



SAPHARI

SAFE AND AUTONOMOUS PHYSICAL HUMAN-AWARE ROBOT INTERACTION



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Final models and algorithms for collaborative activities

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Executive summary

The objective of the WP7 is to endow the robot with the task planning, monitoring and control abilities that are necessary for a robot that shares its space and tasks with a human partner.

This deliverable refers to task WP7.1 “Models and algorithms for collaborative activities”. It corresponds to the elaboration of a comprehensive set of concepts that will allow to effectively building the decisional component of the targeted robot control system. Based on this, Task T7.5 aims at providing an implementation of the proposed models with the specification of a human-aware robot controller (see D7.5.1@M36).

The work in WP7.1 allowed producing several results and publications on 4 complementary issues:

- Symbolic and mental models for collaborative objects manipulation
- Reasoning about collaborative tasks
- Models for Human-Aware Task Planning
- Models for supervising human-robot communication during the execution of collaborative tasks

Based on this work we converged on a proposal of a control architecture that will be implemented in Task 7.5. It integrates the planning and control schemes of collaborative robot able to conduct human-robot activities:

- A symbolic knowledge base and ontology to manage the symbolic and mental models that a teammate robot should reason about in order to elaborate effective and acceptable collaborative behavior.
- The elaboration of task-oriented geometric reasoning and their instantiation in the context of close human-robot object manipulation (the taskability graph concept and the CRAM control language)
- The development of high-level task planner that explicitly deals with human and robot activities
- A scheme of a system that supervises and regulates human-robot interaction and communication during the execution of cooperative activities and its first instantiation for attentional monitoring and dialogue management in simple human-robot interactive scenarios.

We describe here below the main aspects mentioned above and give examples of how they can be deployed. This work has been conducted through close collaboration between CNRS-LAAS, UNINA and UniHB. EADS contributed also to the overall design.

1 Introduction

The goal of T7.1 is to investigate and propose models and methods to achieve human-robot collaborative interaction. In this context, CNRS-LAAS, UNINA and TUM/UniHB contributed in the following topics which, we believe, correspond to the key needs, in terms of models and decisional processes:

1. Symbolic and mental models for collaborative objects manipulation
2. Reasoning about collaborative tasks
3. Models for Human-Aware Task Planning
4. Models for supervising human-robot communication during the execution of collaborative tasks

The models proposed here will serve for the design of a supervision system for a collaborative robot that is able to take into account not only the task achievement but also communication and monitoring needed to support interactive task achievement in a flexible way and acceptable way.

Let us define concretely our context:

- A robot and one or several humans share a physical environment, typically a workshop or a domestic environment
- The environment is composed of walls and furniture that are static
- What is dynamic is the fact that humans and robot move and manipulate objects

It is important to note that the envisaged tasks involve essentially navigation and manipulation tasks in a priori known and mapped environment. The objects that are manipulated are also known. Other actions that essentially call for placement and manipulation (such as screwing, gluing, assembly) can easily be taken into account at this level of abstraction.

We present here below the various models that have been elaborated and how they can be used in collaborative robot control architecture:

- We briefly present the adopted control architecture (section 2).
- Then we summarize the key issues which have been investigated in terms of models (section 3) and how they are used by a number of decisional components involved in the overall architecture (section 4).
- We finally provide examples of how such components are used (section 5).

Contributions: CNRS has essentially worked on the symbolic and mental models that the teammate robot should reason about in order to elaborate effective and acceptable collaborative behavior and on the planning aspects, which exploit these models. UNINA focused on the models for supervising human-robot communication during the execution of collaborative tasks. UniHB investigated reasoning issues linked to human-robot collaborative tasks.

2 The overall architecture

The overall Human-Robot Interaction framework is depicted in Figure 1. It is based on the the Human-Robot Interaction system developed at LAAS [Fiore14] and integrates essentially a Human Aware Task Planner (HATP) a supervisory system, and a set of specialized motion planners. This system is composed of several layers which are detailed below.

SPARK. The SPATial Reasoning and Knowledge (SPARK) component, responsible for geometric information gathering [Millez14]. SPARK embeds a number of decisional activities linked to abstraction (symbolic fact production) and geometric and temporal reasoning. SPARK maintains the geometric positions and configurations of agents, objects, and furniture coming from perception and previous or a priori knowledge. SPARK elaborates also perspective taking features, enabling the system to reason on other agents' beliefs and capacities.

Knowledge Base. The facts produced by SPARK are stored in a central symbolic knowledge base. This base maintains a different model for each agent, hence divergent beliefs can be maintained. For example, two agents can keep the information of two different positions referring to the same object.

HATP. The Human-Aware Task Planner [Lallement14] is based on a Hierarchical Task Networks (HTN) refinement process where an iterative task de-composition is exploited to reach the atomic actions. HATP is able to produce plans for the robot as well as for the other participants (humans or robots). By setting a different range of parameters, the plans can be tuned to adapt the robot behavior to the desired level of cooperation. HATP is able to take into account the different beliefs of each agents when producing a plan, including actions that support and elicit joint attention.

Collaborative Planners. This set of planners are based on POMDP models which are used to estimate the user intentions in joint actions (e.g. handovers). The POMDP policy selects high level actions (like continue to plan or wait for the user), which are then adapted by the supervisory system to the current situation [Fiore14]. More specifically, the supervisory system refines and executes each action in the HATP generated plan, using the collaborative planners to adapt its actions to those of the other agents during a joint action execution.

Supervisory System. The supervisory system is to orchestrate the overall planning and execution cycle. Indeed, it manages plan generation and flexible execution of the plan while interacting and monitoring the human. This module integrates the attentional system, where human monitoring and action execution functionalities are incapsulated into suitable behaviors. This integration will be detailed in the next subsection [Alami13, Rossi2013, Fiore14].

A set of Human aware motion, placement and manipulation planners. These trajectory planners define the robot motions taking into account the environment and the agents constraints [Mainp11, Pandey13].

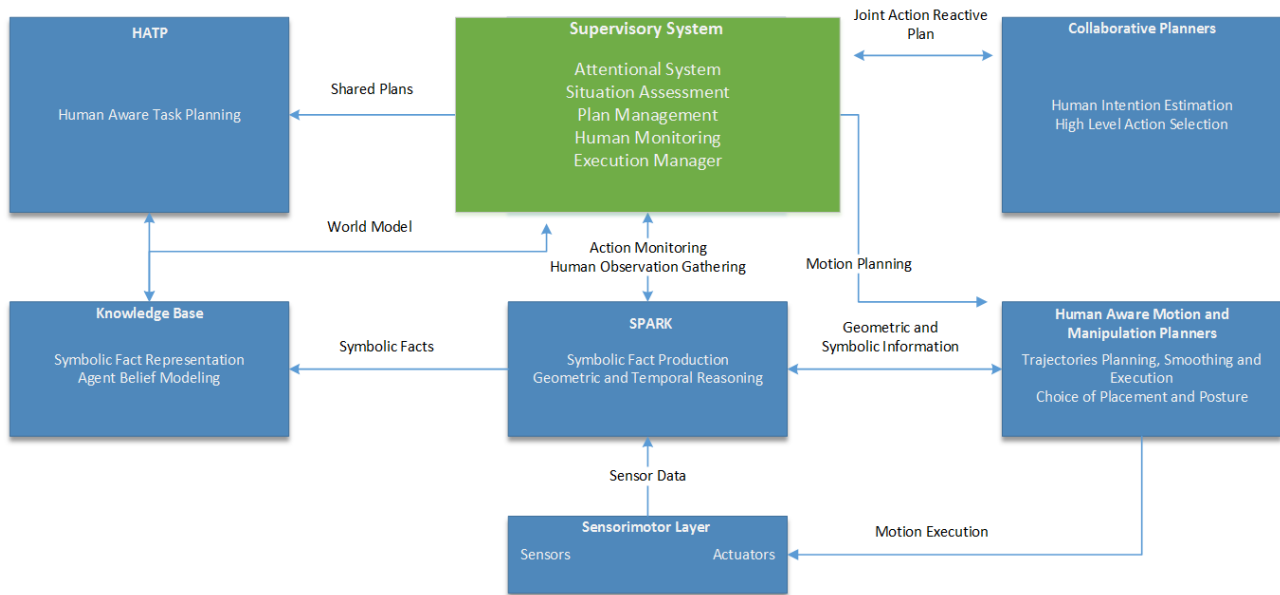


Figure 1: Human-Robot Interaction Architecture.

Note that a more detailed description of the supervisory system is provided in Deliverable D7.5.1 (Specification of a human-aware robot controller) with a focus on control while this document focuses on the models and how they can be used by the decisional components involved in this architecture.

3 Symbolic and mental models for collaborative objects manipulation architecture

Human-robot collaboration requires equipping the robot with explicit reasoning on the human and on its own capacities to achieve its tasks in a collaborative way with a human partner. In order to investigate and refine the models, CNRS-LAAS has adopted a constructive approach based on effective individual and collaborative robot skills and the necessary models needed to implement them [Alami13]. The envisaged control system is especially designed for a cognitive robot, which shares space and object manipulation tasks with a human [Lemaignan13b].

These abilities include geometric reasoning and situation assessment based essentially on perspective-taking and affordances, management and exploitation by the robot of each agent beliefs (human and robot) in a separate cognitive model, human-aware task planning and human and robot interleaved plan achievement.

The role of knowledge repository component envisaged here in the robot control architecture is to permanently maintain a state of the world in order to provide a basis for the robot to plan, to act, to react and to interact.

The main ingredients that we think are essential in this context are:

- The consideration of perspective-taking, i.e. the ability of the robot not only to build a model of the world for itself but also to estimate what its human partners see

- The ability to compute efficiently affordances for itself and to estimate the affordances of its human partners in a given situation [Pandey13d] (this aspect has been introduced in year 1 and is used in the task planner WP7.3)
- And, a more original and key aspect, the ability (1) to maintain a history of beliefs based on presence and focus of attention of humans and (2) to reason on possible divergent beliefs [Warnier12, Millez14].

All this corresponds to a permanent activity based on a number of inter-related processes:

- First, the robot must be able to handle spatial reasoning and anchoring where "anchoring is the process to establish and maintain in time the correspondence between symbolic knowledge and sensory data".
- Secondly, it must be able to gain explicit reasoning on the human it interacts with. That means not only that the knowledge must be grounded between the robot and its human partner but also that the robot must be able to maintain an explicit representation of the knowledge of its partner apart of its own knowledge. That will allow the robot to compare its own beliefs with the one of the human and to infer similarities as well as differences and ambiguities. Thus, the robot must be able to handle a kind of "theory of mind" specially adapted to the context.

Detailed description and discussion of these issues can be found in [Lemaignan-13a]

Perspective taking and affordance

We have proposed to use a set of symbolic facts that are computed on-line by the robot and that describe the world, the agents and the relationships between them (Figure 2).

These relations can be classified in two categories: *allo-centric* relations, i.e., that are independent from the viewpoint, and *ego-centric* relations, whose meaning is agent-dependent.

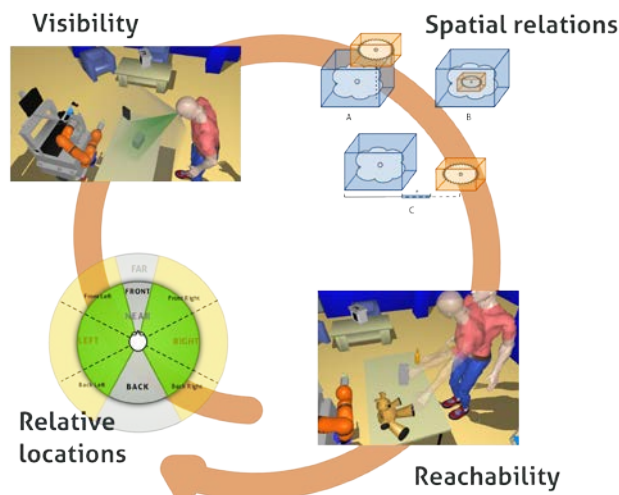


Figure 2: Some of the spatial relations and affordances that are computed

Allo-centric relations include facts like <object> **is in** <location>, <object>, **is on**, **is next to**... *Egocentric relations* are computed for each agent, from their viewpoints. This includes simple capabilities like "sees", "looks at", "can reach" and more complex evaluation of affordances (so called *mightabilities*, Figure 3).



Figure 3: Analysis of affordances: field of joint accessibility [Pandey13d]

Mental models managed by the robot

The second model relates to the mental representation of agents interacting with the robot, introducing a “*theory of mind*” for the robot [Alami13]. The representation of the mental perspective of other agents has a particular importance in human-robot interaction. It relies on the ability to literally view the world from a standpoint, which is not *egocentric*. This cognitive ability is referred as *perspective taking* (we have already presented our work on perspective taking in the previous section).

The idea of a *theory of mind* emerges from the perspective taking ability. It can be defined as the ability for one to understand and acknowledge that other intelligent agents can have their own mental state (that includes beliefs, intents, desires, knowledge) that is possibly different from one’s own. The attention plays a central to the development and recognition of a theory of mind.

We introduced above how we keep track of distinct beliefs for each agent. We believe this feature is helpful for understanding human speech, action and focus of attention (see below), i.e. to interact with humans. Indeed, as the robot knows what human believes it can decide what information human needs and then whether to speak or not according to the current situation or plan realization. A position belief management has been used on a robot in order to test them.

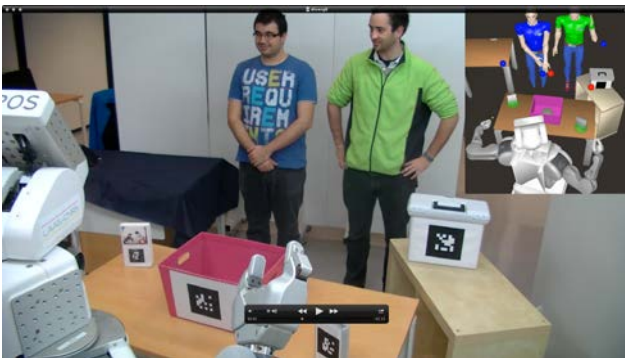
Figure 4 is an illustrative example [Warnier12, Milliez14]. These are screen-shoots from the 3D model display of the spatial reasoning module, taken during real experiments. It involves our cognitive robot and two humans, Green (wearing a green shirt) and Blue (blue shirt). The robot is able to build visual perspective of each “agent” when he is present and to infer their belief and, when it happens, detect situation where the beliefs are divergent.



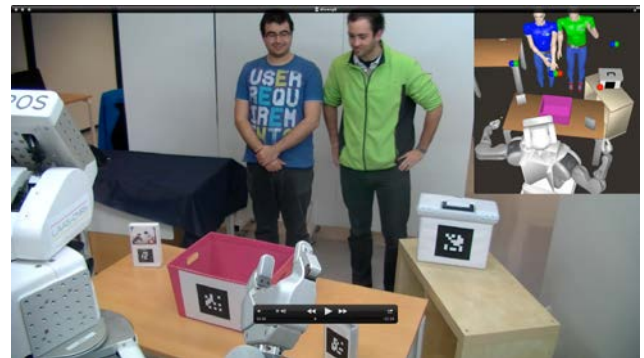
Blue is here (Robot is an observer)



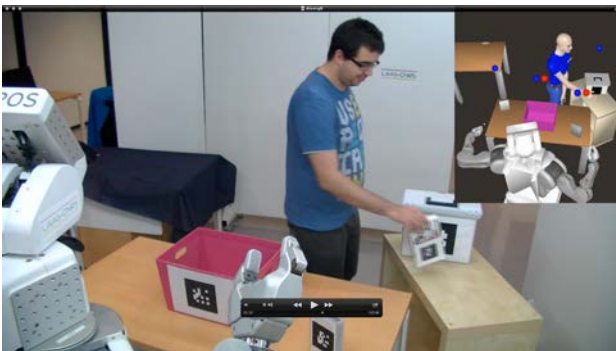
Green comes in



Robot computes that Green does not know (yet) about the objects



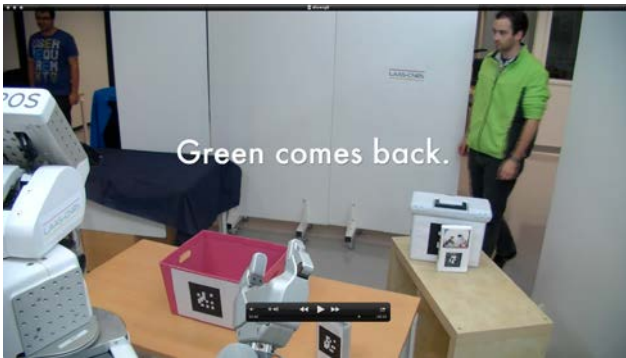
Robot infers that now Green knows about the objects (since they are visible to him)



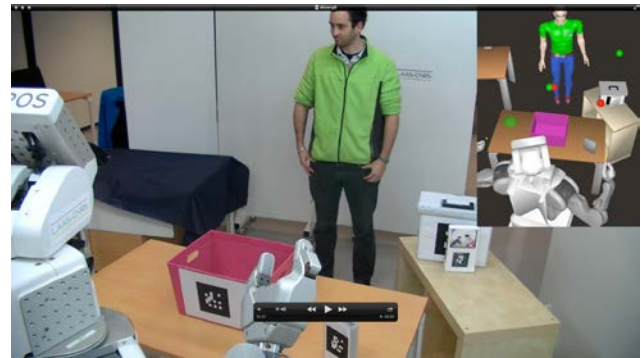
Green leaves ... Blue moves the white box



Robot computes the new situation



Blue leaves – Green is back



Robot infers that Green does not know now where is the white box (it has been move and it is not visible to Green)

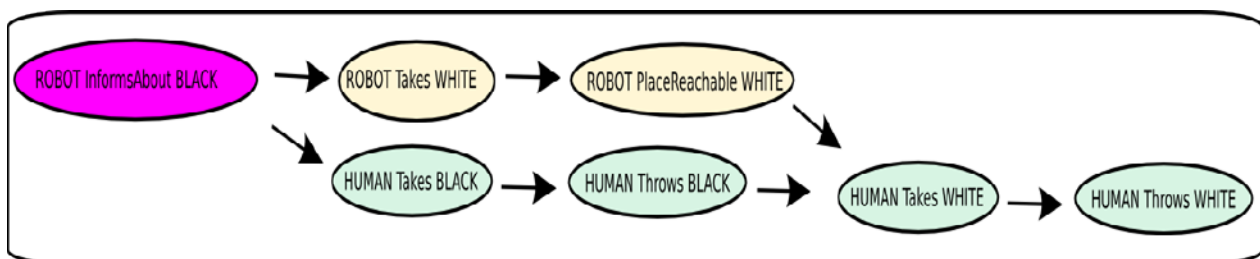


Figure 4: Management of divergent beliefs. The robot tracks the beliefs, infers that Green is not aware of where is the “black” box. It is able to elaborate a plan where it informs the human about its position before asking him to take it and throw it in the big box.

Reasoning about collaborative tasks

A reasoning system has been developed by UNIBH, that allows for inferring which objects are reachable only by a human, which objects can be reached only by the robot and which objects can be reached by both.

It is based on an extension of a Prolog interpreter for geometric reasoning and the generation of solutions using sampling based on likelihood maps:

- The first part of the system, Prolog based reasoning in a geometric environment is best explained on a simple example: find all objects that are reachable for the robot. Objects and the robot are present in the Prolog fact database as instances, i.e. they can be enumerated and for each object, predicates can be proven. In particular, the predicate to be proven in our example is *reachable*. To find all objects that are reachable for the robot, the system collects all objects for which this predicate holds. To prove the truth-value of the predicate, it is sufficient to just try to find a solution for inverse kinematics with the goal pose being the location of the object.
- The second problem is finding locations for which certain constraints (such as reachability) hold. This problem is more complicated because it normally is computationally too expensive to enumerate all possible locations and prove the constraints for each solution. Additionally, most often, many equally good solutions are possible. The system generates solutions by first computing a likelihood map using heuristics. For instance, for locations that are reachable for

the human, all locations that are closer than a certain threshold are used. For put-down locations that are reachable for the human and that are stable, only locations that are on the table and closer to the human than a certain threshold are considered, i.e. the likelihood of these locations in the likelihood map is set to a value greater than zero. Finally, the likelihood map is used as a probability density function, one sample is drawn and the solution is verified using Prolog predicates such as *reachable*.

Considering the CRAM language, it has been extended by establishing new classes of symbolic plan parameter descriptions --so-called designators-- for agents, e.g. the robot itself and humans, body-parts of agents like arms, limbs or heads, and risks, such as expected touches or unexpected collision which should be protected by the reactive controller and recovered from by the plan-based controller. These incomplete descriptions allow for abstract specification at compile-time and are resolved by the system at run-time.

Models for supervising human-robot communication during the execution of collaborative tasks

We have elaborated models and methods for supervising human-robot communication and interaction during the execution of collaborative tasks. In particular, we focused on dialogue management and its links with attentional monitoring and control.

The multimodal communication between the human and the robotic system is modeled by a dialogue management system adapted for a human-robot interaction scenario. Following the approach by [Young et al. "The Hidden Information State model: A practical framework for POMDP-based spoken dialogue management," Computer Speech and Language 24, 2010, Elsevier) we exploit POMDPs to model the dialogue between the human and the robot. This model permits to account for contextual interpretation of ambiguous situations and behaviors. The POMDP model has been employed in speech recognition literature, while its exploitation in multimodal communication and human-robot context is novel. As far as the attentional system is concerned, we are investigating bottom-up and top-down attention allocation mechanisms in the human-robot interaction context. Following the approach of [Buratt08, Buratt10] we considered, a frequency-based model of attentional allocation deployed in simple hand-over scenarios [Buratt12]. While bottom-up mechanisms for attention allocation in HRI have been investigated before [Buratt12], we have investigated a supervisory system that allows us to integrate top-down attentional regulations given a structured task to be achieved (e.g. human-aware plan provided by the planner, dialogue model, etc.). In this context, the aim is to monitor and modulate not only the execution (e.g. cooperative plan), but also the multimodal communication between the human and the robot [Iengo12] (e.g. human posture, gestures, intentions, etc.).

Interaction Models for Dialogue Management.

In order to represent the knowledge about interaction, the system is provided with a set of interaction models, which describe how the dialogue can develop. These models characterize several features of the system: the real intention of user is hidden; the results of classification are not error-free; the interpretation of a gesture could be multiple; an interpretation could lead to different system action, according to dialogue flow. The update dialogue states are formulated as a POMDP. The architecture of our dialogue management system is depicted in Figure 5: the user actions are interpreted, the dialogue context is then estimated and, depending on the human, environmental, and dialogue state an action/communication is produced (dialog policy) in output. Since the set of states could be very large,

approximated solutions are more suitable than exact ones. We deployed approximation methods based on Point-based Value Iteration and Augmented MDP [Lucignano2013].

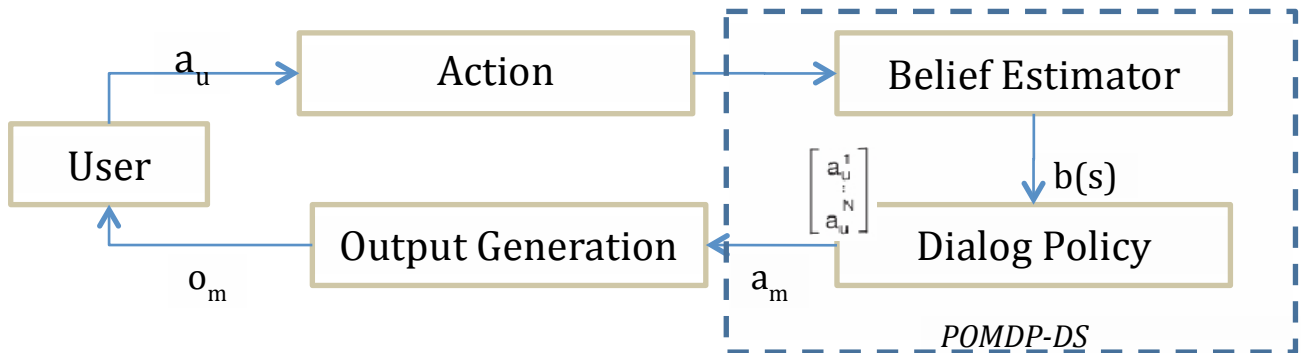


Figure 5: Dialogue Manager

Integration of the Supervisory Attentional System with the Dialogue Manager

We have designed a framework that integrates the Supervisory Attentional System with the Dialogue Manager [Lucignano2013]. This framework has been modeled taking into account the structure of the Multimodal Interaction Module [Rossi2013] designed within WP5. In this framework, the human-robot interactive policy is directed by the Dialogue Manager, which is assisted by the Supervisory Attentional System guiding the robot towards the execution of hierarchical tasks. In particular, we proposed a model where the dialogue policy (solution of the POMDP [Lucignano2013]) is enhanced by a top-down attentional mechanism with contextual and task-related contents. More specifically, the generated dialogue policy represents an interaction template, which is instantiated and continuously adjusted by the attentional system with respect to both the environmental and the operative context. The attentional control system modulates and polarizes the interactive execution, by enhancing the attentional behaviors aligned with the operative (top-down) and environmental state (bottom-up), while inhibiting the incoherent ones. The overall integrated architecture that connects the Attentional System and the Multimodal Interaction Module is depicted in Figure 6.

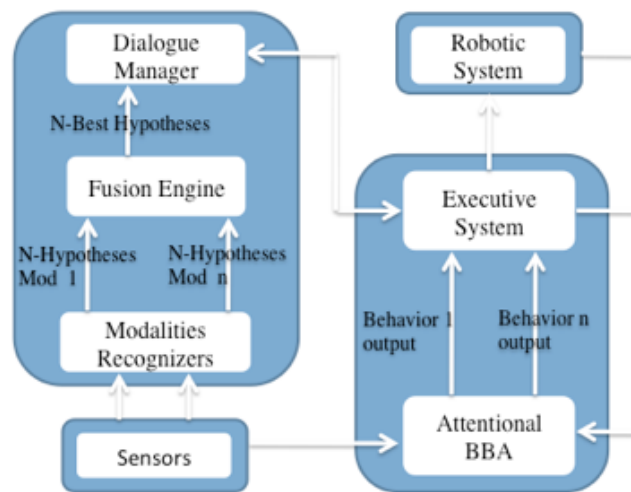


Figure 6: The integrated Framework: HRI Dialogue Manager and Attentional Framework.

4 Key components of the control architecture

We present in this section a set of key components, which have been developed to be integrated in the adopted control architecture.

SPARK (SPAtial Reasoning and Knowledge)

SPARK is the component that retrieves data from all the robot sensors and brings them together into a unique data structure. This structure is used online to compute geometrical facts, used by the other components of the architecture.

We can classify these facts in three categories: facts that describe the relation between an object and either an agent or another object, facts that give information about an agent, and facts that describe the relationship between agents.

The following facts are part of the first category:

- A IsOn B: true when object A is on top of object B.
- A isIn B: true when object A is contained in object B.
- A isNextTo B: true when object A is close to object B.
- A isBigger/smallerThen B: true when object A is bigger/smaller than object B.
- A isReachableBy B: true when object A can be reached by agent B. In order to compute this fact, we use inverse kinematics on the agent.
- A isVisibleBy B: true when object B can be seen can be seen by agent B (agent head/eye motion are permitted).

The following facts give information about an agent:

- A isPresent: true when agent A is in the same area as the robot.

- A armPose: describes the position of the arm of the robot. Possible values are closeToBody and extended.
- A isMoving: true when agent A is moving.

The following facts describe the relationship between agents:

- A isOrientedToward B: true when agent A is facing agent B.
- A distanceTo B: describes the distance between two agents. Possible values are close, far, danger. Danger means that the two agents are so close that motions could lead to a collision.
- A HandDistanceToBody B: describes the distance between an agent's hand (the fact is computed for the agent's left and right hand) and another agent's body. Possible values are close, far, danger.
- A right/left HandDistanceToHand B: describes the distance between two agent's hands. Possible values are close, far, danger.

These facts are updated regularly by SPARK and can be retrieved anytime from the supervisor.

The link between SPARK and the Collaborative Planners is made through the supervision system of the cognitive architecture. The supervision system communicates using the GENOM middleware with SPARK in order to retrieve the needed facts/information, computes a set of observation from these facts, and sends them to the Collaborative Planners.

HATP: a Human-Aware Task Planner

In the previous sections, we have seen how symbolic knowledge is produced and stored from the real physical world. In this section, we present one possible way to use these symbolic models of the environment and interacting agents to produce a plan of actions for a complex goal.

In order to devise how a given goal can be accomplished, the robot has to elaborate a plan i.e. a set of actions to be achieved by the robot and its human partners. This is the role of HATP (Guitton12) (for Human Aware Task Planner). HATP is based on a Hierarchical Task Network (HTN) refinement, which performs iterative task decomposition into sub-tasks until reaching atomic actions. The planning domain defines a set of methods describing how to decompose a task and can be seen as the *how-to* knowledge of the robot. HATP is able to produce plans for the robot's actions as well as for the other participants (humans or robots). It can be tuned by setting up different costs depending on the actions to apply and by taking into account a set of constraints called social rules. This tuning aims at adapting the robot's behavior according to the desired level of cooperation of the robot.

Agents and action streams

The robot plans not only for itself but also for the other agents. The resulting plan, called "shared plan" is a set of actions that form a stream for each agent involved in the goal achievement. Depending on the context, some "shared plans" contain causal relations between the agents. For example, the second agent needs to wait for the success of the first agent's action to be able to start its own action. When the plan is performed, causal links induce synchronization between agents. Figure 7 illustrates a plan with two streams.

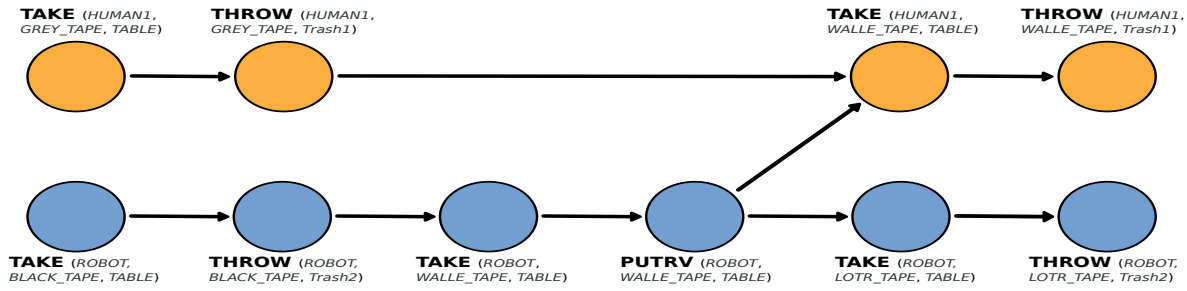


Figure 7: A plan produced by HATP with 2 coordinated streams of actions: the human stream and the robot stream.

Action costs and social rules

A cost and a duration function are associated to each action. The duration function provides a duration interval for the action achievement and is used, in one hand, to schedule the different streams and, in the other hand, as an additional cost function. In addition to these costs, HATP also takes into account a set of social rules. Social rules are constraints aiming at leading the plan construction towards the best plan according to some human preferences. The social rules we have defined so far deal with:

- Undesirable state: to avoid a state in which the human could feel uncomfortable;
- Undesirable sequence: to eliminate sequences of actions that can be misinterpreted by the human;
- Effort balancing: to adjust the work effort of the agents;
- Wasted time: used to avoid long delays between the actions of the human partner;
- Intricate links: to limit dependencies between the actions of two or more agents.

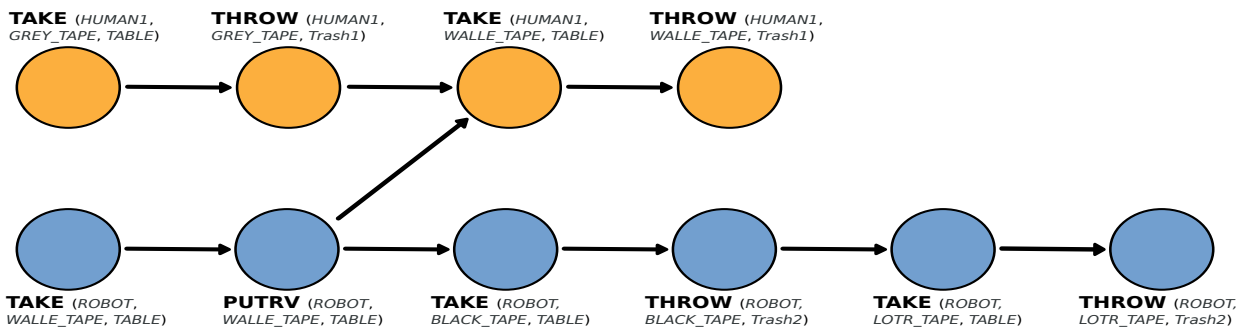


Figure 8: A plan with the wasted time social rule

Figure 8 illustrates an alternative plan to the previous one (figure 7) if the wasted time social rule is used. The obtained shared plan is the best plan according to a global evaluation of these multiple criteria.

Several levels of cooperation

It is also interesting to observe that, by tuning its costs and adapting its social rules, HATP can be used to compute various alternative plans. These plans can be categorized into several levels of cooperation (or involvement of the robot)

- Helping the human to achieve his goal by acting for him

- Sharing concrete resources by handing some objects
- Collaboration of the robot and the human by coordinating their actions towards a human-robot joint goal.

Collaborative Planners

Collaborative planners are implemented to deal with joint actions i.e. actions that need the robot and the human to work in close interaction and exchange action related signals [Fiore14]. Estimating humans' intentions is a key issue in such situations, because humans have very variable and complex behaviors, which include both verbal and non-verbal communication.

We propose to represent human's intention as a hidden variable to estimate, and formulate the problem of executing a cooperative action, such as a handover, with a human as a Mixed Observability Markov Decision Problem (MOMDP). An MOMDP models the decision process of an agent in a non-completely observable environment. The model can be seen as a middle ground between a POMDP, where the system state is hidden, and an MDP, where the system state is observed.

Formally an MOMDP is a tuple $(S, A, O, T, \Omega, R, \gamma)$ where $S = \{S_h \times S_o\}$ is a set of states, with hidden and observed subsets, A is a set of actions, O is a set of observations, T is a set of conditional transition probabilities, Ω is a set of conditional observation probabilities, R is a reward function and γ is a discount factor.

To cooperate with humans in different tasks we can define a set of Collaborative Planners, each one related to a task, and represent them as MOMDP. As MOMDP can become very complex problem, when the system state become too big, we create an abstract and simple state space, focusing on the intention estimation problem, and leave to the cognitive architecture of SAPHARI the task of adapting the MOMDP answers to the current situation.

We created a set of common parameters that are shared by these models. The system state is formed by a hidden and observed set of variables.

We define the following hidden variables:

- Intention
 - Description: represents the user's involvement in the task.
 - Values: not interested, not engaged, engaged.
- Status
 - Description: represents if the user is having problems executing the task.
 - Values: okay, problems.

We define the following observed variables:

- InRange:
 - Description: represents if the user is in interactive range.
 - Values: true, false.
- Task:
 - Description: represent the status of the task.
 - Values: depend on the actual task.
- Time:

- Description: used when the robot needs to wait for a certain amount of time (controlled by the supervision system).
- Values: ok, expired.

Further, we define the set of actions A:

- Continue Plan, Wait, Abandon, Engage, Replan.

The set of observations O , their probabilities Ω , and the reward function R are specific on the actual task. The transition function T is partially equivalent in every Collaborative Planner. The difference lies in the Task variable, which will have a different transition function in every Collaborative Planner.

At each time step, when executing a cooperative action with a human, the supervision system of the SAPHARI cognitive architecture gathers the observation and updates the corresponding Collaborative Planner, receiving a high-level action that will be adapted to the current situation.

We implemented a Collaborative Planner for the handover action, where an agent needs to handle an object to another agent. In this case the observed variable Task can assume the value “not completed, waiting for grasp, completed”.

For this task we defined the following set of observations:

- Distance:
 - Description: represents the distance of the user from the robot.
 - Values: close, far, out of range.
- Orientation:
 - Description: represents the orientation of the user related to the robot.
 - Values: toward robot, other, unknown.
- Arm Position:
 - Description: represents the pose of the user’s arm.
 - Values: extended, close to body.

These observations are computed by a set of human monitors implemented in the component SPARK.

We conclude this section with an example. The robot is trying to give an object to a human agent. At the start, the human is turned in another direction, speaking with a co-worker. The MOMDP estimates its intention as “Not Engaged” and chooses the action “wait”. The robot places its arm in an intermediate position. When the user turns toward the robot and extends its arm the new set of observations reflect this fact and the MOMDP identify the user’s intention as “engaged”, selecting the “continue plan” action. The robot extends its arm, waiting for the user to grasp the object.

A controller that integrates Task Planning and Attentional Execution

UNINA extended the design of the executive system in order to integrate the Human-Aware Task Planner (HATP). This requires the definition of suitable methods to invoke the planner and monitor the execution of the planned activities. The overall architecture is depicted in Figure 9. The attentional system is composed of two layers: an attentional executive system [Cac14a, Cac14b, Cac14c] and an attentional behavior-based system [Bro14, Noc14]. The latter provides bottom-up attentional regulations of concrete sensorimotor processes, while the first layer is responsible for executing and monitoring structured tasks, providing top-down attentional regulations. In this framework, action schema definitions represented in the Long Term

Memory (LTM) are instantiated in the working memory (WM) for their execution. In order to integrate the HATP planner, the hierarchical tasks specified in the planning domain are to be also represented in the LTM as abstract or concrete schemata (corresponding, respectively, to methods and actions). The planning activity can be invoked by the attentional system exploiting a suitable interface behavior that interacts with the HATP system providing the initial state and the planning requests. As a result of the planning activity, the behavior receives a plan of actions, which can be flexibly performed either by the robot or by the human, depending on the task and the context.

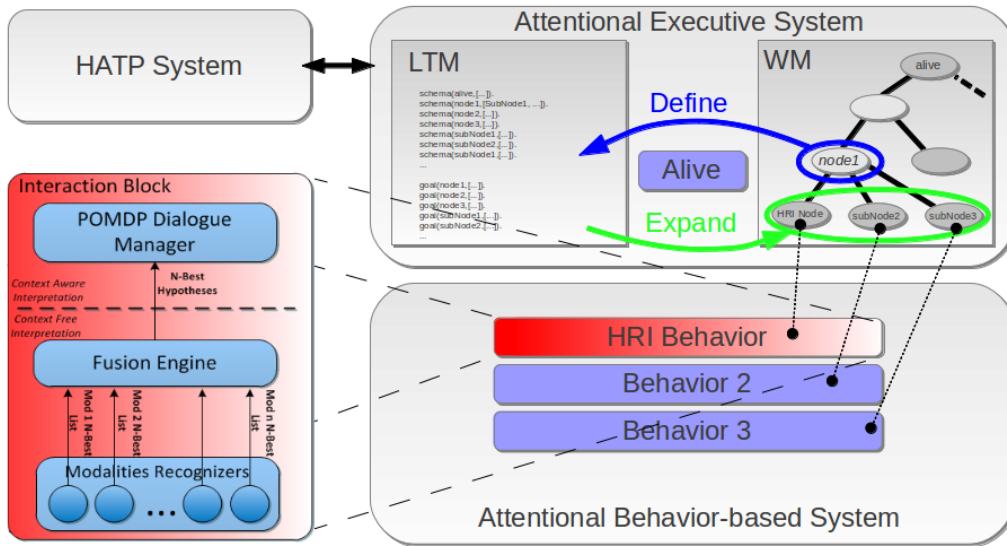


Figure 9: Integrated framework that combines multimodal interaction, attentional executive system, dialogue manager, and human aware task planner.

5 Instantiation and Examples

This section is intended to provide concrete examples of instantiation of the attentional behavior monitoring system and how it has been adapted to human-robot teamwork, the reasoning mechanisms dealing with collaborative tasks, and finally the elaboration of human-robot shared plans.

Attentional behavior monitoring for human-robot teamwork

When facing with human-robot teamwork, contemporary paying attention on both surrounding environment and teammates is required. Limited resources (sensors, bandwidth, computational limitations, etc.) prevent an agent to continuously execute and monitor multiple parallel tasks. Inspired by the behavior of human beings, paying frequent attention to timers while approaching deadlines, we provided robots with general monitoring strategies based on attentional mechanisms, for filtering data and actively focusing only on relevant information. We considered a convoy task (led by a human or a robot) as a benchmark to evaluate and compare human and robot monitoring behaviors. Convoy driving requires that both the leader and the follower accomplish the task. Namely, the leader (a robot or a human being), as well as the follower (a robot), has to monitor the teammates behavior and to adapt its own in order to not outdistance them. Moreover, the human subject monitoring strategy, while leading a convoy, can be observed. We tested our framework in a real world scenario (see Figure 10) [Ros14a, Ros14b].

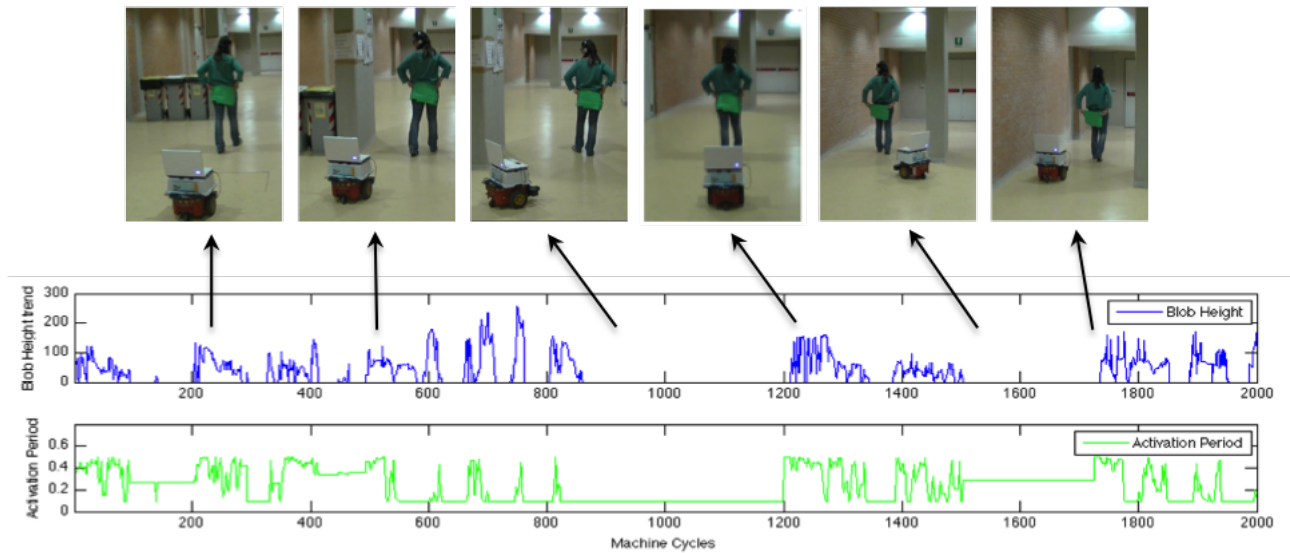


Figure 10: FollowMate behavior of the Follower with respect to a Human Leader.

A comparison of the robotic monitoring strategies with respect to the ones adopted by humans has been used to assess the effectiveness of the approach.

Models of Humans and their link with Reasoning about collaborative tasks

To perform its job in a human-safe way the plan-based robot controller obviously needs to be aware of the human. Specifically, it needs to be aware of the human's configuration and her position in the workspace, her current activity, and hypothesize about her future activities. The underlying representations of these aspects of the human co-worker are part of the work in task T7.1. Furthermore, estimating current and subsequent human activities based on tracking algorithms developed in WP4 and a shared model of the current collaboration task is also partly a responsibility of T7.1. To make this task tractable we focus on repetitive collaboration task, in which sub-steps and the involved objects are known a priori and are at least partially ordered.

T7.1 investigates the modeling of safety-related concepts such as risks, e.g. possibility of injuring a human co-worker through impact, or allowed interactions, e.g. the robot expects the human to slightly touch its elbow during one sub-task, as part of the plan language. These concepts will be implemented as extensions to the CRAM plan language, which so far only deals with robot manipulation activities in isolated workspaces. For instance, CRAM includes an abstracted representation of a tracked human co-worker. Regarding this representation, we can employ ellipsoids to represent limbs of the human body. Figure 11 visualizes the human tracking pipeline. Figure 11(a) shows the RGB-D input coming from the sensor. After pre-processing, segmentation, and human tracking the perception systems has identified and labeled several parts of the human body (see Figure 11(b). This is software was developed for deliverable D4.3.1. In the plan-based controller, we approximate pre-specified subsets of these labeled regions as ellipsoids to represent body parts we want to address in the plan, e.g. right upper arm, upper body, or head --as visualized by Figure 11(c). Finally, to communicate with the reactive controllers of WP6 (T6.3) we reconstruct the volume of the ellipsoids with spheres as the reactive controllers allow specification of collision objects in terms of spheres.



Figure 11: Human tracking pipeline from raw RGB-D input (a), over segmented and labeled regions of the human body in the point clouds (b), to an ellipsoid-based representation in the plan-based controller(c).

A context for human-robot collaboration planner an industrial setting

We discuss here below how we have instantiated an example included in the AIRBUS use case (WP8.3). Aircrafts assembly includes the installation of electrical systems. These are mainly individual or bundled wires of several meters in length used to power and to control all the electrical elements (sensors, actuators and controllers). A large number of brackets are manually positioned and fixed to the structure. They hold the electrical systems to the structure at short intervals in order to restrict their movement during flight.

Figure 12 shows an Ariane 5 launcher (left) and the upper skirt (right). The complete bracket assembly operations are performed manually and individually at the time.

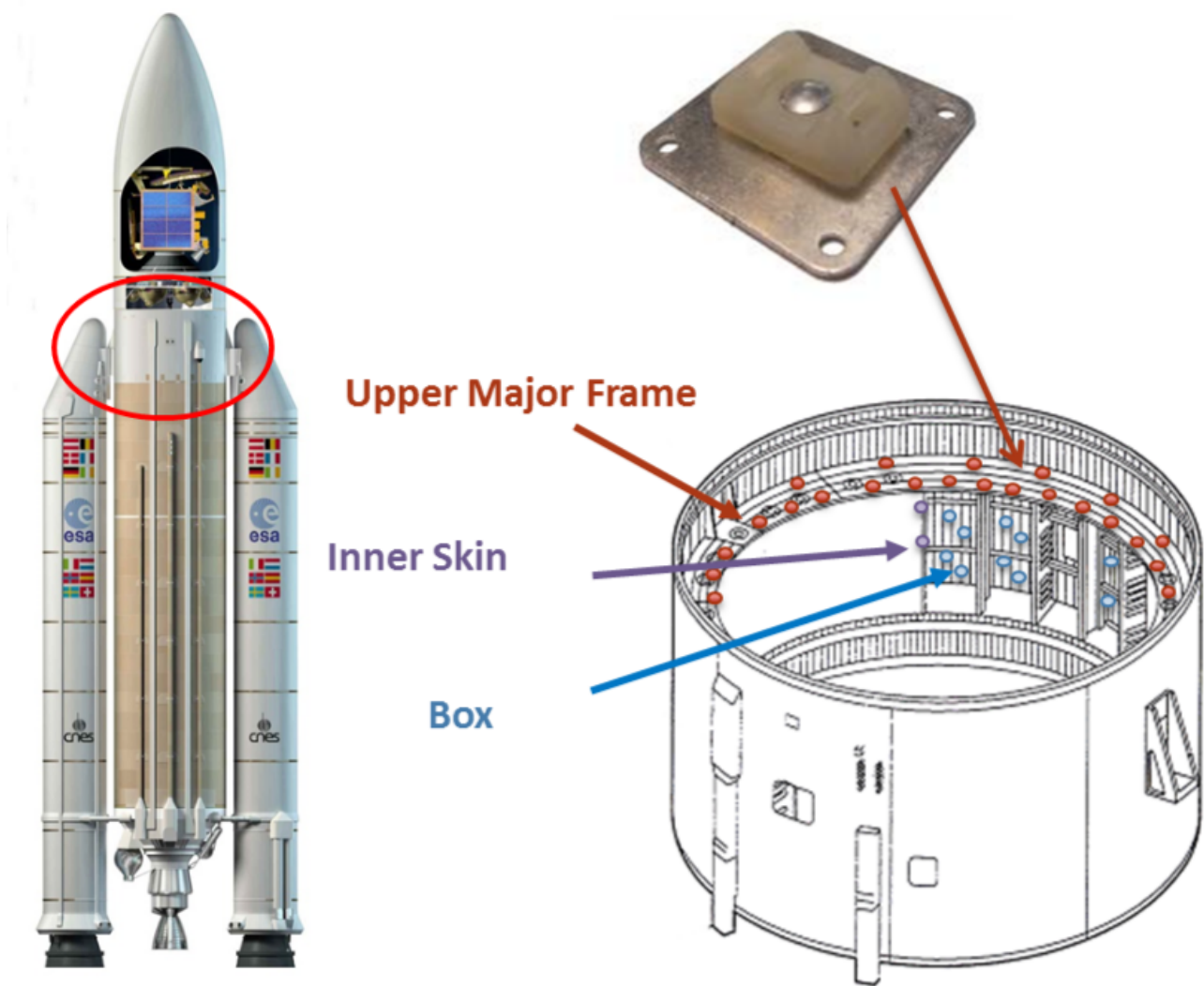


Figure 12: Ariane 5 launcher (left) and the upper skirt (right). The upper skirt is the section located on the top of the main cryogenic stage and below the payload area (satellites). An enlarged view of a bracket is shown above.

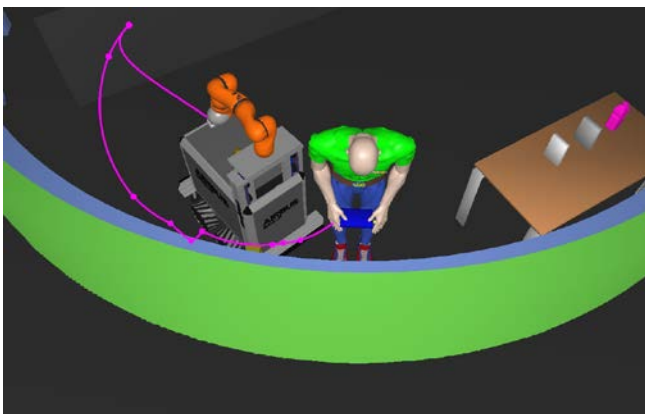
The introduction of a collaborative robot to assist the operator on the bracket mounting process is considered. In particular two tasks could be performed in collaboration:

- First, the fetching of both the brackets and the products (solvent, glue) used to fix them. These items are stored in boxes or specific containers and the operator typically walks back and forth from their storage position to the bracket insertion position. The introduction of a collaborative mobile manipulator allows the operator to reduce his travel distances and to focus on higher added value tasks. There is consequently a need for the robot to navigate in order to achieve fetch)and-carry tasks and to hand over objects to the workers.

- Second, the correct bracket position can be pointed out by the robot. For this operation, thanks to its ability to localise itself very precisely in the environment, the robot could be used to indicate to the human the exact spot where the task should take place (e.g. by projecting an image using an augmented reality technique). Besides, the robot should adopt a posture which does not disturb the worker or prevent him to achieve his own task in a convenient way.

The three planners proposed in the architecture can find a pertinent application here and be used by the mobile manipulator robot to synthesize a pertinent behaviour.

- a high-level task planner which provides to the robot the ability to schedule on-line its next actions as a teammate resulting in what can be seen as a "shared plan" involving interleaved human(s) and robot(s) actions. Here again there is a benefit to produce a plan that not only achieves the goal but also reduces burden and unnecessary actions of the human workers (see next sub-section)
- a planner called "hand-over placement planner" which is able to compute, depending on the context, where a human-robot hand-over operation can be performed. Indeed, depending on the situation, the "standard" solution, which consists in computing a path for the robot to reach the human and deploy its arm, can be insufficient. The worker can be in a place where he is not reachable by the robot or he can be under time pressure. In such cases, we would like the robot to compute a "rendez-vous" place and configuration of both agents (the worker and the robot) and to pro-actively head towards it (Figure 13(b));
- a human-aware motion planner which is able to produce safe and human-friendly motion (navigation and/or manipulation) in the workshop between human workers and also to compute placements and postures of the robot which limit discomfort of the workers when they are in a working place (Figure 13 (a))



(a) A motion in the close vicinity of the worker computed by the "human-aware motion planner"



(b) A placement configuration computed by a "hand-over placement planner"

Figure 13: two contexts for human-aware motion planning

Elaborating shared plans

Such plan elaboration can be implemented using HATP. The planning domain defines a set of methods describing how to decompose a task and can be seen as the How-to knowledge of the robot.

In HTN planning framework most part of the knowledge about the domain is provided in a procedural way to the planner which, in the industrial case, is really suitable. There are two types of tasks: methods and actions. A method is composed of subtasks (methods or actions again) that are partially-ordered. Those ordering constraints allow to force precedence of a task over other tasks. However a method can have several of such partially-ordered tasks which allows to give several ways to accomplish the task the method solves. On the other hand an action is a elementary task, that can not be decomposed, and that can be executed by the system.

One important issue is to produce plans for the robot actions as well as for the other participants (humans or robots). It can be tuned by setting up different costs depending on the actions to apply and by taking into account a set of constraints called social rules.

The aim of this example section is to highlight the features of HATP. For the task considered here, two humans have to fix brackets with the help of a robotic assistant. The robot's aim is to ease the process, the human workers will only focus on the task while the robot brings the parts and tools for all operations. The problem is such that some parts are easier for the human to do, such as pick a bracket from a box of tangled brackets, which is too challenging for the robot. On the other hand the robot plays a role in the assembly since it places itself near the human and project the exact position where to put the bracket as it is capable to locate itself more precisely that what a human could do.

The goal, is to assemble a bracket but in order to glue it in the right position some operations are needed: first the spot should be cleaned by the human, the robot should then give the bracket to the human, the robot then places itself near the human and projects on the scene the exact spot where the bracket should be placed. The human can then place and glue the bracket. However the glue and the solvent (the cleaning product) are only in limited quantity so the robot has to bring them at the right moment to one worker or the other. At the beginning of the experiment there are two tubes of solvent and one tube of glue. Their initial location might change from a run to the other, but they can be on one of the humans' desk or in one of the two stocks (the stock that is close to the desks or the one that is far).

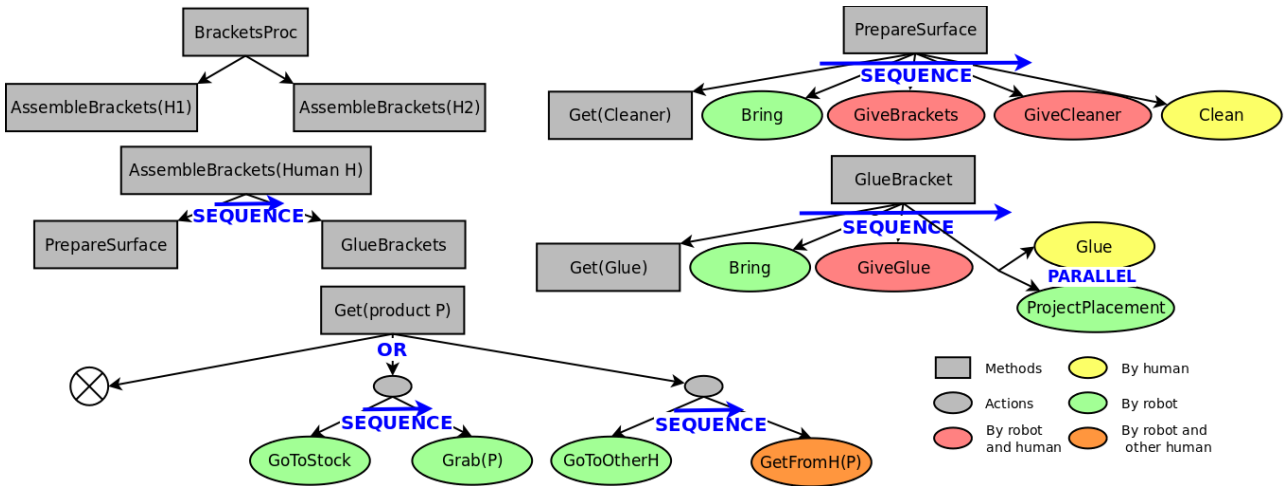


Figure 14: This decomposition contains methods (grey rectangular shapes), and actions which are represented by colored ovals (with a specific color per agent or for joint actions involving two agents). The top-level method is *BracketsProc* which is decomposed in two methods one for each human. *AssembleBrackets* is hence called once per human, and contains the two main operations to assemble a bracket: clean the spot and glue the bracket. Both *PrepareSurface* and *GlueBracket* need a product to be carried out (respectively the cleaner/solvent and the glue). The robot has then two ways to fetch a product: go to the stock and grab it, or get it from the other human. The crossed circle (bottom right in the figure) represents the case where the human already has the needed product.

The domain description to this problem is depicted in figure 14. Considering all the possible decompositions and variable bindings we get a total of 160 possible plans. The solution found reduces as much as possible the use of *GetFromH* and make the robot go to the stock to fetch the products, even if the geometric path seems longer. Indeed the penalty of joint actions is a lot higher than the cost to go to the stock. We set a high penalty to prevent the robot from disturbing the humans. The “best” task plan solution is presented in figure 15: yellow actions belong to the robot (*ROBOT*), the blue ones belong to the first human (*HUMAN_1*) and the green ones to the other worker (*HUMAN_2*). One can see that the robot does most of the job since it is responsible for carrying the different products and parts.

The action depicted in the blue dashed rectangle 1 is a handover. It is a joint action which involves the robot and the first human. The second rectangle presents actions that the robot and the agent do in parallel. In this case actions are needed before and after to synchronize the actions and to ensure that the robot stays during all the glueing process.

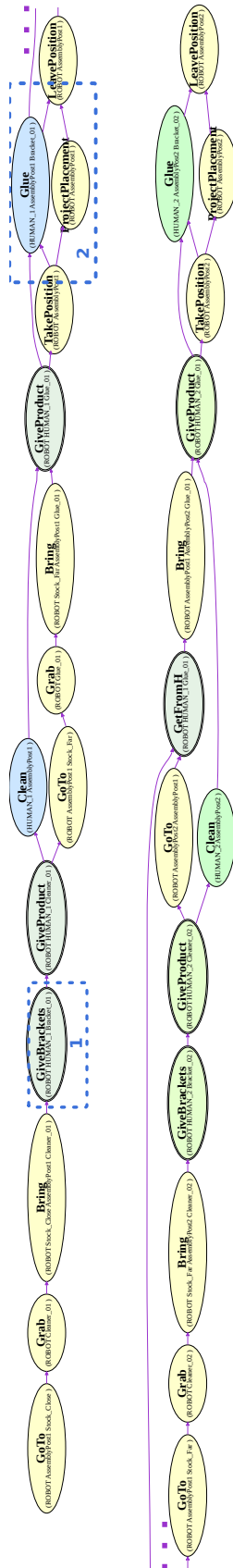


Figure 15: A shared plan elaborated by HATP

Conclusion

We have presented in this document the models and schemes that have been elaborated and which constitute, in our point view, a coherent basis for developing an interactive robot endowed with the relevant abilities to synthesize and control collaborative object manipulation behaviors with humans.

This models will are used in T7.5 (Cognitive executive control for a collaborative robot) in order to control the robot and to invoke the different decisional and planning components based on an informed context that explicitly take into account the state of the world, the state of the task and the state of the robot partner beliefs.

Several (partial) prototype implementations have been done during the elaboration of the models in order to refine the design of the overall architecture as well as the planning and decisional algorithms. Experience gained by using these prototypes. The next step will be the instantiation of these contributions into the SAPHARI use cases.

References

SAPHARI publications

- [Alami14] On human-aware task and motion planning abilities for a teammate robot. Rachid Alami, Mamoun Gharbi, Benjamin Vadant, Raphael Lallement and Adolfo Suarez. In Proc. of WS RSS 2014.
- [Alami13] Rachid Alami, "On Human Models for Collaborative Robots", The 2013 International Conference on Collaboration Technologies and Systems (CTS 2013), May 20-24, 2013, San Diego, California, USA
- [Broquere14] An Attentional Approach to Human-Robot Interactive Manipulation. X. Broquere, A. Finzi, J. Mainprice, S. Rossi, D. Sidobre and M. Staffa. International Journal of Social Robotics, Springer, pp. 1-21, 2014.
- [Buratt12] E. Burattini, A. Finzi, S. Rossi, M. Staffa, "Attentional human-robot interaction in simple manipulation tasks," HRI 2012: 129-130.
- [Cac14a] Attentional Top-down Regulation and Dialogue Management in Human-robot Interaction, R. Caccavale, A. Finzi, L. Lucignano, S. Rossi, M. Staffa. In Proc. of HRI-2014.
- [Cac14b] Attentional regulations in a situated human-robot dialogue. R. Caccavale, E. Leone, L. Lucignano, S. Rossi, M. Staffa, A. Finzi. In Proc. of Ro-MAN-2014.
- [Cac14c] Attentional Top-down Regulations in a Situated Human-Robot Dialogue, R. Caccavale, A. Finzi, L. Lucignano, S. Rossi, M. Staffa, in HRI-2014 workshop on "Attention Models in Robotics: Visual Systems for Better HRI".
- [Clodic13] Aurélie Clodic, Séverin Lemaignan, Amit Kumar Pandey, Lavindra de Silva, Mathieu Warnier, Rachid Alami, "On robot decisional abilities for human-robot joint action", Poster session, 5th Joint Action Meeting (JAM 2013), Berlin, July 26- 29 2013
- [Cutugno2013] Multimodal Interaction and Attentional Regulation in HRI, F. Cutugno, A. Finzi, S. Iengo, S. Rossi and M. Staffa. *6th International Workshop on Human-Friendly Robotics (HFR 2013)*, Rome (Italy), October 2013
- [Fiore14] On Planning and Task achievement Modalities for Human-Robot Collaboration. M. Fiore, A. Clodic and R. Alami in ISER 2014.
- [de Silva13a] Lavindra de Silva Amit Kumar Pandey Rachid Alami, "An Interface for Interleaved Symbolic-Geometric Planning and Backtracking", IEEE/RSJ International Conference on Intelligent Robots and Systems, November 3-8, 2013, Tokyo, Japan
- [DiNocera12] D. Di Nocera, A. Finzi, S. Rossi, M. Staffa. "Attentional Action Selection Using Reinforcement Learning", In proceedings of the 12th International Conference on Adaptive Behaviour (SAB2012), Odense, Denmark, 27-31 August 2012
- [DiNocera2013] Attentional Shifting and Curiosity: a Reinforcement Learning Approach, D. di Nocera, A. Finzi, S. Rossi and M. Staffa. *1st BRICS Countries & 11th CBIC Brazilian Congress on Computational Intelligence*, Recife (Brasil), September 2013

[Guitton12a] Julien Guitton, Matthieu Warnier et Rachid Alami "Vers une gestion des croyances pour la planification Homme - Robot", JFPDA 2012, 7èmes Journées Francophones Planification, Décision, et Apprentissage pour la conduite de systèmes, LORIA, Nancy, May 2012

[Guitton12b] Julien Guitton, Mathieu Warnier and Rachid Alami, "Belief Management for HRI Planning", BNC@ECAI 2012, Belief change, Non-monotonic reasoning and Conflict resolution, August 2012, Montpellier, France

[Ghallab13] Malik Ghallab, Dana Nau, Paolo Traverso, "The actor's view of automated planning and acting: A position paper", Artificial Intelligence, 2014.

[He13a] Wuwei He, Daniel Sidobre, and Ran Zhao, "A Controller Based on Online Trajectory Generation for Object Manipulation", accepted, Journal of Human-Robot Interaction

[He13b] He Wuwei, Sidobre Daniel, and Zhao Ran, "A Reactive Trajectory Controller for Object Manipulation in Human Robot Interaction", ICINCO 2013, International Conference on Informatics in Control, Automation and Robotics, July 31, 2013, Reykjavík, Iceland

[Iengo12] S. Iengo, A. Origlia, M. Staffa and A. Finzi. "Attentional and Emotional Regulation in Human-Robot Interaction". Ro-Man 2012, 2012.

[Iengo14] Continuous Gesture Recognition of Flexible Human-Robot Interaction. S. Iengo, S. Rossi, M. Staffa and A. Finzi. In Prof. of ICRA 2014

[Lalle14] Raphael Lallement, Lavindra de Silva, and Rachid Alami. HATP: An HTN Planner for Robotics. In 2nd ICAPS Workshop on Planning and Robotics, PlanRob 2014, 2014.

[Lemaignan12a] S. Lemaignan, M. Gharbi, J. Mainprice, M. Herrb, R. Alami Roboscopie : a theatre performance for a human and a robot Proceedings HRI '12 Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction, Pages 427- 428, ISBN : 978-1-4503-1063-5 doi 10.1145/2157689.2157831

[Lemaignan12b] S. Lemaignan, G. Echeverria, M. Karg, J. Mainprice, A. Kirsch, and R. Alami, "Human- robot interaction in the MORSE simulator" Proceedings HRI '12 Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction, Page 181-182

[Lemaignan13a] Severin Lemaignan, Rachid Alami, Amit Kumar Pandey, Matthieu Warnier, Julien Guitton, "Towards Grounding Human-Robot Interaction", Book chapter in "Bridges between the Methodological and Practical Work of the Robotics and Cognitive Systems Communities - From Sensors to Concepts", Springer Intelligent Systems Reference Library (to be published).

[Lemaignan13b] Severin Lemaignan, Mathieu Warnier, E. Akin Sisbot, Rachid Alami, "Human-Robot Interaction: Tackling the AI Challenges", Submitted to Artificial Intelligence.

[Lemaignan13c] Séverin Lemaignan and Rachid Alami, "Explicit Knowledge and the Deliberative Layer: Lessons Learned", IEEE/RSJ International Conference on Intelligent Robots and Systems, November 3-8, 2013, Tokyo, Japan

[Lemaignan14] S. Lemaignan, Rachid Alami, A Few AI Challenges Raised while Developing an Architecture for Human-Robot Cooperative Task Achievement, AAAI Publications, 2014 AAAI Fall Symposium Series

- [Lucignano2013] L. Lucignano, F. Cutugno, S. Rossi, and A. Finzi. A dialogue system for multimodal human-robot interaction. In Proc. of ICMI, 2013, ACM, 2013.
- [Millez14] Grégoire Milliez, Mathieu Warnier, Aurélie Clodic, and Rachid Alami. A framework for endowing interactive robot with reasoning capabilities about perspective taking and belief management. In Proceedings of the 23rd IEEE International Symposium on Robot and Human Interactive Communication, 2014.
- [Pandey12a] A. K. Pandey and R. Alami, "Visuo-Spatial Ability, Effort and Affordance Analyses: Towards Practical Realization of Building Blocks for Robot's Complex Socio-Cognitive Behaviors", 2012, CogRob-AAAI.
- [Pandey13a] Amit Kumar Pandey and Rachid Alami, "Towards Effect-Based Autonomous Understanding of Task Semantics for Human-Robot Interaction", International Journal of Social Robotics (IJSR).
- [Pandey13b] Amit Kumar Pandey, Aurélie Clodic, Lavindra de Silva, Severin Lemaignan, Mathieu Warnier, Rachid Alami, "Bottom up development of a robot's basic socio-cognitive abilities for joint action", Poster session, 5th Joint Action Meeting (JAM 2013), Berlin, July 26- 29 2013
- [Pandey13c] Amit Kumar Pandey, Muhammad Ali and Rachid Alami, "Towards Task-Aware Proactive-Sociable Robot based on Multi-State Perspective-Taking", International Journal of Social Robotics, Volume 5, Issue 2 (2013), Page 215-236 (IJSR-2013).
- [Pandey13d] Amit Kumar Pandey, and Rachid Alami, "Mightability: A Multi-State Visuo-Spatial Reasoning for Human-Robot Interaction", Experimental Robotics, Springer Tracts in Advanced Robotics, Khatib, Oussama; Kumar, Vijay; Sukhatme, Gaurav (Eds.), Volume 79 (2014), Pages 49-63 (STAR-2014).
- [Pandey13e] Amit Kumar Pandey and Rachid Alami, "Affordance Graph: A Framework to Encode Perspective Taking and Effort based Affordances for day-to-day Human-Robot Interaction", IEEE/RSJ International Conference on Intelligent Robots and Systems, November 3-8, 2013, Tokyo, Japan
- [Pandey14-1] Amit Kumar Pandey and Rachid Alami, "Ingredients and a Framework of Dexterous Manipulation Skills for Robots in Human Centered Environment and HRI", Journal of Robotics Society of Japan, Volume 32, No. 4 (RSJ-2014).
- [Pandey14-2] Amit Kumar Pandey and Rachid Alami, "Towards Human-Level Semantics Understanding of Human-Centered Object Manipulation Tasks for HRI: Reasoning About Effect, Ability, Effort and Perspective Taking", International Journal of Social Robotics (IJSR 2014).
- [Pan15] Amit Kumar Pandey "Towards Socially Intelligent Robots in Human-Centered Environment", Springer Tracks on Advanced Robotics (STAR). (Under publication)
- [Rossi2013] S. Rossi, E. Leone, M. Fiore, A. Finzi and F. Cutugno. An Extensible Architecture for Robust Multimodal Human-Robot Communication. *IEEE International Conference on Intelligent Robots and Systems - IROS*, Tokyo (Japan), November 2013
- [Ros14a] Attentive Monitoring for Team Coordination: a Human-Robot Convoy Example. S. Rossi, M. Staffa, A. Adaldo, F. Alderisio, V. Magnanimo. International Workshop on Autonomous Robots and Multirobot Systems (ARMS), in conjunction with AAMAS, Paris, France, May 6, 2014.
- [Ros14b] Human Inspiration and Comparison for Monitoring Strategies in a Robotic Convoy Task. S. Rossi and M. Staffa. 13th International Conference on Adaptive Behaviour (SAB 2014), From Animals to Animats 13, LNCS 8575, Springer 2014, pp. 310-319.

[Warnier12] Warnier M., Guitton, J. Lemaignan, S. Alami, R., "When the robot puts itself in your shoes. Explicit geometric management of position beliefs", IEEE RO-MAN 2012, September 2012.

Other publications from the authors on the topic

[Beetz12] Michael Beetz, Lorenz Mösenlechner, Moritz Tenorth, Thomas Rühr, "CRAM -- a Cognitive Robot Abstract Machine", In 5th International Conference on Cognitive Systems (CogSys 2012), 2012.

[Buratt10] E. Burattini, S. Rossi, A. Finzi, and M. Staffa, "Attentional modulation of mutually dependent behaviors," in *Proc. of SAB-2010*. LNAI 6226, 2010, pp. 283–292.

[Buratt08] E. Burattini and S. Rossi, "Periodic adaptive activation of behaviors in robotic system," *IJPRAI*, vol. 22, no. 5, pp. 987–999, 2008.

[Moesenlechner11] Lorenz Moesenlechner and Michael Beetz, Parameterizing Actions to have the Appropriate Effects, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), September 25-30 2011, San Francisco, USA

[Pandey10] A. K. Pandey and R. Alami, "Mightability maps: A perceptual level decisional framework for cooperative and competitive human-robot interaction," in IROS, 2010, pp. 5842 – 5848.

[Tenorth12] Moritz Tenorth, Michael Beetz, "A Unified Representation for Reasoning about Robot Actions, Processes, and their Effects on Objects", In 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2012.

[Tenorth13] Moritz Tenorth, Michael Beetz, "KnowRob -- A Knowledge Processing Infrastructure for Cognition-enabled Robots. Part 1: The KnowRob System ", In International Journal of Robotics Research (IJRR), 2013. (Accepted for publication.).