Human Posture Prediction during Physical Human-Robot Interaction

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***Abstract*—In this paper we propose a method to predict, in probabilistic terms, the human postures of an individual for a given robot trajectory executed in a collaborative scenario. We formalize the problem as the prediction of the human joints velocity given the current posture and robot end-effector velocity.**

The key idea of our approach is to learn the distribution of the null space of the Jacobian and the weights of the weighted pseudo-inverse from demonstrated human movements.

I. INTRODUCTION

Cobots (i.e., industrial manipulators for collaboration) and exoskeletons are designed to physically interact with humans and to assist their movement in accomplishing one or more tasks [1]. The general objective is to reduce the human physical effort and improve his/her ergonomics, which requires the evaluation of several ergonomics criteria, most often determined by the human posture [2].

An open problem, when a robot wants to assist the human, is that humans are not entirely "controllable": humans are highly redundant systems that are over-actuated for many manipulation tasks. Individual preferences of movement and musculoskeletal problems might add to the intrinsic variability of the human movement, thus increasing the variance of all possible postures in response to a robot action. For these reasons, when the human is physically coupled with the robot to accomplish a task, it is not possible to know with certainty how a human will move when the robot imposes a trajectory, which makes it challenging to select the best trajectories for the robot in collaborative tasks. In this context, data-driven probabilistic models of human movements, learned from demonstrations, can provide interesting insights into human preferences while capturing the variance of demonstrated movements. A limit of this kind of solutions is that a small error in the joint estimation can cause a large error in the estimation of the end-effector position (i.e., the human hand), which makes the prediction kinematically inconsistent. This error poses a nontrivial problem, especially when the human is physically coupled to the robot because it can compromise the quality of the collaboration.

For a known end-effector trajectory and an initial human posture, we want to determine the probability distribution of the human postures along the trajectory of the end-effector. Our main idea is to learn, from the human demonstrations, a model in the null space of the DHM Jacobian, which describes a set of human configurations that lead to the same end-effector position. The problem can be formalized as computing the conditional probability:

$$p(\dot{q}|q,\dot{x}) \quad \text{s.t.} \quad \dot{x} = J(q)\dot{q}\,, \tag{1}$$

where the second term is the kinematic constraint which determines the set of possible solutions.

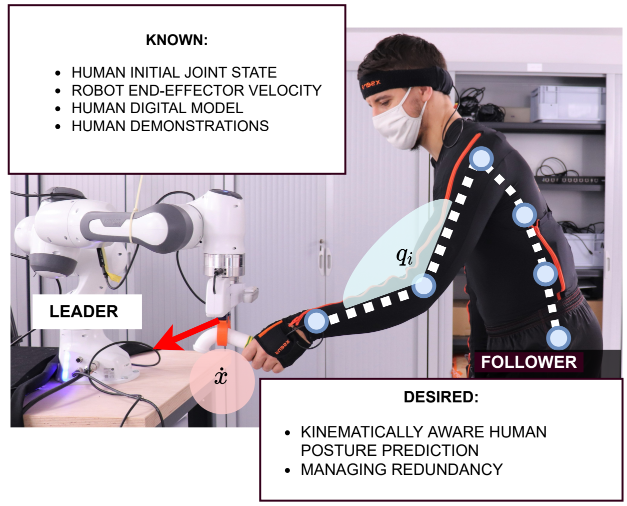

Fig. 1. The human posture is influenced by the robot's trajectory during physical interaction, but the human may adopt different postures during each task execution. In this paper we want the robot to predict the human posture given a known Cartesian trajectory of its end-effector and prior observations of the task executed by the human. The human posture is measured online by a wearable Xsens MVN suit.

II. METHOD

We assume that the human/DHM follows this classic control law from robotics ([3], [4]):

$$\dot{q} = J^{\dagger}_{W}(q)\dot{x} + (I - J^{\dagger}_{W}(q)J(q))z(q) \tag{2}$$

where $z(q)$ is a vector of null-space velocities and W are the weights of the weighted pseudo-inverse $J^{\dagger}_{W}$. The EE velocity $\dot{x}$ is known. Our objective is to learn $z(q)$ and W from data. In this way, the solutions we find must always satisfy the kinematic constraint: $\dot{x} = J(q)\dot{q}$. In our works we proposed to learn a distribution over $z(q)$ conditioned by the current joint state and the EE velocity using GPs and a gradient-free stochastic optimizer (BIPOP-CMA-ES [5]) to select the best parameters W.

Once the model is trained, it can be used to predict the human joints' trajectories given the current configuration q_t and the expected EE trajectory executed by the robot $\{x^d_1, \ldots, x^d_T\}$ by applying sampling procedure. In this way we get a Monte-Carlo estimation of the distribution over the human joint trajectories according to the learned model [6].

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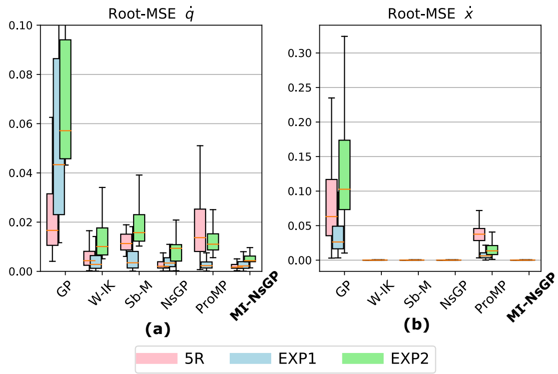

Fig. 2. Comparison of methods for joint velocity prediction: (a) R-MSE between the mean of the predicted joint velocity and real value (b) R-MSE over the EE velocity. The methods were evaluated on three experiments: (red) simulated 5R planar robot controlled by a biased IK function; (blue) human posture prediction during a human-robot collaboration task; (green) human posture prediction during a human-robot collaboration task using different tasks in the training-set and in the test-set).

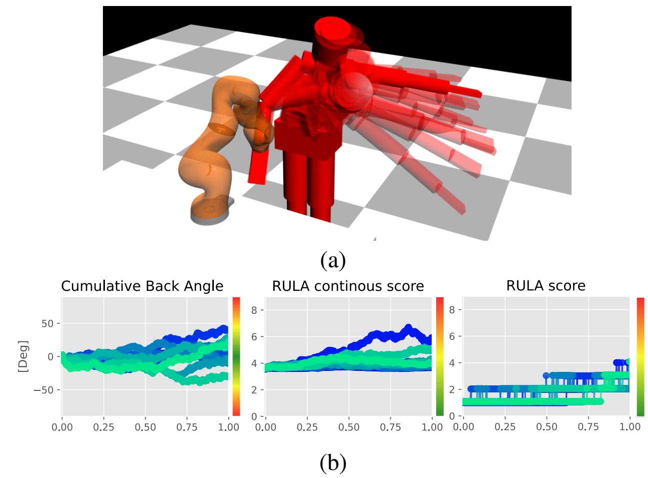

Fig. 3. (a) The DHM in Simulation, showing the variance of the solutions calculated via Monte-Carlo integration. (b) Ergonomic scores computed on different sampled trajectories: RULA, REBA, RULA continuous, cumulative back angle.

III. Experiments

To evaluate our method (denoted as MI-NsGP), we compare it experimentally to alternative approaches that use only a subsets of our elements (i.e., we make several ablation experiments). Moreover we compared our method with a state-of-the-art method for predicting joint trajectory while satisfying a task space motion primitive [7].

All methods were evaluated on three experiments. The first (**5R**) consists of predicting the joint state of a simulated 5R planar robot controlled by a biased IK function. The second (**EXP1**) and third (**EXP2**) consist in predicting the human posture (i.e., joints) during a co-manipulation trajectory, where a human is physically attached to the Franka robot to do a task. **Results:** Overall, our method (MI-NsGP) leads to significantly better likelihood values than all the control approaches. Moreover its performance is comparable with the state-of-the-art method for human posture prediction (ProMP). Regarding the ability to satisfy the kinematic constraint, we observed that model based methods (W-IK, Sb-M, NsGP, MI-NsGP) always have bigger likelihood and smaller root-mean-square error with respect to GP regression. Some considerations are possible on the results obtained. In fact, the joints which move less (e.g. lumbar joints) have a smaller W with respect to those which are more involved in the execution of the movement (e.g. shoulder and elbow). In the prediction phase we evaluated the calculated trajectories using four different ergonomics scores from the state of the art in human ergonomics [8]: RULA, REBA, RULA continuous and cumulative back angle (Fig. 3b). The purpose is to show that the probabilistic IK also impacts the prediction of ergonomics scores, which is critical information for a collaborative robot.

IV. Conclusions

We presented a method for predicting human posture in a Human-Robot Collaboration scenario where the human hand motion is constrained by the robot's end-effector. We propose a two-phase method: in the first phase, we leverage a dataset of human demonstrations to learn a distribution over the null-space of the human Jacobian using a Gaussian Process; in the second phase we optimize the weights of the weighted pseudo-inverse of the Jacobian. Our method computes a probabilistic estimation of the future postures that satisfy the kinematic constraints imposed by the physical link between the human and the robot, and at the same time is coherent with the human preferences of movement.

In the future, we want to consider the full human model in the posture prediction and integrate the algorithm into our framework for ergonomics control, which aims to optimize a collaborative robot's motions to maximize the comfort and the ergonomics of the human collaborator. A byproduct of our method is the probabilistic computation of ergonomics scores for a given robot's EE trajectory, which is a critical element for planning the robot's trajectories. Further, we want to remove the leader/follower hypothesis, and address the case where the leadership role may vary over time.

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