. METHOD

Let us start with a simplified robot's dynamics specified in the task space where gravity and centrifugal forces are compensated:

$$M\ddot{x}_r = F_c + F_h \tag{1}$$

where $x_r \in \mathbb{R}^3$ is the real position of the end-effector. $M \in \mathbb{R}^{3\times3}$ is the mass matrix. $F_h \in \mathbb{R}^3$ represents forces applied by human based on his/her intention. $F_c \in \mathbb{R}^3$ is the impedance control force enabling the robot to track a desirable velocity profile ($\dot{x}_d \in \mathbb{R}^3$) as follows:

$$F_c = -d(\dot{x}_r - \dot{x}_d) \tag{2}$$

where $d \in \mathbb{R}^+$ is the impedance gain. We further assume that the robot knows a set of N possible tasks represented by stable DS, such that the ith task is encoded by $f_i(x_r) : \mathbb{R}^3 \mapsto \mathbb{R}^3$. Therefore, we introduce the following linear combination of such dynamics as the motion generator:

$$\dot{x}_d = \sum_{i=1}^{N} b_i \; f_i(x_r) \tag{3}$$

where $b_i \in [0,1]$ (with $\sum_{i=1}^{N} b_i = 1$) are the corresponding task-beliefs. This formulation provides smooth transitions across tasks. Although DS are typically used for motion generation, as in (3), they can also be used for task identification; i.e., they can evaluate similarity between current motion of the robot (influenced by human-interaction) and an arbitrary task. We use such similarities in the following adaptation rule to enforce the task with the highest similarity to the human-induced velocity:

$$\dot{\hat{b}}_i = \varepsilon \; [\dot{e}_h^T f_i(x_r) + (b_i - 0.5)||f_i(x_r)||^2] \tag{4}$$

where human-induced error is $\dot{e}_h = \dot{x}_r - \dot{x}_d$ and $\varepsilon \in \mathbb{R}^+$ is the adaptation rate. In this adaptation mechanism, belief-updates ($\dot{\hat{b}}_i$) are initially computed based on the similarities (i.e., inner product) between each DS (f_i) and the human-induced velocity-error ($\dot{e}_h$). The second term ensures the convergence to one task if the human retreats form the interaction (i.e., $\dot{e}_h = 0$); e.g., convergence to the task with $b_i > 0.5$ if exists. Furthermore, we modify the belief-updates ($\hat{b}_i$) to ensure only one belief increases; i.e., the most similar task w.r.t. human interaction. To do so, we use a winner-take-all algorithm to compute the final belief-updates ($\dot{b}_i$); see Algorithm 1. Finally, the beliefs are updated based on a given sampling-time and limited between 0 and 1.

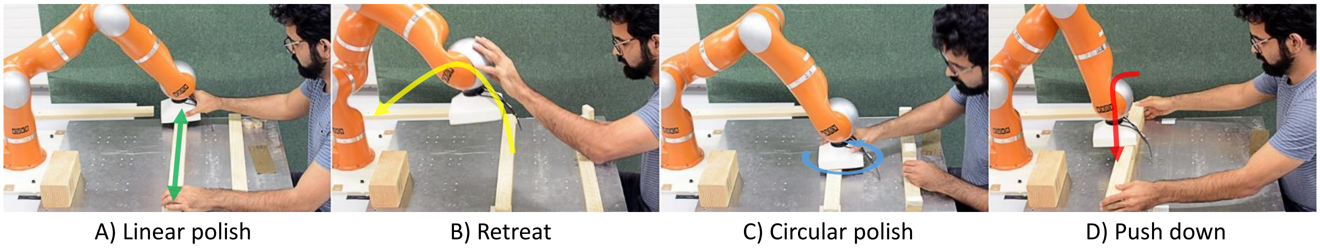

Fig. 1. An example of task-adaptation in compliant human-robot interaction. The user and the robot perform a series of manipulation tasks jointly. The robot recognizes the intention of human and adapts its behavior; i.e., switches to the corresponding task. **(A)** The human can ask the robot to polish linearly, **(B)** leave the workspace , **(C)** polish circularly, or **(D)** push down on a object. For this experiment, we use $\varepsilon = 1.5$ for adaptation rate, and $d = 100$ for impedance gain in 2 where the maximum velocity generated by DS is $0.2m/s$.

Algorithm 1: Winner-take-all

$w \leftarrow \arg\max_i \; \dot{\hat{b}}_i$
if ($b_w = 1$) **then**
  $\dot{b}_i \leftarrow 0$ for $\forall i$
  return $\dot{b}_i$
end
$v \leftarrow \arg\max_i \; \dot{\hat{b}}_i \quad \forall i \neq w$
$z \leftarrow (\dot{\hat{b}}_w + \dot{\hat{b}}_v)/2$
$\dot{b}_i \leftarrow \dot{\hat{b}}_i - z \quad \forall i$
$S \leftarrow 0$
for i **do**
  if ($b_i \neq 0$ *or* $\dot{b}_i > 0$) **then**
    $S \leftarrow S + \dot{b}_i$
  end
end
$\dot{b}_w \leftarrow \dot{b}_w - S$

III. RESULTS

In this section, we consider a scenario where a robot and the human polish and assemble a wooden structure; see Fig.1. The robot consists of a 7-DOF KUKA LWR 4+ arm with a flat (plastic) end-effector where a sand-paper is attached. The robot is capable of performing four different tasks encoded by DS: polishing linearly, polishing circularly, pushing down on a part, and retreating from the shared workspace. The generalization provided by the DS enables the robot to perform any of the tasks from any point in its workspace. We systematically assessed all possible switchings across tasks. The first subplot (Fig.2.A) shows how, upon human perturbations, the beliefs are adapted. Specifically, the previous task loses its beliefs (falling from 1 to 0) while the new one takes over; the changes in the belief of all other tasks being negligible. It roughly takes 1 second for the belief to rise (from 5% to 95%). However, this rise-time depends on the quality of the human-demonstration, *distinguishability* of the tasks, and the adaptation rate (ε). Fig.2.B illustrates the power exchanges during the interaction. The human-user spends mechanical power to demonstrate his/her intention. Initially (up to 1 second), the robot rejects the human perturbations when the wining task is still below 0.5. After gaining enough confidence in the new task (i.e., belief higher than 0.5), the robot becomes the active (providing positive effort) and the human the passive partner.

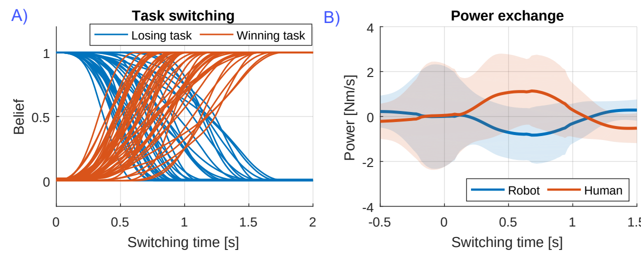

Fig. 2. Result of the proposed adaptation mechanism when switching across two tasks: **A)** The robot switches from one task to the other as a result of change in its belief following the interaction with the human **B)** The human-user requires to exchange mechanical power with the robot to demonstrate his/her intention.

IV. DISCUSSIONS & CONCLUSIONS

Having *"distinguishable"* tasks is one of the requirement for an efficient adaptation. Moreover, the convergence behavior is improved when the human demonstrates the target task with a higher precision. These conditions help the robot to observe enough dissimilarity to the current task and enough similarity to the target task. The sensitivity to such similarity/dissimilarity is controlled by ε. In short, the speed of convergence depends on: 1) inner-similarity of the tasks, 2) the quality of the human perturbations and 3) the adaptation rate. Therefore, the convergence behavior can be improved by designing the tasks (encoded by DS) to be dissimilar as possible to produce legible motions [12]. Moreover, naive users might require a learning phase to be able to express their intention and achieve a better convergence behavior. Finally, one can increase the convergence speed by increasing the adaptation rate cautiously with respect to undesirable dynamics. A conservative choice of ε ensures a robust adaptation (i.e., avoiding fluctuations) where the number of possible tasks is higher.

As reported in the results section, switching from one task to another requires human effort. This effort depends on convergence speed and the robot impedance. The longer the adaptation, the more effort the human spends. Moreover, the human effort is proportional to the stiffness and the damping that he/she feels. Therefore, One solution to reduce human effort is to reduce the impedance parameters at the cost of permanently deteriorating the tracking performance of the robot. Nevertheless, this serves as a hint to vary

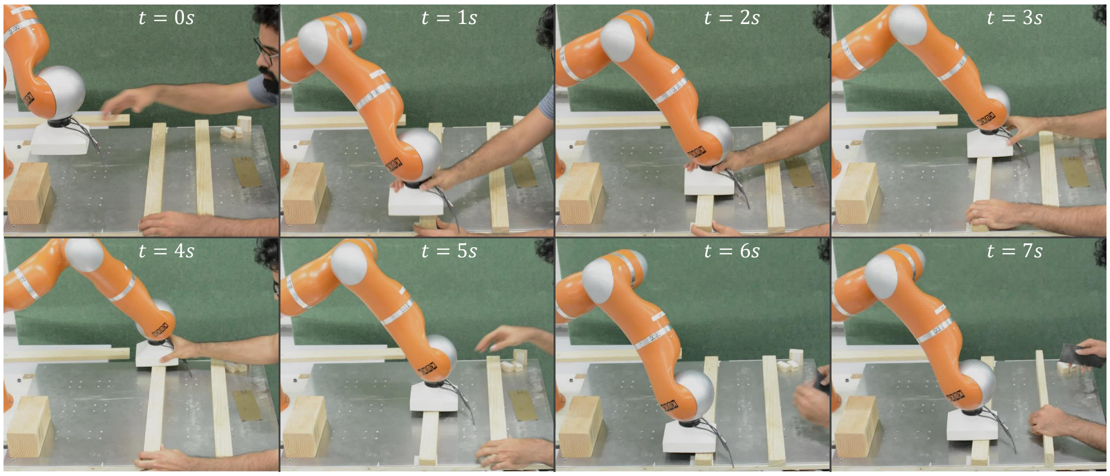

Fig. 3. Snapshots of the task-adaptation in the manipulation task. The robot is initially in the retreat task. Staring around $t = 1s$, the human starts to demonstrate the linear polishing task. From $t = 4s$ the robot start to perform the linear polish autonomously.

the impedance based on the interaction forces to have a compliant behavior while in contact with human (e.g., low damping, to reduce human effort for adaptation) and proper impedance during task-execution (e.g., high damping, to increase the tracking performance); see [13] for such parameters adaptation upon detection of force variations. However, the challenge is to distinguish between the forces intended by human and undesirable disturbances (which requires high stiffness for rejection). [14], [15], [16] propose different approaches to distinguish between intended and unexpected contacts that can be useful in our framework.

Human behavior has a crucial impact, and in general, on any online algorithm with a human-in-the-loop. For instance, we experienced cases where the human user falsely assumes that the robot recognized his/her intention and stops the demonstration prematurely. This potentially leads to a misrecognition which we impute more to the human-user rather than the algorithm. Nevertheless, this case shows us the importance of transparency where the human user has a precise inference of the robot's state. In our case, using synthesized speech or a display indicating the dominant task can improve the transparency of the interaction.

To conclude, we presented a dynamical-system approach to task-adaptation which enables a robot to comply to the human intention. We extended the DS-based impedance control [17] where, instead of one dynamical system (encoding for one task), several dynamical systems can be considered. We introduced an adaptive mechanism that smoothly switches across different dynamical systems. Experimental results confirm that our method allows for smooth and seamless human-robot interaction. Finally, for more experimental and analytical evaluations of this method see [18].

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