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Physical Human Robot Interaction in Imitation Learning

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Abstract— **This video presents our recent research on the integration of physical human-robot interaction (pHRI) into imitation learning. First, a marker control approach for real-time human motion imitation is shown. Secondly, physical coaching in addition to observational learning is applied for the incremental learning of motion primitives. Last, we extend imitation learning to learning pHRI which includes the establishment of intended physical contacts. The proposed methods were implemented and tested using the IRT humanoid robot and DLR's humanoid upper-body robot Justin.**

I. INTRODUCTION

Physical human robot interaction in imitation learning can be roughly classified into interaction during execution and interaction during learning. In most works, kinesthetic teaching was realized by deactivating individual selected joints (e.g. by setting very low servo gains). As a consequence, these approaches often lead to unsynchronized motions because the teacher moves motors one by one rather than demonstrating natural coordinated movements. These limitations can be overcome by combining imitation of human's whole body motion with a compliant behavior for physical interaction.

Physical interaction during motion execution is especially relevant for manipulation tasks and for tasks involving human-robot joint actions. In the latter case, the robot has to adjust its behavior to the human's actions. This requires an 'understanding' of higher level interaction rules as well as basic adaptation of learned motion primitives in accordance with the human's motions. However, teaching the robot to execute intentional physical interaction with humans has been hardly studied.

II. HUMAN MOTION IMITATION

In order to imitate human's whole body motions, we proposed a marker control approach [1]. The main idea is to connect virtual springs between the marker positions on a human and corresponding points on the robot (see Fig. 1(a)). When the cloud of marker points moves in space, the robot's motion will be guided by the forces generated from these springs. Instead of implementing the virtual springs directly, we let them act on a simplified simulation of the robot upper body dynamics including a free floating base link. This allows to implement the approach on a position controlled robot.

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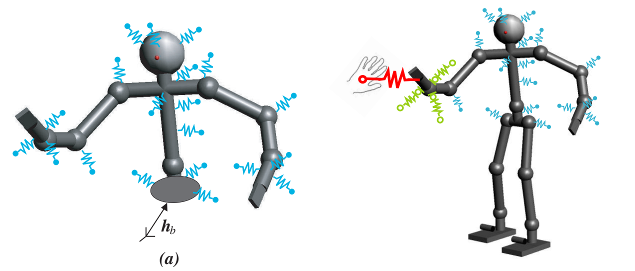

(a) (b)

Fig. 1. (a) Marker control: Virtual springs are connected between the reference marker points and corresponding points on the humanoid robot. (b) Modified marker control for intended contact establishment.

III. INCREMENTAL LEARNING BY PHYSICAL COACHING

In order to achieve intuitive teaching of natural motions, we proposed a method for incremental learning by using physical interaction [2]. A schematic overview is shown in Fig. 2. In order to ensure synchronization of complex whole body motions on a humanoid robot, our imitation learning procedure starts with observation learning (i.e. whole body motion retargetting from a human demonstrator to a robot by marker control [1]) prior to kinesthetic motion refinements. During the iterative kinesthetic teaching, in which a human supervisor physically interacts with the robot, the user can correct undesired aspects of the retargetted motion resulting from kinematic differences and mapping errors. Since the human might accidentally disturb the robot motion in an undesired way during the physical coaching, a customized impedance control is proposed. The proposed impedance controller allows to combine tracking of motion primitives in free-space with a kinesthetic modification by a human supervisor.

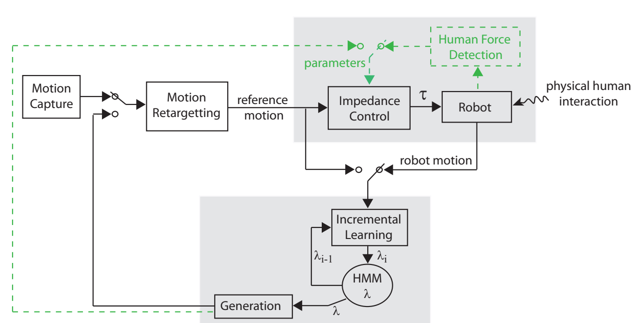

Fig. 2. System overview of incremental learning by physical coaching: Acquired motion primitives are iteratively refined by physical interaction with a human teacher.

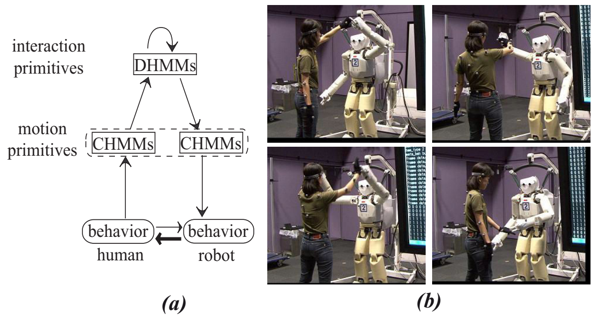

Fig. 3. (a) Mimetic communication model. (b) Physical human robot interaction experiments.

IV. Mimetic Communication for pHRI

With the baseline of the motion imitation, the "mimesis model" is adopted as a general framework for motion learning, recognition, and generation. Therein, motion primitives are represented by hidden Markov models (HMMs) which allow a concise stochastic representation of spatiotemporal patterns and have well established computational methods.

For learning pHRI, the mimesis model is extended in a hierarchical design, shown in Fig.3(a) [3], because the interaction patterns can be represented as a sequence of motion primitives between two agents, which provides a compact representation and modular structure. The interaction primitives contain information about the action of an agent, reaction of the other, contact timing, and contact positions. Through this model, the motion of the human partner is recognized and the intended interaction of the human is estimated. The estimated interaction primitive is taken as the high level controller, which decides an appropriate motion primitive for the robot to perform. Furthermore, the robot reference trajectory, generated from the selected motion primitive, is adapted in real-time to the human's motion in the physical world. The adaptation is done by modifying the marker control approach, as sketched in Fig. 1(b). The idea is to attach another virtual spring between the robot's hands and the corresponding human's hands (e.g., where contacts occur) during the expected contact timing. In order to realize the pHRI, the robot's behavior is made compliant during all the motions by applying impedance control.

V. EXPERIMENTS

The aforementioned methods are implemented and evaluated using the IRT humanoid robot (Fig. 3) and DLR's humanoid upper-body robot Justin. Figure 4 shows a qualitative presentation of the incremental learning including the kinesthetic refinement process. In this experiment, five manually segmented demonstrations (one observational and four kinesthetic demonstrations) of a dancing motion were provided by a human. In the first demonstration, the human's movement was measured by the motion capture suit and retargetted to the robot by the marker control algorithm [1]. Originally the human performed the dance, moving his right hand horizontally in front of his face. However, in the retargetted robot's dance, the robot's hand is above its head (Fig. 4(a)). Therefore, the human teacher corrects the right hand motion by pulling it down during the robot's execution (Fig. 4(b)). The human refined the robot's whole body motion four times in total, by pulling the right hand down, rotating the torso, and positioning the left hand away from its mobile base. Figure 4(c) shows the generalized motion primitive after four refinement steps.

Snapshots during pHRI based on the mimetic communication model are shown in Fig. 3(b). During a 17-minute-long experiment, the success ratio for the interaction primitives recognition was 97%. The mimetic communication strategy allows to recognize human motions, to find appropriate interaction patterns, and to generate robot motions online. By using the motion adaptation strategy, the robot actively established desired physical contacts with the human.

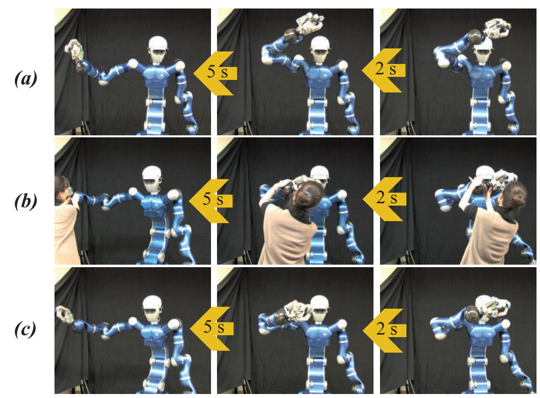

Fig. 4. Kinesthetic motion refinement: Subfigure (a) (from right to left) shows the snapshots from the original motion primitive. In (b) and (c), the snapshots during and after the physical coaching for refinement are shown.

VI. CONCLUSIONS

This video shows our recent work in the field of programming by demonstration and physical human robot interaction. As a baseline, an imitation method for commanding humanoid whole body motion was shown. Then, a refinement process of learned motion primitives using kinesthetic teaching was proposed. Imitation learning was extended to learning pHRI where the robot actively makes intended physical contacts with a human. The concepts were evaluated using two humanoid robots.

ACKNOWLEDGMENTS

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