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PP	Restricted to other programme participants (including the Commission Services)	
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CO	Confidential, only for members of the consortium (including the Commission Services)	

Abstract:

In this deliverable we present our work toward the implementation of a humanoid robot system able to imitate human actions on objects, to generalize actions to novel situations, and to learn rules through human advice.

The deliverable consists of demonstrations, for which we provide the videos.

Keyword list: Sensorimotor primitives, object representations, humanoid robot learning, imitation learning

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0. Executive Summary

This deliverable shows the demonstrations realized on the PACO-PLUS robotic systems in WP8.2 toward an imitation learning system for object manipulation tasks. The main objective is to implement a robot that is able to learn actions and associations between the perceived objects and possible actions through observation of a human demonstrator as well as to learn rules through human instruction.

The deliverable consists of the following demonstrations

- Generation of discrete movements using dynamic movement primitives (DMPs) for grasping and manipulation tasks, where the robot is able to generalize learned actions to novel situations and to sequence actions to allow object manipulation.
- Learning periodic action sequences using dynamic movement primitives, where the robot learns the appropriate periodic pattern and can modulate the frequency of movements on-line.
- Decision making framework which integrates the rule learning system, the PKS planner, and a teacher to allow the robot to interactively learn and execute complex tasks in a kitchen scenario. Processes like teacher interactions, rule generation, surprise and rule correction, generation of macro rules, and the online interaction of the rule system with the PKS planner are demonstrated.
- Teaching a humanoid robot through pointing and reaching gestures using parametric hidden Markov models (PHMMs) as a unifying representation both for action recognition and learning.

1. Generation of discrete movements using dynamic movement primitives (DMP) on ARMAR-III (UniKarl)

We continued our work on the generation of discrete movements on ARMAR-III using dynamic movement primitives in the context of the realization of an imitation learning system for object grasping and manipulation tasks. As shown in [4] and already reported in Deliverable D2.3.1, we extended the framework of dynamic movement primitives to action sequences that allow object manipulation. We suggested several improvements of the original movement primitive framework and added semantic information to movement primitives, such that they can code object-oriented actions. We demonstrated the feasibility of our approach in an imitation learning setup, where a robot learned an object stacking task and a pick-and-place task from a human demonstration, and could generalize this task to novel situations. We exploited the robustness of dynamic movement primitives against perturbations for obstacle avoidance, which was realized by adding a coupling term to the underlying differential equations of motion. The ability to avoid obstacles in Cartesian space was demonstrated in experiments that included continuous sequences of pick and place operations.

The video “**DMPs -on-ARMAR.avi**” shows experimental results performed on the humanoid robot ARMAR-IIIb. Three DMPs are used for the realization of a pick-and-place task and object stacking task. Movement segmentation algorithms were applied to the demonstrated movements to generate a set of DMPs from a single but complex demonstration. Semantic information has been added to the segmented movement primitives to allow the system to recall movement sequences and apply them in object manipulation tasks.

The feasibility of this approach has been demonstrated in simulation as well as on the humanoid robot ARMAR-IIIb. The robot learned the object-stacking task and the pick-and-place task and generalized these tasks to novel situations.

2. Learning periodic action sequences (JSI)

In this work we consider sequences of actions on objects that result in periodic movements. For this purpose we studied dynamic systems that can encode rhythmic movements. We developed a two-layered system for (1) learning and encoding a periodic signal without any knowledge about its frequency and waveform, (2) modulating the learned periodic trajectory in response to external events, and (3) demonstrating the use of the proposed algorithm for performing periodic tasks on the humanoid robot HOAP-3. The first layer of the system is a dynamical system responsible for extracting the fundamental frequency of the input signal, based on adaptive frequency oscillators. The second layer is a dynamical system responsible for learning of the waveform based on a built-in learning algorithm. By combining the two dynamical systems into one we can rapidly teach new trajectories to robots. Furthermore, the trajectories are robust to perturbations and can be modulated to cope with a dynamic environment. The learned movements can quickly adapt to changes in frequency and shape, e.g. to non-stationary signals, such as hand-generated signals and human demonstrations. This dynamic nature of the learning process allows the coach to adapt the movements to the objects involved in the task execution. The video "**Drumming.mpg**" shows the process of learning the appropriate drumming movements and on-line frequency modulation to change the rhythm of drumming.

The system is computationally inexpensive, works on-line for any periodic signal, and can be applied in parallel to multiple dimensions. The video shows the initial learning of periodic movements to achieve good contact with the drums, the final drumming behavior, and on-line frequency modulation. This work [2] is the periodic counterpart to our research on goal-directed action learning that we reported on in D2.3.1, where we focused on discrete movements.

3. Interactive rule learning system and PKS on ARMAR (CSIC, UniKarl, BCCN)

The video "**Rule-Learning-on-ARMAR.avi**" demonstrates a decision making framework for the humanoid robot ARMAR-III in the context of a simple kitchen scenario. The framework integrates the rule learning system, the PKS planner, and a teacher to allow the robot to interactively learn and online execute complex tasks in a kitchen scenario [3]. Among others, the video shows processes such as interaction with a teacher, rule generation, surprise and rule correction, generation of macro rules, and the online interaction of the rule system with the PKS planner.

The application in the demo consists of arranging cups on a sideboard to avoid collisions when moving a glass from one position to another. The robot is only allowed to perform simple straight movements for moving the cups, i.e. moving a cup to the left, to the right, forward or backward. The length of the displacements is specified by a number of positions with about eight centimeters distance to each other. For instance, one movement specified by the teacher could have the following semantic "move the green cup two positions to the right".

The learning of action rules takes place incrementally from scratch with the help of a teacher. Given a task specification consisting of a cup to be moved (the green cup in the video) and its final desired position, the PKS planner tries to build a plan from the current situation with the rules learned so far. If no plan is found due to the lack of knowledge then a human teacher instructs the robot by specifying the action that should be performed. The robot executes the action and generates a first approximation of the action rule and the associated probabilistic cause-effect from the observed changes. Rule refinement is triggered to resolve surprises when the outcome of a rule execution does not have an expected result. This situation is shown in the video under "situation 2" when a blocking object prevents the movement of the green glass. The generated and refined rules are constantly provided to the PKS.

4. The application of parametric hidden Markov models to rule learning (AAU, JSI)

We utilized parametric hidden Markov models (PHMMs) [3] as a unifying representation both for action recognition and learning. In the case of arm movements, we encode PHMMs by observation states that consist of Cartesian 3-D positions of a shoulder, sternum, elbow, wrist, thumb, index-finger and its knuckle. The advantage of such a representation is that the goal of the considered actions (reaching and pointing) is explicitly encoded in the final state of the PHMMs, which makes it easier to find parameterization for action interpolation. To realize interpolation that preserves the shape of the action trajectory, a proper alignment of the different exemplary actions, i. e. the alignment of corresponding hidden Markov states, is essential. We solved this problem by constraining the state transitions.

As an example, we studied the problem of teaching a humanoid robot through pointing and reaching gestures. The goal was to put differently shaped objects into a children’s toy box with differently shaped holes corresponding to different shapes. The robot learned symbolic rules (which object belongs to which hole) and continuous action knowledge (how to move the objects and release them into the appropriate hole) from a human demonstration. In the execution phase, the objects could be placed at any location on the table and the appropriate action was invoked by pointing towards an object, recognizing the pointing action, and executing the action associated with this object. See the video “**PHMM-rules.mpg”**

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