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Abstract:

In this Deliverable, we report on the implementation of the proposed three-level PACO-PLUS cognitive architecture on the humanoid robot ARMAR. Several components developed in other workpackages are selected and integrated on ARMAR to demonstrate 1) learning the association between object and action 2) learning the association between human actions and those of the robot as well as 3) learning action rules and generating and performing of plans in a defined domain.

Keyword list: Cognitive architecture on ARMAR, integration, grasping, pushing, action synthesis, rule learning, high-level planning and reinforcement learning.

Table of Contents

1. EXECUTIVE SUMMARY	3
2. PROGRESS TOWARD THE IMPLEMENTATION OF THE COGNITIVE ARCHITECTURE .	3
2.1 GRASP REFLEX AND CoVIS ON ARMAR (UNI-KARL, SDU).....	3
2.2 GRASP DENSITIES AND CoVIS (SDU, ULG, UNI-KARL).....	4
2.3 GRASPING BASED ON BOX DECOMPOSITION ON ARMAR (UNI-KARL, KTH).....	5
2.4 PUSHING FOR GRASPING ON ARMAR (IJS, UNI-KARL)	5
2.5 ACTION SYNTHESIS ON HOAP-3 AND ARMAR (JSI, UNI-KARL, AAU)	5
2.6 GRASP RECOGNITION AND MAPPING ON ARMAR (UNI-KARL, KTH)	6
2.7 PKS ON ARMAR (UNI-KARL, UEDIN)	6
2.8 RULE LEARNING SYSTEM ON ARMAR (UNI-KARL, CSIC, BCCN)	6
2.9 REINFORCEMENT LEARNING ON HOAP-3 (BCCN, JSI)	7

1. Executive Summary

A challenging task and ongoing activity in the project is the implementation and the evaluation of the proposed three-level PACO-PLUS cognitive architecture on the humanoid robot ARMAR-III. Within this activity, software interfaces and control flows between different components on the different levels have been identified and implemented to allow the integration of the developed components in the software control architecture of ARMAR-III. Several components were selected and are currently being integrated on ARMAR to demonstrate 1) learning the association between objects and actions 2) learning the association between human actions and those of the robot as well as 3) generating and performing of plans in a defined domain. The already integrated components on ARMAR are:

- Grasping reflex on ARMAR (UniKarl, SDU)
- Grasping on ARMAR based on learned object specific grasp densities (ULg, SDU, UniKarl)
- Grasping on ARMAR based on box decomposition representations of objects (UniKarl, KTH)
- Pushing behavior, which was learned by exploration using neural networks (JSI, UniKarl).
- Action synthesis and recognition based on imitation and coaching (JSI, UniKarl, AAU).
- Grasp recognition and learning of grasp strategies from a human teacher (UniKarl, KTH).
- Learning action rules for moving and pushing objects (UniKarl, CSIC, BCCN).
- Generating and executing plans in the presence of incomplete knowledge using PKS (UniKarl, UEDIN).

In addition, filling and pouring, which were learned by reinforcement learning have been successfully implemented and tested on the HOAP-3 robot at JSI (BCCN, JSI). This work will be transferred to ARMAR in the last project period.

2. Progress toward the implementation of the cognitive architecture

The aimed-at cognitive architecture consists of three processing levels as shown in Fig. 1). The low level is responsible for sensorimotor processing, the mid level represents an interface between sensorimotor representations of the low level and symbolic representations of the high level. Details related to the architecture were reported in D1.2.1 in the second reporting period and in the Deliverables D4.2.3 and D4.3.5 in the third period.

2.1 Grasp reflex and CoVis on ARMAR (UniKarl, SDU)

The integration of the grasp reflex using the Cognitive Vision System (CoViS) from SDU on ARMAR-III at UniKarl has been completed. The work comprised the following steps: A stereo calibration method of the Karlsruhe humanoid head which determines calibration matrices compatible to CoViS was successfully developed. In a further step, communication interfaces between ARMAR's robot control system and the CoViS architecture were implemented. These interfaces provide methods to transfer stereo images from the robot head to CoViS via TCP-IP and return the calculated grasping hypotheses to the robot. The CoViS parameters were adjusted for extracting feasible grasp hypotheses for ARMAR through adding additional constraints defined by robot workspace and the nature of feature.

For grasp execution a visual servoing method has been implemented, which allows both position and orientation control of the TCP. Currently, the separate phases of image acquisition, hypotheses computation and

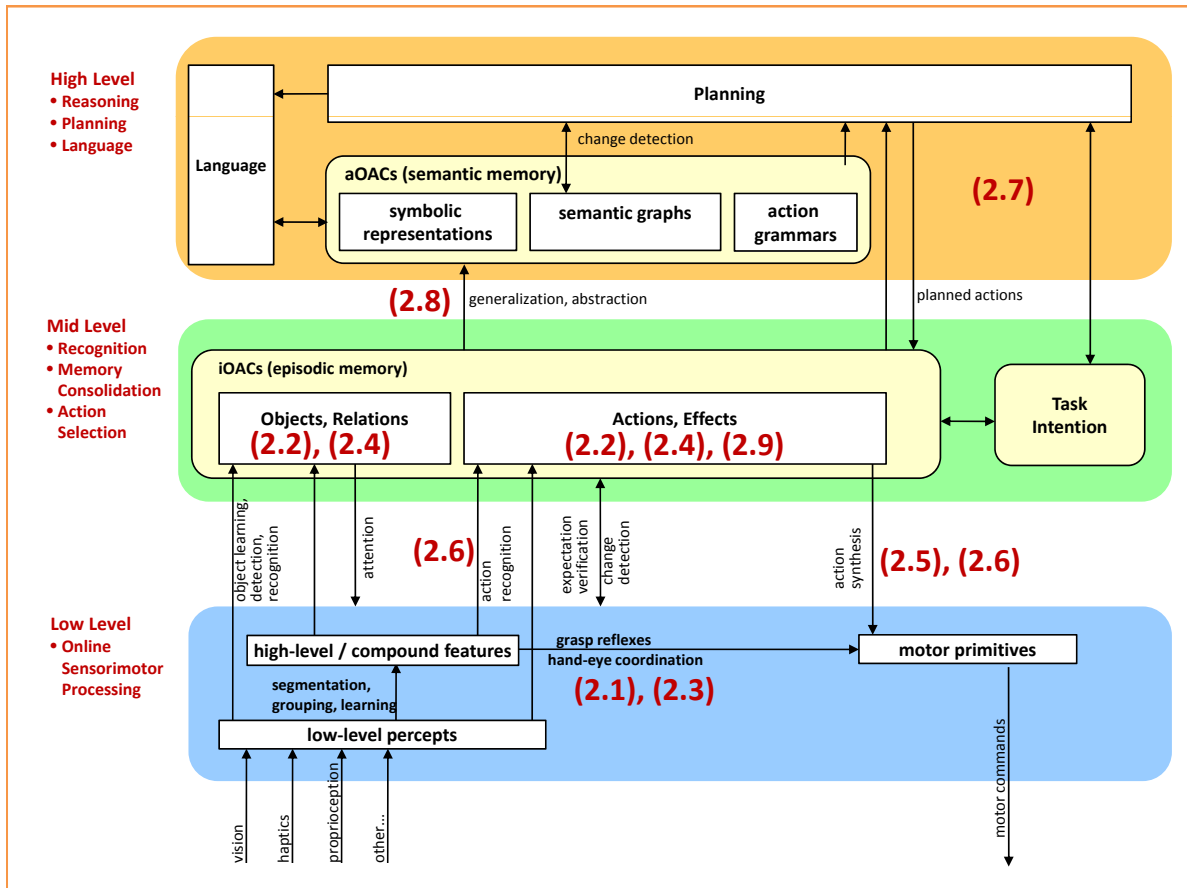


Figure 1: The PACO-PLUS cognitive control architecture. The already integrated components developed in the different work packages and described in this Deliverables are shown in this figure. The numbers in the figure correspond to the section numbers, i.e (2.4) correspond to section 2.4 "Pushing for grasping on ARMAR".

grasp execution become integrated in a complex scenario, where ARMAR verifies grasping hypotheses on unknown objects situated on the table. First experiments have been performed and will be continued. In the current implementation, the generated grasp hypothesis are specific to a two-jaw gripper which makes it necessary to deal with the grasp mapping to the five-finger hand used on ARMAR.

2.2 Grasp densities and CoViS (SDU, ULg, UniKarl)

Two important functionalities that have been developed at ULg in co-operation with SDU, namely pose estimation based on multi-modal primitives and the learning of grasp densities by exploration and imitation (see [5]) are currently integrated with the Cognitive Vision Software (CoViS) developed at SDU. Since CoViS has already been successful transferred to UniKarl (see section 2.1) the two functionalities will be available once the integration in CoViS has been finalized which is expected to happen in March 2009.

ULg provides a C++ library of functions implementing their multi-sensory hierarchical object model. This library receives as input observational data from CoViS, and defines an interface through which the robot application working at SDU is able to perform object pose estimation needed in the planning context. The interface is clearly defined and can be used for other scenarios as well. The CoViS observational data corresponds to the visual primitives and the primitive-grounded grasp reflexes. Both are exchanged through XML-based interfaces.

2.3 Grasping based on box decomposition on ARMAR (UniKarl, KTH)

In this work, we present the implementation and integration of a complementary approach to the grasp reflex (see Section 2.1) on ARMAR. The complementary properties of both approaches are described in Deliverable 4.1.3, Section 3.1. Given an object detection and pose estimation skill, grasp generation methods can be applied to known objects in order to assign a list of grasp hypotheses to each model. We have integrated the box decomposition approach proposed earlier in [9, 8] in a model-based scenario, based on a-priori known objects from the Karlsruhe object models database¹.

On ARMAR, texture-based object recognition and pose estimation were implemented using information from that database. If an object is detected, its identification and pose are communicated to a remotely integrated BoxGrasping server. While box constellations of each object in the database are computed beforehand, a selection and ranking of the generated grasps is done dynamically on each request, dependent on the object pose, but also on heuristics and simulated grasp-quality learning described in [8]. The final set of ranked hypotheses is sent back to ARMAR and checked for kinematic reachability before a selection is done. If no hypothesis was sent, the object is assumed to be non-graspable.

2.4 Pushing for grasping on ARMAR (IJS, UniKarl)

The focus of this research is to develop and demonstrate the learning of pushing actions for grasping on the humanoid robot ARMAR. Details about the explorative learning of a pushing behavior can be found in D4.1.3 (see also [12]). The results of this research have already been tested on a Mitsubishi PA-10 robotic arm and on the humanoid robot HOAP-3. In both cases a UDP interface has been designed to control the robots from Matlab. A similar UDP interface has been developed also for ARMAR robot. The UDP interface enables more straightforward transfer of the methods between different robotic systems. Due to safety reasons the communication protocol is strictly predefined.

The implemented pushing behavior expects instructions from a higher-level planning system about where to push the object in order to bring it to a graspable position. For example, a plate on a table has to be pushed to a table edge, where the robot is able to grasp it. Another example is pushing of objects which are outside of the robot workspace. Here, the robot can use a tool (a handle) and bring the object into the workspace for subsequent grasping. The interface to the planning system will be implemented in the last year of the project.

2.5 Action synthesis on HOAP-3 and ARMAR (JSI, UniKarl, AAU)

Our research on action synthesis and recognition is based on imitation and coaching. Details about it can be found in Deliverables associated with Workpackages 2 and 3. The most important results include goal-directed action synthesis using splines (D3.1.3), recognition and synthesis with parametric hidden Markov models (D3.2.3), and imitation and movement generalization using dynamic movement primitives (D2.3.1). This research and the developed software is the result of collaboration between UniKarl, JSI, and AAU. The proposed learning algorithms have been demonstrated on various robotic platforms available to PACO-PLUS partners including ARMAR (see Deliverables D8.2.1, D8.2.2, and D8.2.3). While some of the software for action recognition and synthesis has been developed and tested on different platforms, the developed interfaces are suitable for rapid porting to ARMAR using a UDP interface, which was implemented in collaboration between JSI and UniKarl. Action synthesis on ARMAR requires the availability of a number of visuomotor processes including smooth pursuit, foveation, visual servoing and active 3-D vision. This research was reported in the Deliverables D1.1.1 (month 24), D1.1.2, D2.1.3 and D2.1.4 and the developed

¹Karlsruhe Object Models Database <http://wwwiainm.ira.uka.de/ObjectModels>, developed within the German Humanoid Robotics Project SFB588 <http://www.sfb588.uni-karlsruhe.de>

visuomotor processes have already been implemented on ARMAR and its head (see Deliverable D1.1.2 and [3]).

Extensive work has also been done on the implementation of the Master-Motor Map (see D8.2.2 from the last reporting period and [4]), which enables the transfer of humanlike movements to a humanoid robot and forms the basis for imitation on ARMAR (see D8.2.3 and [6]).

In the last year of the project we shall increase our efforts regarding the implementation of the developed algorithms for action synthesis (and their extension) on ARMAR. We shall concentrate on tasks such as reaching and grasping and the integration with other learning approaches developed in PACO-PLUS.

2.6 Grasp recognition and mapping on ARMAR (UniKarl, KTH)

The purpose of this integration effort is to enable ARMAR to learn grasp strategies from a human teacher. Learning of grasp strategies is an important component of robot learning of manipulation tasks from human demonstration, the focus of interest in Workpackage 3.2.

Using the methods described in D3.2.3 it is possible to locate the hand of a human in each frame of ARMAR's stereo video sequence. Given the hand position (without knowledge of individual finger positions) during a grasping action, the human hand orientation and type of grasp (according to the Cutkosky grasp taxonomy) is recognized and mapped to ARMAR's embodiment, using the method described in [10] and [11].

2.7 PKS on ARMAR (UniKarl, UEDIN)

High-level planning capabilities are currently being supplied to the ARMAR robot platform by the PKS planner [13, 14], which UEDIN is extending for use in robotic and linguistic domains as part of WP4 and WP5. PKS is a state-of-the-art knowledge-level planner that constructs plans in the presence of incomplete information. Unlike traditional planners, PKS builds plans at the "knowledge level", by representing and reasoning about how the planner's knowledge state changes during plan generation. PKS is able to construct conditional plans with sensing actions, and supports numerical reasoning, run-time variables [7], and features like functions that arise in real-world planning scenarios.

Like most AI planners, PKS operates best in discrete, symbolic state spaces described using logical languages. As a result, an important focus of the integration work between UEDIN and UniKarl has centred around the design of a high-level action representation that abstracts ARMAR's capabilities for goal-directed planning in the UniKarl kitchen domain.

Ongoing software-level integration also continues to use UEDIN's socket communication library and message passing protocol (developed as part of WP4), which facilitates the exchange of messages between the planner and lower-level system components. Forthcoming modules being implemented by UEDIN, such as a high-level plan execution monitor, will also be integrated with the ARMAR platform.

Details about the high-level planning domain specification, and UEDIN's communication and message passing architecture can be found in D4.3.5.

2.8 Rule learning system on ARMAR (UniKarl, CSIC, BCCN)

The software integration of the rule learning system on ARMAR will provide the robot with the capability of on-line learning action rules, without the need of hand-coding of the world dynamics required for high-level tasks execution. It will permit ARMAR to learn and perform new tasks, through a natural robot-teacher interaction and using a novel constructive learning approach [1], [2].

Action rules will be coded in the form of PKS planning operators to enrich in real time the knowledge available for the planner for plan finding and execution. Rule generation and refinement will take place after every single step in the plan, using the current experience gained during the execution. Whenever there is a gap of knowledge that prevents the planner to find a plan, the rule system learns new rules to fill the gap using teacher instructions. Learned rules could also relieve significantly the amount of deliberation needed by the PKS as they might merge repetitive sequences of actions, or plans found with large computational cost.

The integration will take place in March 2009. The initial application selected to evaluate the integration consists in learning action rules to reach and place objects without collisions on a table full of objects, using actions for grasping and pushing to move objects aside when needed. Action affordance will depend on objects shape, situations on the table, and movement restrictions.

2.9 Reinforcement learning on HOAP-3 (BCCN, JSI)

Filling and pouring actions, which were learned by reinforcement learning have been successfully implemented and tested on the HOAP-3 robot at JSI. For more details about this, the reader is referred to Deliverable 4.1.3.

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