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# Learn, Plan, Remember: A Developmental Robot Architecture for Task Solving

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***Abstract*—This paper presents a robot architecture heavily inspired by neuropsychology, developmental psychology and research into "executive functions" (EF) which are responsible for the planning capabilities in humans. This architecture is presented in light of this inspiration, mapping the modules to the different functions in the brain. We emphasize the importance and effects of these modules in the robot, and their similarity to the effects in humans with lesions on the frontal lobe. Developmental studies related to these functions are also considered, focusing on how they relate to the robot's different modules and how the developmental stages in a child relate to improvements in the different modules in this system. An experiment with the iCub robot is compared with experiments with humans, strengthening this similarity.**

**Furthermore we propose an extension to this system by integrating with "Epigenetics Robotic Architecture" (ERA), a system designed to mimic how children learn the names and properties of objects. In the previous implementation of this architecture, the robot had to be taught the names of all the necessary objects before plan execution, a learning step that was entirely driven by the human interacting with the robot. With this extension, we aim to make the learning process fully robot-driven, where an iCub robot will interact with the objects while trying to recognise them, and ask a human for input if and when it does not know the objects' names.**

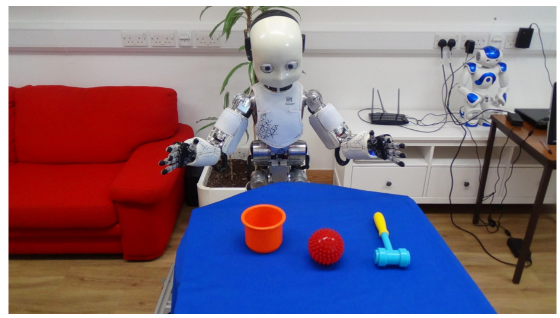


**Figure 1:** Initial setup of the experiment, with an iCub robot looking at a table with unknown objects.

## I. Introduction

Real-world interaction, with people and objects alike, is a challenging issue for robots. Whilst humans evolve in a dynamic world where they adapt to different situations, and possess cognitive skills (e.g., categorization and lexical biases in language learning) that allow them to acquire information from the world and to *learn* from it, these capabilities in robots are still in their infancy and, thus, robots face significant challenges in unstructured environments. It is of utmost importance that we provide these tools to a robot, so that it can learn and adapt to the surrounding world and interact with humans in a productive way. One way to implement such a system is to take inspiration from humans, and to some extent replicate these skills in robots.

Research in neuroscience and developmental psychology has provided good insights into children's developmental stages and how they acquire new skills throughout this learning process. It has been found that, for instance, children rely more on shape than on color when learning labels for new objects, which in turn allows them to *generalise* to other objects with similar visual features when interacting with them [1]–[3]. In the same way, actions and movements learned by a child are usually generalised to different objects, based on their perception of that object, without the need to learn an entire new action to deal with similar, yet different, objects [4]. This generalisation has the potential to improve current and future robotic platforms, since training a robot for every type of action, on every type of object, would be extremely impractical and inefficient. These abilities, the repertoire of possible actions that a robot can execute across a range of objects, are often labelled *affordances*, a topic of increasing importance in the field of robotics [5].

A vital characteristic in robotics is *planning*. In order to solve complex tasks, a robot should consider different approaches, selecting from its repertoire which action to do for a given state to achieve a certain goal. This field has seen a lot of research in the past, from physical navigation through a cluttered environment to symbolic task-solving problems [6]–[8]. However, some real-world problems arise from the fact assuming the environment is static is highly impractical, the robot has to interact with dynamic objects whose behaviour cannot be modelled easily, in addition to the sensor data being corrupted by noise, and so on. To avoid these issues a robot can re-plan its path every step of the way, but this raises some more issues: should the robot keep a memory of its surroundings? How far in time should these memories be? How reliable should it be? What if the robot gets stuck in an endless loop, performing the same action over and over again? The answer to these questions is not unique nor trivial, and different situations often require different solutions. This is, however, a field where humans perform very well and seemingly effortlessly, being able to plan for both short-term task-solving problems and for long-term life decisions, making a compelling case for the study of human planning skills, and trying to adapt them to robots.

Research in the field of developmental neuropsychology has shown that planning in humans is performed by a set of functions called "executive functions" (EF), present in the prefrontal cortex. These functions are related with working memory, action planning and goal management. Fuster [9] classified these functions into three different segments: i) a function dealing with working memory and its development over time (short term memory, STM); ii) a preparatory function dealing with action selection; iii) an interference control function. These functions have been mapped into EFs by Welsh [10], based in previous research [11]–[14], that suggests these mechanisms have extended periods of learning, more extensive than some aspects of language.

From these findings in neuroscience and developmental psychology, we propose a robot architecture designed to learn its surroundings, plan to complete a task given by a human, and adapt to disturbances to the execution. This architecture is an extension of the one presented in previous works [15], providing the iCub [16] robot with more autonomy to explore and learn the objects surrounding it. The paper will thus be segmented in the following way: in Sec. II we briefly review previous work in planning architectures and the inspiration from neuroscience and psychology, with special focus on this last point; in Sec. III we explain the previous architecture [15], the mapping to neuroscience and psychology and the extension developed in the current work; finally, in Sec. IV we present results of the present architecture and their linking to human problems, and in Sec. V we report our conclusion and future work in human-inspired robot architectures.

## II. Related Work

Presented on this paper is an extension of the architecture proposed by Antunes [15]. It relates different concepts ranging from action affordances, probabilistic planning, natural language understanding, and so on. We briefly present some relevant work regarding these concepts, with special focus on planning in robotics. For more details on this, see [15], [17]. We then analyse neuroscience and developmental psychology works that inspired this architecture, providing a glimpse into the development of planning in children.

*1) Natural Language Understanding:* More than just understanding words, an important step for robots to interact successfully with humans is to be able to relate words and concepts, which would allow the robot to plan in a totally abstract world of semantics. For the current architecture we used PRAXICON [18], a network of concepts that allows the robot to translate a complex human request into a sequence of general actions that will achieve that goal.

*2) Planning Methods:* This subsection is divided into two different segments: i) planning in the now and ii) multi-level planners.

Planning in the now, or "real-time" planning, is a complex task in the field of robotics. In the works of Kaelbling and Lozano-Pérez [7], [8], [19] they tackle this problem by updating the robot's view of the world and re-planning on it, while keeping the task as simple as possible through a hierarchy of actions that decomposes complex tasks into simpler, smaller tasks, an approach suggested first by Nourbakhsh [20]. A similar concept is used in the present work, planning from high levels of abstraction (natural language) down to simple motor actions. Such an implementation requires the use of different types of planners, which leads to the second point: Multi-level planners.

Several works use multiple planners to solve tasks, typically using predetermined sets of instructions that guide lower-level planners. In the present architecture we use three levels of planning, from abstract, natural language planning, to probabilistic symbolic planning, to motor planning. In particular, we make use of Lang's PRADA [21] for the probabilistic planning, due to the easy integration with robot affordances.

*3) Affordances:* The term *Affordances* corresponds to the ability, or lack thereof, of a robot when interacting with the world. If a robot can grasp a ball, then we can say the action of grasping a ball is *affordable* to the robot. In the works of Ugur and Sahin [22], [23], an affordance-based planner was used, considering the different rates of success depending on the actions and objects used. In the work of Gonçalves [24], these affordances are encoded as a percentage of outcomes, given a certain action and object descriptors. Due to the generalisation on the descriptors, it is possible for the robot to predict effects of an action based solely on its previous experience, even if the object is different from the trained observations, based on its features. This probability on the outcomes links very well with PRADA, allowing for an easy integration on the architecture. For a more extensive review on affordances see also [5].

*4) Learning Category Objects:* In the particular case of the iCub robot, object learning was usually performed through a mixed use of SIFT descriptors and template matching or learning methods (Regularized Least Squares (RLS), Support Vector Machines (SVM)) [25]. More recently, with the increased accuracy of Deep Neural Networks and their availability, object labelling became a "solved" issue [26]. These methods, however efficient they are, do not map well into how human children learn objects. Instead, we will use the works of Morse [17], integrating it on the present architecture, making use of the SOM architecture in ERA to learn and categorize the objects seen by the robot in a developmental way.

*5) Planning in Children:* Planning is not yet fully understood in humans. In a study from Goel and Graftman [27],

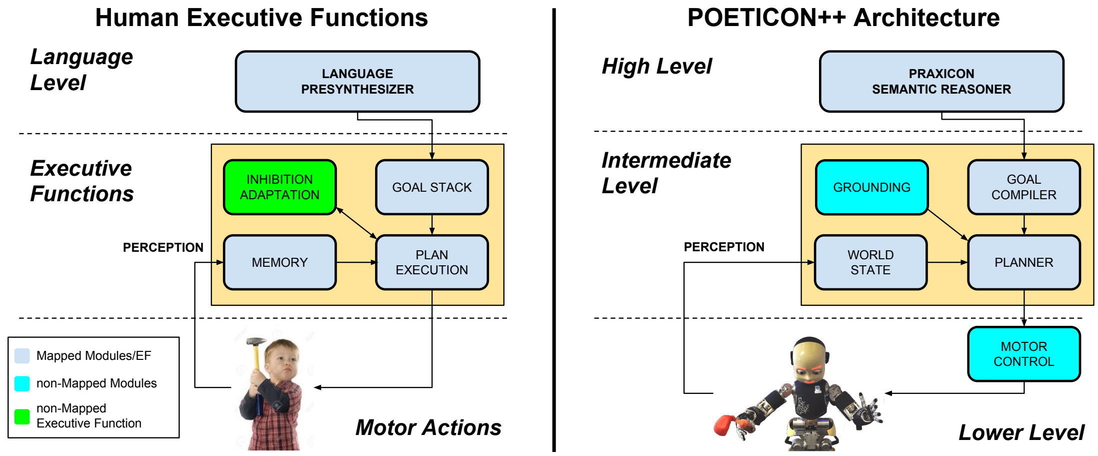



**Figure 2:** Mapping between human EFs (left), and the modules developed for the POETICON++ project (right). Boxes in gray correspond to the EFs mapped to robot modules; light blue (Grounding and Motor Control) corresponds to extra modules not related to EFs, and; green (Inhibition/Adaptation) corresponds to EFs not mapped directly to robot modules. It should be noted this executive function was implemented as a heuristic in the Planner module.

several patients whose frontal lobe (the part of the brain associated with planning) was partially or totally removed were tested on their efficiency to solve problems usually related with planning, like the Tower of Hanoi. The study showed that these patients had issues solving this game, particularly for the complex cases involving 4 disks, but it also concluded that this was not due to any lack on *planning*, but rather with problems in maintaining stacks of sub-goals during the execution, and it concludes that the game itself does not test for planning deficiencies. It does, however, conclude that there are different properties to general planning that might affect some tasks, like in the stack of sub-goals. This conclusion appeared years before in a different study [9], that compiled empirical data suggesting the frontal cortex to be connected to memory, interference control and goal-stacks.

In the works of Luria [11] a relationship is established between language and planning, with language acting as a "presynthesis" of the action plan, guiding the planning process during the execution. Patients with lesions on the frontal lobe would have problems in creating this presynthesis, which in turn would lead to problems in the execution of the task. They would also have issues with adapting behaviour, committing the same errors over and over again, even if they were aware of the failure. Interestingly, this two-level planning process has a parallel in robotics, with a lot of effort put into developing techniques for combined motion and task planning, especially in order to deal with robot perception and uncertainty in the world [28].

The review on developmental neuropsychology by Welsh and Pennington [10] provides more insight into the presence and development of EFs in children, which functions are present in the frontal lobes, and what type of tasks are affected by lesions on those areas. Studies with rhesus monkeys allowed several researchers to pinpoint the lesions that caused problems in problem-solving tasks, mostly focusing on the three points: i) memory; ii) goal-stack, and iii) action inhibition and adaptation. These studies were extended to infant monkeys and compared to performance on human children, providing an insight into the development of these functions: at 11-to-12 months, human children become capable of adapting their plans, inhibiting responses based only on their perception. From 18 to 30 months, children start displaying self-control behaviour, tested in delayed-action tasks. Research into preschool through adolescence children [29]–[31] reveals an increasing performance in the prediction of goal-oriented outcomes, a result of the development of the ability to generate problem-solving sets.

To conclude, while EFs appear at very early stages (up to 30 months old), it is not until well into adolescence, with a refining of these functions, that humans are capable of making full use of them. A development of working memory, associated with an increased ability to formulate problem-solving sets also resulting from further experience and learning, allows humans to plan and refine their strategies when solving tasks.

## III. Robot–Human Planning Comparison

Robots have many issues when solving tasks requested by humans in the real world. They often cannot account for sources of interference, they fail some actions without being able to recover, and are also plagued with issues regarding their interaction with objects in the world around them. They are not, however, incapable of planning: their issues come more from poor world categorization, poor action grounding and/or learning, and from hardware limits.

As it was discussed in Sec. II, this is *exactly* the case for children, since they are not incapable of planning per-se, but rather: i) have difficulties regarding their interaction with the world; ii) their working memory is not developed enough to be able to "store" everything that is happening around them; and iii) they do not yet have the skills to solve many problems or to categorize what is going on. It is to be hoped that, by studying the ability to plan in human children (i.e., their EFs, and how they develop), we might be able to improve our robots so that they, too, can solve tasks at least as well as humans, in the future. The present paper shows how such a human-inspired architecture can successfully complete tasks while dealing with uncertainties and external influences, mapping the different modules and heuristics to the different functions in the human brain.

As previously mentioned, Luria [11] proposes the connection between planning and language, in the formation of a "presynthesised" plan. This connection between language and planning can, in fact, be understood as two separate levels of planning: i) high level planning, living in the abstract world of language, that would plan a solution based only on linguistic knowledge and memory of previous solutions, and ii) intermediate level planning, living in a symbolic world, grounded with the perception of our surroundings and our own skills and limitations. Language would then provide an abstract solution to the problem, that could then be followed by the intermediate planner while adapting to our surroundings. This structure can be seen in Fig. 2, "Human Executive Functions".

When mirroring this structure into a robot, we find the structure to be very similar (Fig. 2, right side): for the presynthesis, we consider PRAXICON [18] as our language planner. PRAXICON consists of a network of language concepts, relating different concepts like *knife* and *cutting*, which can be perceived as a memory of such concepts being found before. The presynthesis then becomes a decomposition of a concept into its constituents: *pour coffee* is decomposed into the actual actions of *reach pot*, *grasp pot*, *reach mug* and *pour*. It should be noted that during this process, nothing is known about the world other than the presence of the items themselves: *pot, coffee, mug*. These instructions do not take into account obstructions, distance to said objects, and whether they are full or not. These situations are dealt with by the intermediate level of planning.

For this second level of planning, we consider the implementation of a probabilistic symbolic planner, which permits the use of actions with different rates of success grounded to the actual objects in the environment. We implement this planner as a "planner in the now", meaning that it will plan actions for every step, action or change in the world. The instructions provided by the language planning will guide this intermediate planner in reaching the final goal of a task. This linking between language and symbolic planning is done by a *Goal Compiler* module that simulates the effects of the instructions provided by the language planning, based on previous knowledge on the effects of such actions. The grounding of these actions is done by querying the robots *Affordances* [24], based on the visual descriptors of the objects, and is performed in a Grounding module (represented by the blue box "Grounding", Fig. 2). Finally, the robot needs to keep track of changes to the world, actions performed previously, and the place of objects that have been occluded. This function is related to the "working memory" executive function in humans, that allow them to keep track of these same actions and other changes in the world, in order to react appropriately. In our architecture, this task is performed by a "World State" module, keeping track of objects, their names, position and descriptors, along with some important properties like reachability, position in stacks when occluded by other objects, and so on.

To the two levels of planning inspired in the frontal lobe EFs another planning layer was added in order to properly execute the actions requested, a lower-level motor planning (represented by the blue box "Motor Control", Fig. 2). This module plans the best movement for a certain action, being responsible for the motor control at the lower level. While not directly associated with the frontal lobe, this function is also inspired in human functions, as shown in the works of Tikhanoff [32].

While this architecture successfully completes a task when no mistakes are made during the execution, it shows some limitations with this simple implementation when external influences or other sources of error are included. In fact, such behaviours mirror similar behaviours in humans, when lesions occur in the frontal lobe: improper tracking of goals (behaviour present in humans with partial removal of frontal lobe) and no adaptation to errors (present in humans with lesions on frontal lobe). It becomes apparent, therefore, that while the architecture successfully emulates some human EFs, it lacks all the constituents of a healthy human brain. These missing functions were then implemented into the architecture as "heuristics" to the intermediate level planner, which deal with goal management and adaptation.

The first heuristic, named "Goal Maintenance" in our architecture, is responsible for checking for the different sub-goals and adapting them when errors are detected. This allows the planner to react to situations where it would be stuck with conflicting sub-goals, or loops in the execution. The presence of this heuristic allows the planner to solve complex stacking situations, where certain objects need to remain stacked in certain positions (like is the case for the Tower of Hanoi game, or making a sandwich [15]).

The second heuristic, "adaptability", deals with repetitive mistakes. As shown before, it is common for humans with lesions and/or removal of parts of the frontal lobe to constantly repeat the same actions, even when they are aware of its failure. This, as was stated before, also happens with the simple version of our architecture, presenting the case for a missing function/module in both these human cases and the robot. We have developed a heuristic that addresses this issue, by evaluating the results of an action and reacting appropriately, by reducing the probability of success of such an action when a failure is detected mid-execution. This evaluation during execution links with action inhibition in humans by basing action selection not only on the perception of a human (or robot), but also on the history/memory of previous actions while solving this task.

Finally, a third heuristic also dealing with "action loops" problems is the "creativity" heuristic. Without this heuristic, the robot would sometimes find itself in situations where following the goal-stack alone was not enough, leading to a

**Figure 3:** Initial setup for the planning experiment with different heuristic strategies, as seen by the iCub. See also Fig. 4.

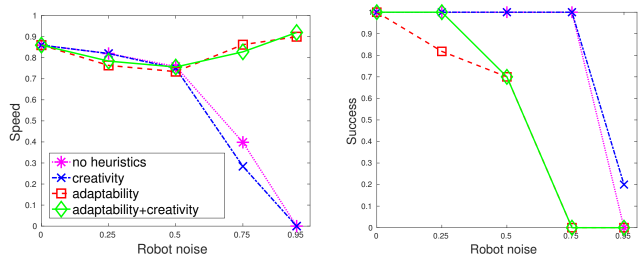
repetitive, failing action to be performed. This was not due to failure in evaluating the action per-se, but in failure to manage the goal-stacks. As before, this points out a possible missing module in our architecture, addressed by this heuristic, that allows the robot to manipulate its goal stack in order to complete the task.

In this section, we have made a case for how human brain functions can be adapted and used for designing an effective robot task-solving architecture, creating a link between different robot modules and human functions. We further studied how the heuristics developed for the architecture were inspired on similar problems in humans with lesions on the frontal lobe, and what EFs they were linked to. This architecture worked on the principle that all objects were learned beforehand, and under a closed-world assumption, meaning that no new objects would be considered, nor would the objects ever disappear.

In practice, however, children have to learn new objects, with new features and new names before they can understand what another human means with their instruction. In order to emulate this behaviour we integrate another system, ERA [17], that simulates the behaviour of a human child learning new objects and their properties. By integrating such module with the planning architecture, we provide the robot with the automation necessary to drive its own learning, with the motivation being knowing all objects surrounding it.

| Exploration action example |
|---|
| ACTION: |
| touch_obj1_with_left |
| CONTEXT: |
| left_clearhand left_ishand ¬isKnown_obj1 |
| OUTCOMES: |
| 0.80 isKnown_obj1 |
| 0.10 ¬isKnown_obj1 |
| 0.10 <noise> |

The iCub robot is provided with a set of "exploration" actions, allowing it to move the object around, look at it from different perspectives, and ultimately ask a human what object it is. An example of an action is provided above where *obj1* is the object the iCub wants to know. Each of these actions is linked to the ERA module, triggering the learning mechanism based on SOMs (Self Organising Maps), which has been proven to effectively simulate how children learn objects [33].




**(a)** Speed. **(b)** Success.

**Figure 4:** Planner metrics obtained experimentally when using different probabilistic planning heuristics in the scenario of Fig. 3. We can see an improvement in speed from a no-heuristics or creativity case (pink dotted and blue dash-dotted lines, respectively) to the cases with adaptability, and the highest rate of success with both adaptability and creativity heuristics (solid green line). Plots from Saponaro et al., Combining Affordances and Probabilistic Planning for Robust Problem Solving in a Cognitive Robot (submitted).

The analysis of the learning is provided in Sec. IV.

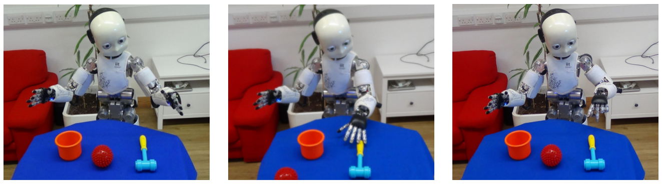
## IV. Results

The experimental results are divided in two different subsections: i) brief presentation of results of the sandwich experiment and ii) results from the extension of the architecture to permit robot-driven object learning.

*1) Sandwich Experiment:* As a proof of concept of the architecture presented in a previous article [15], we decided to test the robot in a "sandwich making" scenario, where the robot would be faced with ingredients distributed in a table (tomato, ham, two bread slices), some of them out of reach of the robot, along with a selection of tools to use, namely a rake and a stick, to pull the objects closer. Several cases were tested as to the use of heuristics in probabilistic planning: i) a case with no heuristics; ii) a case while using the *adaptability* heuristic; iii) a case while using the *creativity* heuristic; and iv) a case while using both *adaptability* and *creativity* heuristics. In these tests, the *goal maintenance* heuristic was always present but not tested, as no external influence was considered.

In order to evaluate these tests, two metrics were evaluated: *Success*, successful completion of the plan (score of 1) or not (score of 0); And *speed*, a function of the number of actions performed, both successful and failed. Each extra action performed will reduce the *speed* score by $1/50$, starting at 1 (very fast experiment) and ending at 0 (very slow experiment). The experiment was repeated 10 times for each robot noise value, and the results were averaged. *Robot noise* is an indicator of the reliability of the robot, corresponding to the *simulated robot action failure*, which integrates all possible causes for a robot action failure, and it ranges from 0 (perfectly reliable) to 0.95 (highly unreliable).

The results obtained for the case considered (sandwich scenario with out of reach object) are displayed in Fig. 4. In these figures we can see a success rate, for the no-heuristics and creativity cases, of 1.0 when robot noise ranges from



(a) (b) (c)

**Figure 5:** Snapshots of the iCub performing different exploration actions: a) looking at the hammer; b) pointing at the hammer and asking the label; and c) displacing the hammer on the table.

0.0 to 0.75. This is explained by the fact that the robot keeps on trying until it finally succeeds to perform an action, independently of how many times it has to try. This is an undesirable result due to how long this would take in an actual collaboration scenario.

However, the effect that the heuristics have on a plan execution is clear: now, the robot can evaluate whether an action is failing or not, and it can adapt to the situation. When no action is possible given the circumstances, it reports the failure and awaits further input.

While this scenario is not the standard experiment performed with humans, which typically use the Tower of Hanoi experiment to test EFs, some comparisons can indeed be made: as in the Tower of Hanoi, without the capability to adapt (either because of a removal of part of the frontal lobe in humans, or because there is no adaptability in the robot) the human and robot both are unable to recognize a failed action and will keep trying it over and over. In the case of robot, the *adaptability* heuristic improved this behaviour by detecting when an action is failing, while the later inclusion of the *creativity* heuristic further improved this, slightly increasing the rate of success of a full plan by exploring different actions.

*2) Robot-Driven Object Learning:* The extension of the architecture with ERA successfully integrates object-learning with task-solving. By providing the robot with object-exploration rules, connected to a learning module, the robot is capable of driving its own learning. This is shown in an experiment where the iCub is faced with three unknown objects: a hammer, a cup and a ball.

When an instruction *put ball cup* is provided, instructing the iCub to put the ball inside the cup, the robot still has no knowledge of any objects. In order to solve this instruction, it must then search the objects until it knows their labels.

The robot initially tries the *look* action, where it looks at the hammer from a different perspective. This small change in perspective (see Fig. 5a) provides ERA with a slightly different set of descriptors, which might be enough to trigger a response. Since the robot has yet to see this object before, ERA cannot provide a label for it, and therefore considers the *look* action failed, reducing its probability through the adaptation heuristic.

In its second try, the robot tries the *touch* action (Fig. 5b). By touching the hammer the robot moves it on the table, providing a new set of descriptors. Again no label was yet learned, and thus it is considered failed and adapted.

With both *look* and *touch* failing, the robot is forced to *ask* a human. The iCub robot points at the hammer, and asks a human for a label (see Fig. 5c). The human provides the label verbally, triggering the learning step in ERA [17].

The robot then continues the learning for the other two objects. Learning can take a number of tries and a combination of the exploration actions. During the task-solving itself, the robot can still use these actions if it stops recognizing an object, providing some robustness to object label loss.

## V. Conclusion and Future Work

In this paper, we have made a case for human-inspired robot architectures for learning, task solving and planning. We have presented an architecture which maps different EFs present in human beings, we have linked specific problems resulting from lesions in human patients to missing functions in our architecture, and we finally extended the system with an object-learning module inspired in developmental psychology and neuroscience.

The experiments presented the capabilities of the robot to solve complex tasks in a real-world scenario. The comparison between the results obtained with the robot and previous experiments with humans highlights the connection between these modules and human EFs.

We conclude by reinforcing the suggestion that human EFs provide good inspiration for successful robotic architectures and developmental models of planning and learning.

This work can be improved in many ways. While there are many studies about planning and neuroscience, there are several areas that are still unknown, such as how memory is linked to planning and how its development influences it. More work in these fields could provide further inspiration for future work in robotics, further enhancing similar architectures.

In the field of robotics itself there are several improvements to be made. In the present work, several assumptions were made: the available abstract actions for the robot were provided by humans, even if their effects were measured through affordances; the semantic network PRAXICON was learned previously, while in humans such a network would have to be built slowly upon exposure to the different concepts; grounding was limited to the symbols previously coded. These points can all be improved, in particular the grounding of actions and symbols, through the use of neural networks that relate physical entities to the symbols the used for planning.

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