SEVENTH FRAMEWORK PROGRAMME

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Chapter 1

Executive Summary

Deliverable 5.3.1 deals with the demonstrations in the context of WP5.3. It shows the execution of cooperative tasks and their learning, where cooperation takes place between two arms, two robots, or a robot and a human. Thus, the deliverable is tightly coupled with the research questions of cooperative tasks in WP4.1. Demonstrations are shown on the KIT and JSI robot platforms. The methodologies are described in deliverable 4.1.1.

The deliverable consist of videos demonstrating

- on-line selection and adaptation of movement primitives,
- tightly-coupled physical human-robot interaction for cooperative manipulation tasks (cooperative object carrying) and coaching, and
- learning object representations by bimanual pushing.

Chapter 2

Description of Results

2.1 On-line Selection and Adaptation of Movement Primitives

To be able to function in unison with humans, a robot must be able to react to perturbations by appropriately adapting its motor primitives. In video **SwitchingMovementPrimitives.mov** we demonstrate how a robot can re-initialize and even completely change its reaching behavior if the movement is perturbed due to the physical contact with a human. The video starts by showing the training process, which is done by kinesthetic guiding. The task is to grasp an object from one or the other side. After training, the robot can select the appropriate reaching movement based on the current Cartesian space position of the robot end-effector. Our new methodology, which is explained in deliverable D4.1.1 and in papers [3, 2], can generate such movements in real-time within the robot sensorimotor loop. If the movement is perturbed due to the contact with a human (or another object), then the movement is immediately re-initialized once the perturbation is over. As demonstrated in the video, the robot does not return back to the original trajectory, but instead it reaches towards the object directly from the new starting position. The smooth behavior shown in the video is due to the properties of dynamic movement primitives (DMPs), which enable smooth transitions when the parameters of DMPs change, and due to the fast calculation of new reaching movement primitives based on the database of training movements.

The last part of the video shows that the robot can also switch to a different movement primitive. In this demonstration the human pushes the robot so that it is forced to move from one side of the object to the other. In this case the database of movements is changed and a new movement primitive can be calculated with our fast method for generalization of DMPs. Once there is no perturbation in the video, the robot finally successfully reaches towards the object and grasps it.

2.2 Tightly-Coupled Physical Human-Robot Interaction

In Xperience, we investigate tightly-coupled cooperative tasks, in which two agents (two arms, robot-robot, human-robot) collaborate to carry big and/or heavy objects. The goal is to learn prediction models of the interaction partner based on cooperative interaction motion primitives and sensorimotor experience consisting of proprioceptive, force and tactile information during cooperative task execution.

The video **Cooperative-Board-Carrying** demonstrate an implementation of a master-slave architecture with the human as the "leader" and the robot as the "follower" in the context of object carrying task. The proprioceptive and force information measured by 6D force-torque sensors, which are mounted in the writs of the robot are used, to make a prediction of the human's motion. The interaction forces between the object and the robot, together with the prediction of the human's motion direction are used to used to generate the robot motions. The task of cooperative carrying of a long board is performed using the humanoid robot ARMAR-III [1]. See also deliverable D4.1.1.

The video **GuidingARMAR** demonstrates coaching of a humanoid robot via kinesthetic guiding. Interaction forces between the human and the robot are used to generate whole body motions of the robot exploiting the kinematic redundancy of the 7 DOF arms and the 3DOF holonomic mobile platform.

This way of coaching based on interaction forces with the human allows kinesthetic teaching on several motions. The video shows coaching of the humanoid robot ARMAR-III [1]. See also deliverable D4.1.1.

2.3 Learning Object Representations by Bimanual Pushing

Video **LearningByBimanualPushing.mov** shows how two arms can be used to repeatedly push an object, accumulate the object appearance images from different viewpoints, and learn its representation. The scientific basis for this work is described in deliverable D2.3.1 and D4.1.1 and in papers [4, 5]. To increase the robustness of object exploration, it was necessary to implement pushing with both arms. As demonstrated in the video, robust exploration behavior can be achieved already by a simple arm switching strategy. In the video the pushing arm is decided based on the position of the object with respect to the robot body. If the object is on the left side of the robot body, the left arm is used, and vice versa. The video shows that in this way the robot can repeatedly push the object and accumulate visual information for learning without getting stuck in a configuration that would prevent it to move the object. The exact starting point for pushing is chosen randomly in part, but always from the left side if the object is positioned on the left side of the robot body and vice versa. The pushing movement from the selected initial pushing position is always directed toward the middle of the table. The video also shows that in this way we can accumulate the images of object appearance for several different objects. Once the robot decide which object to push, it continues pushing the same object fairly reliably. This is important to ensure robust visual learning.

We are still working on making this bimanual exploration process more robust. For this purpose we need to include tactile sending into the system. At the moment we do not monitor if the robot collides with another object, but this can sometimes cause problems (such problems can be seen also in the video) or even a complete failure of the explorative pushing behavior.

References

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