The Interplay of Analogy-Making with Active Vision and Motor Control in Anticipatory Robots

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Abstract. This chapter outlines an approach to building robots with anticipatory behaviour based on analogies with past episodes. Anticipatory mechanisms are used to make predictions about the environment and to control selective attention and top-down perception. An integrated architecture is presented that perceives the environment, reasons about it, makes predictions and acts physically in this environment. The architecture is implemented in an AIBO robot. It successfully finds an object in a house like environment. The AMBR model of analogy-making is used as a basis, but it is extended with new mechanisms for anticipation related to analogical transfer, for top down perception and selective attention. The bottom up visual processing is performed by the IKAROS system for brain modelling. The chapter describes the first experiments performed with the AIBO robot and demonstrates the usefulness of the analogy-based anticipation approach.

1 Introduction

Anticipation is an important function of human cognition – it makes human behaviour more flexible than the behaviour of other animals, it allows us to act before the incident has happened and thus to survive and actively change our environment knowing what the consequences will be. Obviously, anticipation is generated at various levels by various mechanisms. This chapter describes an attempt to demonstrate that analogy-making can be a useful mechanism for anticipation.

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Analogy-making is thought to be a central mechanism in human cognition that underlies various other cognitive processes [1,2]. Thus it is natural to expect that anticipation could also be based on analogy. We believe, however, that the process is bidirectional: not only analogy plays an important role in anticipation, but also analogy-making benefits from human abilities to anticipate. That is why we explore the possibility to use the same basic mechanisms for both processes.

A number of models of analogy-making have been proposed (see a review in [3]). One of the best known models is the Structure-Mapping Theory [4] and its implementation in SME [5] and MAC/FAC [6]. This model has introduced the structural focus of analogy-making, namely that analogy is about mapping of systems of relations. It is a kind of pipe-line model – it insists on the linearity of the processes and separates perception, mapping and retrieval in sequential steps. Although ACME, ARCS [7] and LISA [8] are connectionist types of models and thus are inherently parallel, they still rely on sequential processing and separate mapping from retrieval. None of these models is interested in how the representations are build – they fully ignore the perceptual processes and work on manually coded situations. On the other hand, COPYCAT and TABLETOP [9, 10, 11] have focused on the process of perception and how it integrates with mapping. Moreover, the authors insist that perception cannot be separated from mapping [12]. These models are highly interactive and the processes of perception and mapping run in parallel and influence each other. Unfortunately, these models have no long-term memory and thus they do not explain how memory retrieval is performed and how it interacts with the rest of the processes. COPYCAT and TABLETOP have never been applied in a real world domain and their perceptual abilities are limited to "high-level perception". Thus, they cannot be directly applied in a real robot. However, the ideas behind COPYCAT and TABLETOP have been very instrumental in our research and in extending AMBR with perceptual abilities.

AMBR[1] [13, 14, 15, 16] is a model for analogy-making, based on the cognitive architecture DUAL [17]. AMBR models analogy as emergent phenomena – it emerges from the local interactions of a huge number of micro-agents. This model fully integrates retrieval and mapping processes and demonstrates how they interact and influence each other. The distributed representation of the episodes and the dynamic parallel nature of AMBR's mechanisms are a good starting point for modeling integration between perceptions and high-level cognitive processes. There are several main assumptions of AMBR. Firstly, context is not just a source of noise but is crucial for cognition. The context determines the relevant pieces of knowledge in long term memory (LTM) that can be used for solving the current problem. This context-sensitivity allows the system to be very flexible and at the same time very effective. Secondly, analogy, and particularly the ability for mapping is a central property for cognition. The cognitive system continuously maps the new information (coming from perceptions) with the old one (coming from memory) and adjusts both of them until they fit each other consistently. Thirdly, cognition is dynamic and all mechanisms run in parallel and interact with each other.

This chapter describes an extension of the AMBR model, building an integrated robot architecture that will try to cover all processes needed for real robot anticipation

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[1] AMBR is an acronym for Associative Memory-Based Reasoning

behaviour: from visual perception through selective attention through high-level reasoning to actual physical movements in the environment. This is achieved by combining sparse bottom up visual perception performed by the IKAROS system with mapping this information to elements of LTM – concepts and old episodes – the retrieved portions of the episodes are immediately mapped onto the sparse target description and anticipatory relations are build that will be analogous to the ones in the old episode. These anticipations, about possible properties and relations, guide in a top-down fashion the further visual processing performed by the IKAROS system. Thus, the robot has an active vision system and builds only representations that are mapped to the known information (it does NOT build an extensive representation of ALL aspects of the environment). The extended representation further guides the retrieval and mapping process and finally all three together arrive at an analogy that projects back predictions which cannot be tested by the visual system but would require physical movement of the robot through the environment for actively exploring it.

A simple scenario where the robot anticipation abilities could be tested in reality involves an object hidden somewhere in the house and the task of the robot would be to find it. A robot without anticipation abilities would have to search exhaustively all possible places in all rooms. This will require probably several days or even weeks of search. Clearly, though, when people are confronted with a similar problem, they do not search blindly. They anticipate where the hidden object might be. In most cases we rely on our previous experience – we are spontaneously reminded about previous situations when we have searched for an object and try to transfer this experience to the new target situation. This is what our small dog-like AIBO will do – it will search for its bone hidden somewhere in the room. It is important to mention that this search is not based on a general regularity, such as that the object is always in the drawer, but actually the object can be at different places and still be analogous to one previous episode.

In this first step we have simplified the search by locating everything in one room, but this could be extended in the future. Unlike our previous attempts to build anticipatory mechanisms, this attempt is based on real robot acting in a real environment. This requires implementing all parts of the integrated architecture including visual perception, attention, reasoning, memory, and motor action. Thus even if it is a very simplified version and environment, it has all required capacities put together and working together and influencing each other.

2   Environment and scenarios

We define our tasks and test the model in a house-like environment and in a "find-an-object" scenario.

The house-like environment consists of several rooms and doors between some of them. There are various objects like cubes, balls, and cylinders in the rooms. We used Sony AIBO robots (ERS-7). The goal of the robot is to find a bone (or bones) hidden behind an object. In a more complicated task there could be many robots: some of the robots should find and collect some 'treasures', whereas other robots play the role of

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'guards' that try to keep the treasures and hide them dynamically or block the way of the treasure-hunters. Here, we start with the simplest case. We have one room, which includes the robot itself, and simple objects like cylinders and cubes with different colours (Fig. 1). The bone is hidden behind one of the objects. All objects are visible for the robot.

Fig. 1. Simple scenario – "Where is my bone?"

The AIBO robot has to predict where the bone is hidden based on analogies with past episodes and go for it. The episodes are manually built for the moment, but we plan to work on the learning process by which the newly perceived situations will remain in LTM.

In order to simplify the problems related to 3D vision we decided to have one camera attached on the ceiling having a global 2D view of the scene. There is a colour marker on the top of the AIBO to facilitate its recognition. A web camera server sent the image data via TCP/IP to the network camera module of IKAROS. All software is installed on remote computers which communicate with the robot through wireless network.

3 Integrated Architecture

The integrated architecture of the system consists of several main modules (see Fig. 2):

- AMBR – the core of the system, it is responsible for attention and top-down perceptual processing, for reasoning by analogy, for decision making, and for sending a motor command to the robot controller.
- IKAROS module – a low-level perception module performing bottom up information processing.
- AMBR2Robot – a mediation module, the link between AMBR and IKAROS and the robot controller.
- AIBO robot.
- Camera attached to the ceiling.

A global camera takes visual information of the environment. It is received by the IKAROS module. The visual information is processed and symbolic information about objects in the environment is produced. This symbolic information is used from AMBR2Robot to provide AMBR with bottom-up perception information and also to handle the top-down requests which are described below. ABMR2Robot also waits for a "do-action" message from AMBR, which when received makes the module to control the robot and guide it to the target position using AIBO Remote framework. AMBR does the substantial job of making predictions about where the bone is hidden based on the representation of the current situation and making analogy with past situations. AIBO Remote Framework is a Windows PC application development environment which enables the communication with and control of AIBO robots via wireless LAN.
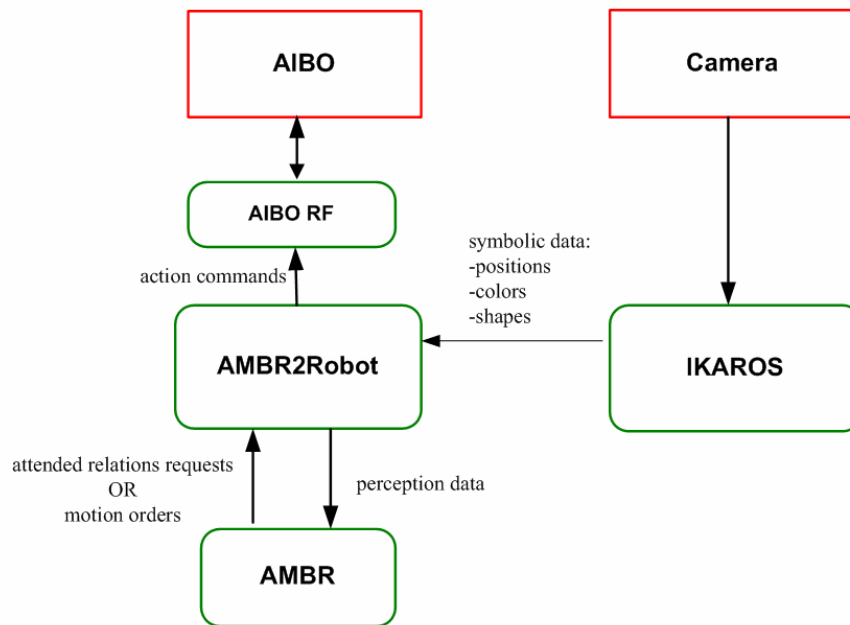

F**ig. 2.** Main modules and data flow between them

3.1 AMBR

The AMBR model for analogy-making is a multi-agent system, which combines symbolic and connectionist mechanisms [13, 14, 15]. Knowledge is represented by a large number of interconnected DUAL-agents. Each agent stands for an object, a relation, a property, a concept, a simple proposition, a procedural piece of knowledge. The connectionist's activation of the agents represents their relevance to the current context. There are two special nodes that are the sources of activation – the INPUT and GOAL nodes – which are representations of the environment and the goals,

respectively. Activation spreads from these two nodes to other nodes (typically instances of objects and relations from the target scene) then to their respective concepts and further upwards the concept hierarchy, then back to some of the concept instances and prototypes. There is no separation between the semantic and episodic memories – they are strongly interconnected.

The active part of the long-term memory forms the Working Memory of the model. Only active agents can perform symbolic operations like for example sending short messages to their neighbours, adjusting their weights, or creating new agents. This is a very important interaction between the symbolic and the connectionist parts of the model. The *speed* of the symbolic operations depends on the activation level of the respective agent. Thus, the most relevant (active) agents work faster, the less relevant – more slowly, and the irrelevant ones do not work at all.

Tables 1 and 2 summarize the main mechanisms and agent-types used in AMBR and describe the role and the routine of each of them. It is important to note, however, that all these mechanisms run in parallel and influence each other.

Table 1. AMBR basic mechanisms

Spreading activation	The activation of the agents represents their relevance to the current context. It spreads just like in a neural network. The sources of the activation are two special nodes – INPUT and GOAL. The AMBR agents that represent the environment are attached to the INPUT, whereas the representation of the target is attached to the GOAL.
Marker emission and passing	Each *instance-agent* (representing a concrete token) emits a marker that spreads to the respective *concept-agent* (representing type) and then upward to the class hierarchy. When a marker from the target situation comes across a marker from a memorized situation, a *hypothesis-agent* between the two marker-origins is created. The hypothesis-agents always connect two agents and represent the inference that these two agents are analogical.
Structural correspondences	There are various mechanisms for structural correspondence that create new hypotheses on the basis of old ones. For example, if two relations are analogical, their respective arguments should also be analogical; if two instance-agents are analogical, their respective concepts should also be analogical, etc.
Constraint satisfaction network	The consistent hypotheses support each other, whereas the inconsistent ones compete with each other. Thus, dynamically, a constraint satisfaction network of interconnected hypotheses emerges. After its relaxation, a set of *winner-hypotheses*, which represent the performed analogy, is formed.

Table 2. Main types of AMBR agents

Instance-agent	Represents tokens, i.e., particular exemplars. The instance-agents can represent objects, as well as aspects and relations.	*Examples:* bone-1, red-21, behind-3…
Concept-agent	Represents types, i.e., classes of similar exemplars. Again, can represent objects or relations.	*Examples:* bone, color, behind…
Hypothesis-agent	Always connects two elements – one from the target situation and one from a memorized one. Represents an inference that there is something in common between the two elements – they have common super-class or they are the respective arguments of corresponding relations.	*Examples:* bone1<-->bone-3, left-of<-->right-of, red-12<->green-8…
Winner-hypothesis	Represents an already established analogical correspondence between two elements. The hypothesis-agents become winners or fizzle out.	The same form like the hypothesis-agents

3.2 Extensions of AMBR for the AIBO robot application

In order to make AMBR a model of the mind of a real robot several new mechanisms were developed and implemented. Most importantly, several analogical transfer mechanisms have been developed which will allow robust predictions based on analogy. The present development is related to the extension of the model with a dynamic top-down perceptual mechanism, a mechanism for control of attention, mechanisms for transferring parts from a past episode in memory towards the now perceived episode (analogical transfer), and mechanisms for planning and ordering actions based on that transfer. All new mechanisms are summarized in Table 3 while the new AMBR agent's types are given in Table 4. Note that all these mechanisms overlap in time and influence each other. It should be stressed that there is no central executive in AMBR. Instead, the AMBR agents interact only with their neighbours and perform all operations locally, with a speed, proportional to their relevance to the current context.

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Table 3. New ABMR mechanisms

Perceptual Anticipation (top-down influence on perception)	By a series of messages, the instance-agents from memorized situations inform the relevant relations in which they participate for all their hypotheses. If a certain relation collects the hypotheses for all its arguments, it creates an *anticipation-agent*. The anticipation-agents are copies of their mentor-relations but all their arguments are replaced with the respective analogical elements from the target situation.
Attention	The attention mechanism monitors all anticipation-agents, sorts them by their activation (i.e., relevance), and at fixed time intervals asks the perceptual system to check the relation represented by the most active one.
Goal-related Anticipation (Transfer of the solution)	When a certain hypothesis transforms itself into a winner-hypothesis, it informs its base element. The latter, in turn, informs the relations, in which it participates. The respective relations erase all anticipations and hypotheses that are inconsistent with the new winner. Thus, in reality, the anticipation mechanism creates many different possible solutions of the problem that compete with each other, whereas the transfer mechanism works by deleting most of them on the basis of the best analogy. As a final result of the transfer mechanism only the solution that is most consistent with the performed analogy remains.
Action	The *cause-agents* (representing causal relations) are equipped with a special routine. Via special messages, the agents, attached to the GOAL node inform the cause-relations, in which they participate, that the latter are close to the goal. After a period of time, if such 'close-to-goal' cause-agent receives information that it participates in a winner-hypothesis, it checks its antecedents for *action-agents* (representing description of a certain action or movement). If all these conditions are met, the action mechanism sends an order for executing the respective action.

Table 4. Specialized AMBR agents

Anticipation-agent	Represents expectation that a certain relation is present in the environment.	*Examples:* ?red-cube-12?, ?behind-bone-cylinder-12?…
Cause-agent	Represents a certain casual relation. It always has antecedents and consequences. One cause-agent can be instance-agent or anticipation-agent.	*Example:* Cause1 **-antecedents:** move-12, behind-2 **-consequences:** find-8

Action-agent	Represents the description of a certain action or movement. The presence of an action-agent in the target situation does not mean that it will be executed. In order for AIBO to execute the respective action, a special procedure for this should be triggered.	*Examples:* Move (AIBO, cylinder-12),

More detailed description of the new AMBR mechanisms follows below.

Top-Down Perception

It is known that when executing a task in order to achieve a specific goal, top-down mechanisms are predominant [21, 22]. This finding is implemented by making AMBR the initiator of information acquisition actions.

At first, the robot looks at a scene. In order for the model to 'perceive' the scene or parts of it, the scene must be represented as an episode, composed out of several agents standing for objects or relations, attached to the input or goal nodes of the architecture. It is assumed that the construction of such a representation starts by an initial very poor representation (Fig. 3) built by the bottom up processes. This includes, usually, only symbolic representations of the objects from the scene without any description of their properties and relations. These are attached to the input of the model (in the example, `object-1`, `object-2`, and `object-3`).

Object-1   Object-2   Object-3
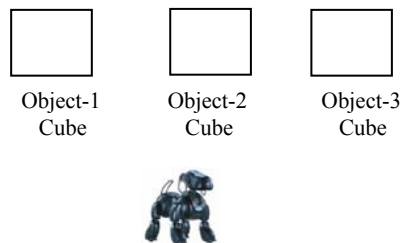Cube   Cube   Cube

Fig. 3. Initial representation of the scene (bottom-up perception)

The representation of the goal is attached to the goal node (usually `find-t`, `AIBO-t`, and `bone-t`). During the run of the system some initial correspondence hypotheses between the input (target) elements and some elements of the memory episodes (bases) emerge via the mechanisms of analogical mapping (Fig. 4).
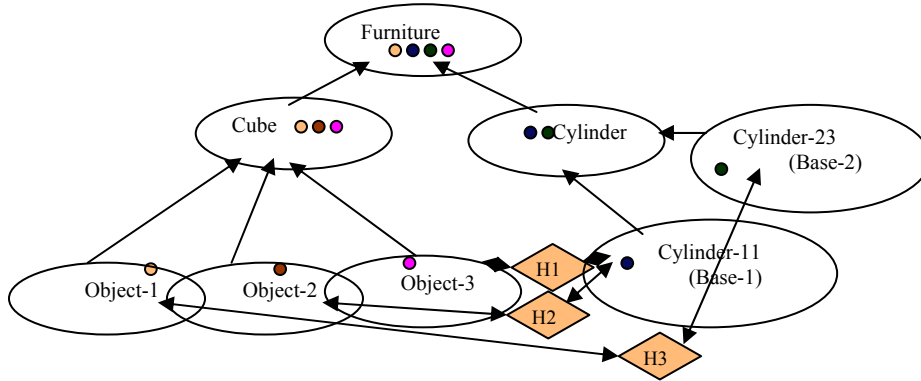
Fig. 4. Creation of hypotheses (H1, H2, H3) on the basis of marker intersections

The connected elements from the bases activate the relations in which they are participating. The implemented *dynamic perceptual mechanism* creates predictions about the existence of such relations between the corresponding objects in the scene. As shown in the example of Fig. 5, Object-1 from the scene representation has been mapped onto Cylinder-11 in a certain old and reminded situation. The activation mechanism adds to working memory some additional knowledge about Cylinder-11 – e.g. that it is yellow and is positioned to the left of Cylinder-23, etc. (Fig. 5) The same relations become anticipated in the scene situation, i.e. the system anticipates that Object -1 is possibly also yellow and could be on the left of the element, which corresponds to Cylinder-23 (if any), etc. Thus, various anticipation-agents emerge during the run of the system.
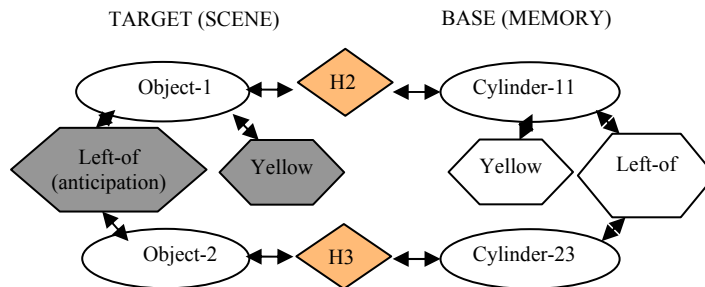

Fig. 5. Formation of anticipation agents in AMBR on the basis of missing in the scene arguments of already mapped relations. (Note that 'left-of' relation is asymmetric and the order of arguments is coded in AMBR although it is not shown in the picture)

Attention

The attention mechanism deals with the anticipations generated by the dynamic perceptual mechanism, described above. With a pre-specified frequency, the attention mechanism chooses the most active anticipation-agents and asks the perceptual system to check whether the anticipation is correct (e.g. corresponds to an actual

relation between the objects in the real scene). AMBR2Robot, as described earlier, simulates the perceptions of AMBR based on input from a real environment (using IKAROS). It receives requests from AMBR and simply returns an answer based on the available symbolic information from the scene.
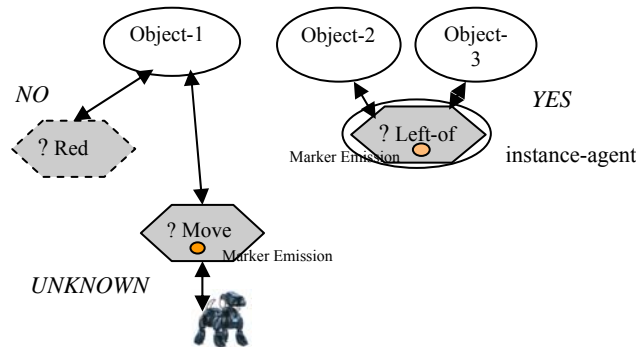

Fig. 6 Processing of the different types of answers of relation questions

The possible answers are three: 'Yes', 'No', or 'Unknown'. In addition to colours ('color-of' relations), spatial relations, positions, etc., it also generates anticipations like "the bone is behind 'object-1'", or "if I move to 'object-3'", I will find the bone". Those relations play a very important role for the next mechanism – the *transfer of the solution* (i.e. making a firm prediction on which an action will be based) – as explained below.

After receiving the answers, AMBR manipulates the respective agent (see Fig. 6). If the answer is 'Yes' it transforms the anticipation-agent into an instance-agent. Thus the representation of the scene is successfully augmented with a new element, for which the system tries to establish correspondences with elements from old episodes in memory. If the answer is 'No', AMBR removes the respective anticipation-agent together with some additional anticipation-agents connected to it. Finally, if the answer is 'Unknown', the respective agent remains an anticipation-agent but emits a marker and behaves just like a real instance, waiting to be rejected or accepted in the future. In other words, the system behaves in the same way as if the respective prediction is correct. However, the perceptual system or the transfer mechanism (see below) can discard this prediction.

Transfer of the solution

Thus, the representation of the scene emerges dynamically, based on top-down processes of analogical mapping and associative retrieval and of the representation in AMBR2Robot and its functioning. The system creates many hypotheses for correspondence that self-organize in a constraint-satisfaction network (see Fig. 7)
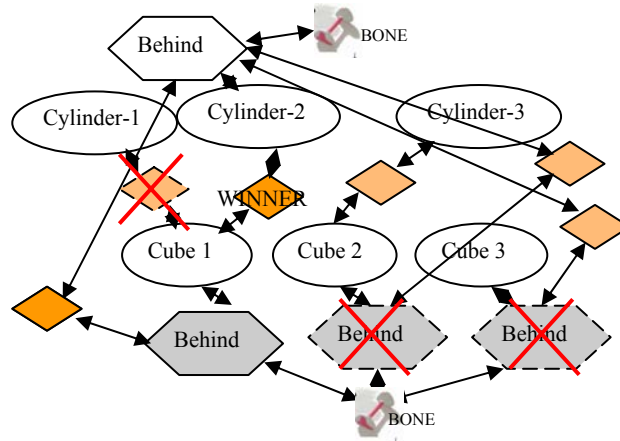
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Fig. 7. Constraint satisfaction network between hypotheses. Winner hypotheses remove many of the inconsistent anticipations until only few anticipation-agents remain.

Some hypotheses become winners as a result of the relaxation of that network and at that moment the next mechanism – the *transfer of the solution* does its job. In fact, the transfer mechanism does not create the agents, which represent the solution. The perceptual mechanism has already transferred many possible relations but now the task is to remove most of them and to choose the best solution. As in the previous examples, let's take a target situation consisting of three cubes and let the task of AIBO be to find the bone. Because of various mappings with different past situations the anticipation mechanism would create many anticipation-agents with a form similar to: "The bone is behind the left cube". This is because in a past situation (sit-1 for example) the bone was behind the left cylinder and now the left cylinder and the left cube are analogical. Because of the analogy with another situation, for example, the anticipation that "the bone is behind the middle cube" could be independently created. Another reason might be generated due to which the right cube will be considered as the potential location of the bone. Thus many concurrent possible anticipation-agents co-exist. When some hypotheses win, it is time to disentangle the situation.

The winner-hypotheses care to propagate their winning status to the consistent hypotheses. In addition, the inconsistent ones are removed. In the example above, suppose that sit-1 happens to be the best candidate for analogy. Thus, the hypothesis 'left-cylinder<-->left-cube' would become a winner. The relation 'behind' from the sit-1 would receive this information and would care to remove the anticipations that the bone can be behind the middle or behind the right cylinder.

As a final result of the transfer mechanism, some very complex causal anticipation-relations like "if I move to the cube-1 this will cause finding the bone" become connected with the respective cause-relations in the episodes (bases) from memory via winner-hypotheses.

Action execution

The final mechanism is *sending an action command* (see Fig. 8). The cause-relations that are close to the GOAL node trigger it. The GOAL node sends a special message to the agents that are attached to it, which is in turn propagated to all cause-relations. Thus, at a certain moment, the established cause-relation "`if I move to cube-1, this will cause finding the bone`" will receive such a message and when one of its hypotheses wins, it will search in its antecedents for an action-agents. The final step of the program is to request the respective action to be executed and this is done again via a message to AMBR2Robot.
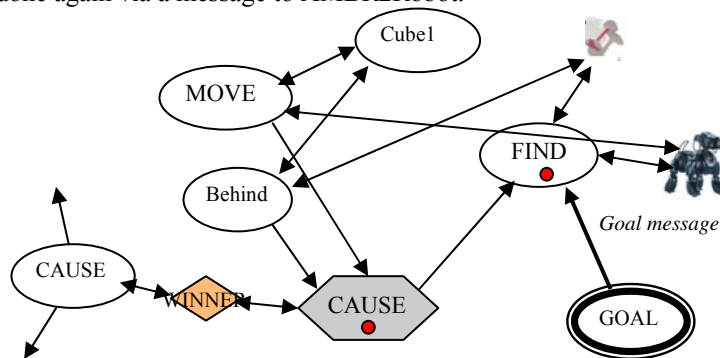

Fig. 8. Hypotheses of the cause-relations receive markers from the GOAL node. If the consequents satisfy the goal, then the actions from the conditions are executed.

3.3 Connecting ABMR with the robot

In order to connect AMBR with the real world several new modules were developed. A major step was to build a perceptive mechanism with active vision elements based on the platform IKAROS [18, 19]. Several modules of IKAROS related to perception were successfully integrated in order to carry out the difficult task of bottom-up visual perception and object recognition. This results in a hybrid system where IKAROS performs the non-symbolic processes best suited for perceptual processing, while AMBR performs the high level symbolic and connectionist operations best suited for analogy making Another module – AMBR2Robot – was developed as a general mediating layer between the perception modules of IKAROS and ABMR. AMBR2Robot supports the selective attention mechanisms, which were described above.

3.4 IKAROS

IKAROS is a platform-independent framework for building system-level cognitive and neural models [18, 19] (see also www.ikaros-project.org). The system allows systems of cognitive modules to be built. The individual modules may correspond to various cognitive processes including visual and auditory attention and perception,

learning and memory, or motor control. The system also contains modules that support different types of hardware such as robots and video cameras. The modules to be used and their connectivity are specified in XML files that allow complex cognitive systems to be built by the individual modules in IKAROS. Currently, there are more than 100 different modules in IKAROS that can be used as building blocks for different models.

In the present work, IKAROS was used for visual perception and object recognition. An IKAROS module receives images from a camera while another module segments the image into different objects based on colour. The result is sent to AMBR2Robot for further processing.

The object recognition proceeds in several stages. In the first stage, the colour image is mapped onto the RG-chromaticity plane to remove effects of illumination and shadows. In parallel, the edges are extracted in the image. These edges are used as preliminary contours of the objects. In the second processing stage, the colours are normalized in-between the edges in x and y-direction to produce homogenous colour regions (Fig. 9). In the third stage, the individual colour pixels are clustered into regions with similar colour. At this stage, a template for each colour is used to form only clusters for colours that are known to belong to the target objects. Each colour is defined as a circle sector around the white-point in the RG-chromaticity plane. In the fourth stage, a rectangular region is formed around each cluster, which is used to delimit each object (Fig. 10). Finally, a histogram of the edge orientations within each object regions is calculated which is then used to categorize the shape of the object.
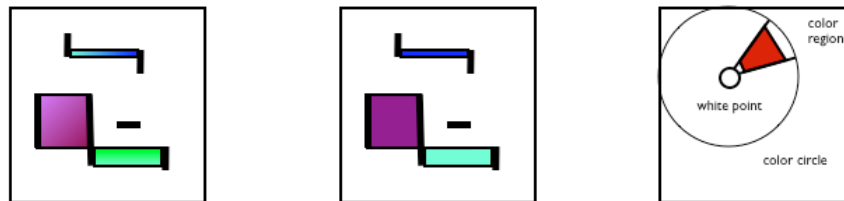

Fig. 9. Left. An initial image with found vertical edges. **Middle**. Colours after normalization between edges. **Right**. A colour region in the RG-chromaticity plane.
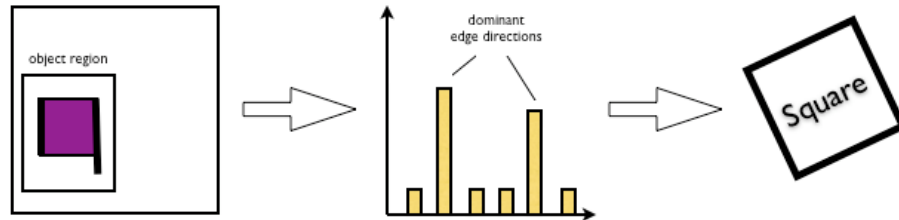
Fig. 10. The recognition of shapes. **Left**. A region is formed around the colour cluster. **Middle**. A histogram of edge orientations is calculated. **Right**. The distribution of edge orientations is used to determine the shape.

Note that we are not trying to find the complete contours of the objects. Instead, the method is based on the distribution of different edge orientations which is a much more robust measure. The different processing stages were inspired by early visual processing in the brain but adapted to efficient algorithms. The mapping to the RG-chromaticity plane discards the illuminant and serves the same role as the interaction between the cones in the retina [23]. The detection of edges is a well known function of visual area V1 [24]. The colour normalization within edge elements was inspired by theories about brightness perception [25] and filling-in [26].

3.5 AMBR2Robot

AMBR2Robot mediates between AMBR, IKAROS and the robot. It provides AMBR with perceptual information from IKAROS and also serves for implementing the selective attention mechanism in the model. The other main purpose of this module is receiving the action tasks from AMBR and executing them using AIBO-RF. We could say that it simulates the link between the mind (AMBR) and the body (perception system, action system).

The work of the module AMBR2Robot formally can be divided into three sub-processes:
1. Bottom-up perception
2. Top-down perception
3. Performing actions

Bottom-up perception

At this stage just a small part of the scene-representation is sent to AMBR. As described above information is further transformed into the form used for knowledge representation in AMBR by creating a set of AMBR agents with appropriate slots and links and connecting them to the so-called input of the architecture.

Top-down perception

As mentioned above AMBR sends top-down requests in the form of questions about the presence of properties and relations about the identified objects. These requests are received by AMBR2Robot and are answered based on visual symbolic

information provided by IKAROS. Relations represent the most important information for analogy-making and are extracted by AMBR2Robot from the scene description which does not contain them explicitly but only implicitly (e.g. in the form of coordinates and not spatial relations).

The main types of top-down perception requests are for:

- spatial relations: right-of, in-front-of, in-front-right-of, etc…
- sameness relations: same-colour, unique-shape, etc…
- colour properties: orange, blue, red, etc…

The spatial relations are checked based on the objects' positions as described by their coordinates and size and with respect to the gaze direction of the robot. Fig. 11 shows how the above example relation request (left-of object-2 object-3) is processed. Positions of all objects are transformed in polar coordinates respective to a robot-centric coordinate system. Then some comparison rules are applied to the coordinates.

For processing the sameness relation the relevant properties (shape or colour) of all the visible objects are compared.
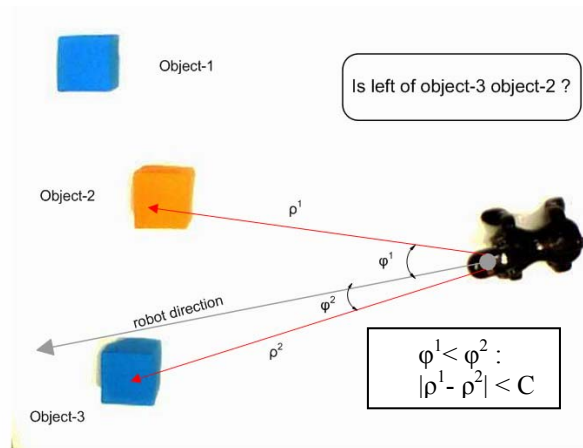

Fig. 11. Processing the spatial relation requests

Action

AMBR2Robot receives action commands from AMBR and, knowing the positions of the target object and the robot, navigates AIBO by sending movement commands via the AIBO Remote Framework (see Fig. 2). During the executed motion, IKAROS is used to update the robot's position in the scene (the other objects in the scene are assumed to have fixed positions) and only the robot is actually being tracked.

The robot is guided directly to the target object without any object avoidance (to be implemented in the future in more sophisticated examples). After the robot has taken the requested position, it is turned in the appropriate direction to push and uncover the target object. At the end it takes the bone if it is there or it stops otherwise.

4 Results

In this chapter the results from a single run of the system are described.

There are two past situations in the robot's memory (Fig. 12.a) The robot faces the situation showed in Fig 12.b
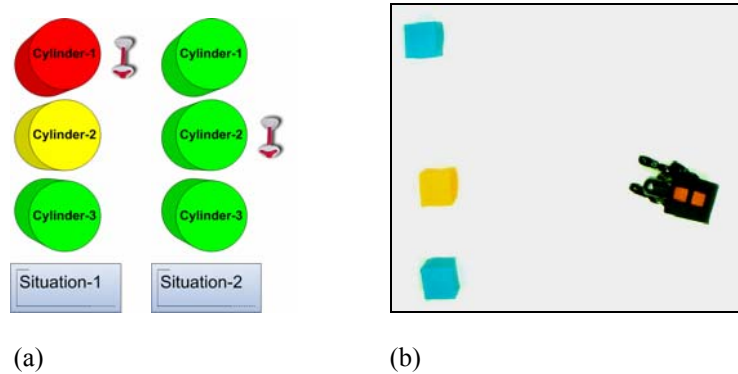

(a)   (b)

Fig. 12. (a) Old episodes in memory **(b)**AIBO is in a room with three cubes with different colours.

The image (from the global camera) is sent to the IKAROS module. In Fig 14 the visual field after RG-chromaticity transformation and the edge histogram for the one of the recognized objects are shown.
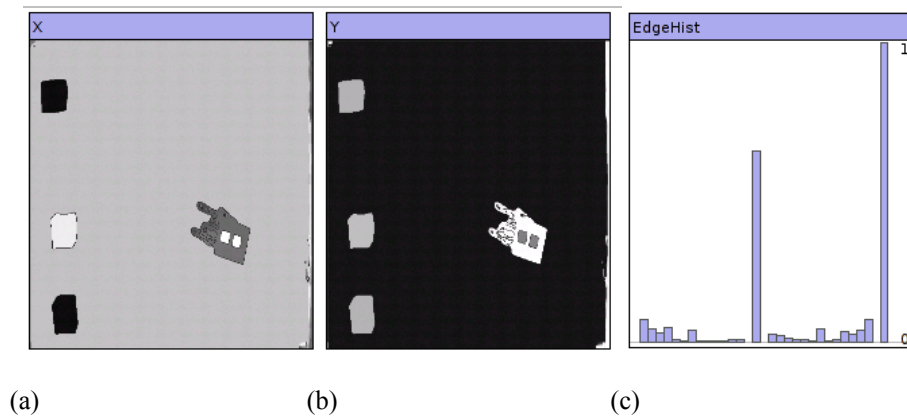

(a)   (b)   (c)

Fig. 13. . **(a),(b) RG-**chromaticity transformation **(c)**Edge histogram for the upper cube

The IKAROS module recognizes the objects and produces the input:

```
object-1, shape=cube, position= (50,85)
object-2, shape=cube, position=(71,303)
object-3, shape=cube, position=(75,429)
aibo-I, position=(438,301), direction=3.387
```

Processing that information AMBR2Robot sends part of it as bottom-up perceptual information to AMBR:

```
object-1: cube, object-2: cube, object-3: cube
```

In the top-down perception part, lots of relation requests are generated from AMBR. Here we show some of them, including the answers from AMBR2Robot:

```
? behind: bone-t -> UNKNOWN
? left-of: object-1 object-2 -> YES
? blue: object-3 -> YES
? green: object-2 -> NO
? in-front-right-of: object-3 aibo-I -> NO
? move: aibo-I object-2 -> UNKNOWN
```

Some of the already created anticipation agents are turned into instance agents according to the answer:

```
anticip-blue-situation-1
anticip-left-of-1-situation-2
```

The name of the agents is formed as follows. 'anticip'- stands for anticipatory . After that follows the name of the relation which it "anticipates". This relation can belong to one of the situations in robots memory (situation-1 or situation-2 in this case) Note that after transforming an anticipation agent into instance one its name remains the same.

After some time AMBR make an analogy with situation-1. Some of the winner hypotheses (in the order they emerge) are:

```
object-3 ←→ right-cylinder-situation1
anticip-blue-situation-1 ←→blue-situation-1
aibo-I ←→ aibo-I-situation-1
anticip-move-situation-2 ←→move-situation-1
object-2 ←→ midle-cylinder-situation1
object-1 ←→ left-cylinder-situation1
```

Many other agents are mapped. After the mapping of the cause agent, the action mechanism is triggered, which sends a motion command to AMBR2Robot.

```
move-to object-3
```

AMBR2Robot guides the robot to the target. Once arrived, the robot uncovers the object and tries to get the bone. Figure 15 shows some images of the robot moving.
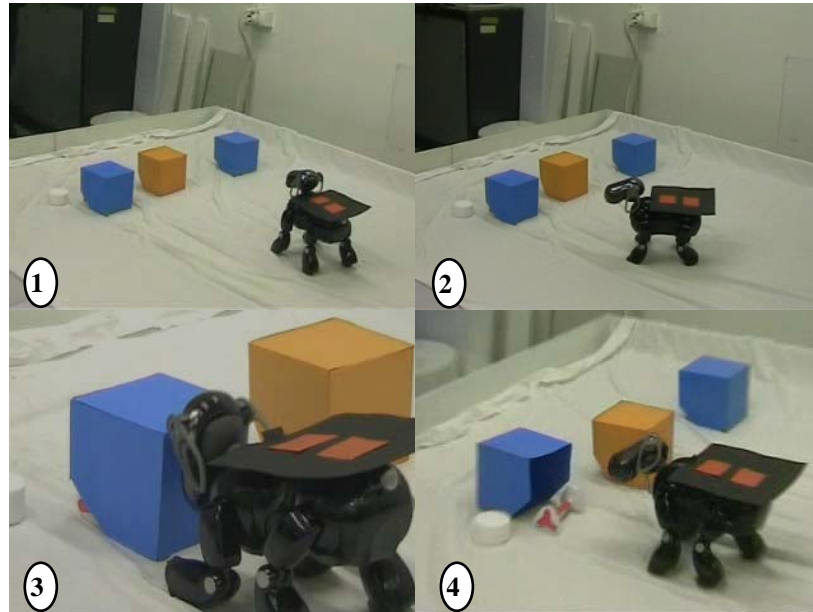
Fig. 14. 1. AIBO is starting to move. 2. approaching the target. 3. uncover object. 4. get the bone [2]

The model is tested in some other situations where other analogies are made. So far, we did not conduct any comparative experiments with other models because it is difficult to determine when an analogy "is right" in this scenario. But it is obvious that if the analogy is right, the performance will be much higher than a full-search method - checking all objects one by one.

6 Summary

In this paper, a new approach of robot anticipatory behaviour is presented which is based on predictions generated from an analogy with past experiences stored as episodes in memory. Anticipation is also used in a top-down perception mechanism, which is using predictions about relations between perceived objects based on hypotheses of correspondence with relevant objects from the past experience of the robot.

The AMBR model of analogy-making has been used as a system reasoning core and has been further extended. The visual information is handled by modules from the IKAROS system and transformed into a symbolic one. AMBR2Robots mediates between the high-level reasoning part of the system and the modules for perception

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[2] This pictures are taken from demonstration at the second year   review meeting of the MindRACES project

and action. In this paper, we presented the experience of implementing a combination of low-level perceptual information and higher-level reasoning in a real robot. The results seem very promising and would allow us to take advantage from the strong side of both approaches, building a genuinely hybrid robot architecture able to deal with complex real life tasks

The architecture was successfully tested in a house-like environment with the tasks of finding a hidden object.

5 Future work

Our plans for the near future are to further develop the bottom-up perceptual mechanisms, improve the attention mechanism, and extend the model with various types of different actions.

We plan future integration with IKAROS system at the level of bottom-up perception system. IKAROS is able to create various salience maps on the basis of the perceptual input and the goals of the system. AMBR can use these salience maps in order to activate various concepts to a different degree. This contextual information will influence the retrieval processes to a higher degree.

The attention mechanism should be connected with the robot camera and particularly, with its gaze. Thus, both the salience maps and the top-down reasoning will influence the head-movement of the robot, and in turn, the order of checking the various predictions.

Finally, the repertoire of possible actions that AIBO can do should be expanded. In the current version of the model, AIBO is able only to move from its initial position to one predefined object. However, it is not yet implemented how it will do this if there are obstacles. We plan to implement A-star algorithms in the robot planning system to avoid obstacles and to move between rooms.

Finally, our long-term plans are to develop also learning and emotional mechanisms, as well as testing AIBO's behaviour in more complex situations that include social interaction. For instance emotions can control some global parameters of the model like the capacity of working memory. The latter could lead to more superficial and less consistent analogies but which are done much faster.

We also plan to develop various mechanisms for 'task understanding', e.g. breaking up an abstract goal into several smaller sub-goals on the basis of analogy with past situations.

In the current implementation all memorized situations are manually predefined and stay static. Learning at different levels must be implemented to account for the experiences of the robot and allow the change of old episodes and the addition of new episodes in LTM.

Modelling social interactions including at least two robots seems also very important to us. For instance one of them will hide the bone, whereas the other one will seek it. Both robots will have various anticipations (and possibly meta-anticipations) about the behaviour of the other one which will give rise to interesting collective behaviour.

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