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Mind RACES

from Reactive to Anticipatory Cognitive Embodied Systems

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PART 1 – Management Overview

1 Document Control

This document is a co-production of all the partners mentioned above. This first deliverable from WP6 is the result of a theoretical analysis of the models and architectures of the participants from the perspective of possible integration of anticipatory mechanisms. It can be considered as a first step toward integration the second being the actual selection of promising integration and implementation in integrated models. The methodology for integration analysis was proposed by NBU and discussed during the third project meeting. On the basis of the meeting discussions and the contributions of all partners the present report has been written.

2 Executive Summary

This deliverable is aimed at establishing the basis for integration of anticipatory mechanisms. It reports the results of a systematic analysis of the possible integration needed to overcome successfully difficult aspects of the scenarios. The analyses presented here will be used for the selection, implementation and experimentation with models integrating two or more anticipatory mechanisms. The results of these latter activities will be reported in D6.2.

3 Methodology of the analysis

In order to use the terminology already adopted by the consortium, in this report the definitions from Deliverable 4.1 have been used and accounted for (see D5):

> "*… **"prediction" refers to the capability of predicting future properties whereas the word "anticipation" and particularly "anticipatory behavior" refers to mechanisms that use predictions to improve other mechanisms including learning and behavior**. Since anticipations cannot exist without the capability of predicting future properties, it is necessary to first understand and differentiate amongst predictive capabilities. Then, it is possible to evaluate potentials for anticipatory behavior.*
> *Particularly, predictive capabilities are differentiated with respect to **(1) the types of predictions represented**, **(2) the quality or accuracy of the predictions, (3) the time scales of the predictions**, **(4) the generality of the predictions**, **(5) the capability of incorporating context information and action decision information for improving predictions**, **(6) the focusing and attentional capabilities of prediction generation, and (7) the capability of predicting inner states.** Anticipatory capabilities distinguish the influence of predictions on **(I) learning, (II) attention**, **(III) action initiation and control,** and on **(IV) decision making**.*"

NBU proposed three potential sets of mechanisms that can serve as a basis for integration of the project participants' models:

- **general cognitive** mechanisms not related to prediction or anticipation.
- **predictive** mechanisms;
- **anticipatory** mechanisms.

The integration of mechanisms of any kind is considered worthwhile if it improves non-trivially the performance of the model compared to a model using a single mechanism or a formal combination of two mechanisms. Therefore, it is important to propose appropriate evaluation procedures and situations from the scenarios allowing to assess the advantages of integrated models. In general, several combination/integration are possible: of general and predictive mechanisms, of predictive and anticipative mechanisms etc. In order to be able to analyze the possible combinations, the interesting mechanisms have to be singled out with respect to their use in the scenarios.

On the other hand a more general integration among partners seems challenging – the integration between more symbolic approaches with a rich high-level representational capabilities (ISTC-CNR, NBU, NOZE, UW-COGSCI) with neural network based or other subsymbolic approaches that implement perception and learning (IDSIA, ISTC-CNR, LUCS, OFAI).

Therefore, a broader perspective on the possibilities for integration between the different architectures is adopted here with a special focus on anticipation.

To achieve this, the following methodology of gathering information and analysis was put forward:

Step 1: review the scenarios and specify the most important mechanisms involved.
Step 2: categorize each of the selected mechanisms in the suggested groups: general cognitive, predictive and anticipatory.
Step 3: review the models of the other partners and select useful mechanisms or model parts that can be added or integrated with the existing ones. (This process was helped by the architecture analysis provided in deliverable D4.1.)
Step 4: propose a specific integration of mechanisms and describe it using a set of criteria given below (see Section 3.2).

The results of Steps 1-4 were systematized further in four tables: one for the general cognitive mechanisms, one for the predictive mechanisms, one for the anticipatory ones and a table containing the possible integrations (see the contributions of the partners below). Additionally, these tables contain information about the possible partnerships within the project. The focus of the possible integration is of course on the predictive and anticipatory mechanisms.

Having filled the different tables to get the global picture, a detailed description is given of the foreseen integration(s). The elaboration of these descriptions was helped by a set of questions. At the end of the analysis for possible integrations a method for evaluating its impact had to be suggested.

This procedure is presented in detail in Subsections 3.1-3.2.

3.1 Integration of Mechanisms

3.1.1 General mechanisms

The scenarios involve a 'real' world situation which has to be approached eventually with a real robot or a simulation, so in order to have a successful achievement of the tasks various mechanisms are needed including predictive/anticipatory ones. In table type 1, the most important mechanisms needed for the successful completion of the tasks (ex. selective attention, perception …) are given with a description of what kind of scenario task they help to solve. Each partner indicates the availability of the mechanism in his architecture or model and in the case of non-availability specifies a project partner who has the needed mechanism.

Figure 3-1. Table type 1

General mechanism(s)	Use in the scenarios	Availability status	Partner

3.1.2 Predictive mechanisms

In table type 2 (see Figure 3-2), the predictive mechanisms, their use in the scenario, their availability and the possible collaboration with another partner had to be given.

Figure 3-2. Table type 2

Predictive mechanism(s) and type	Use in the scenarios	Availability status	Partner

3.1.3 Anticipatory mechanisms

In table type 3 (see Figure 3-3), the anticipatory mechanisms are listed and their availability, connection with general cognitive and/or predictive mechanisms is given. If non-available, as well as their use in the scenarios and their availability.

Figure 3-3. Table type 3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner

3.1.4 Integration of anticipatory mechanisms

One of the main goals of the project is to integrate different anticipatory mechanisms which when combined will outperform any single anticipation mechanism or mechanical combination of them. In table type 4 (see Figure 3-4), anticipation mechanisms candidate for integration are given, the possible integration is suggested together with possible ways of evaluation and the partner(s) which could collaborate are listed.

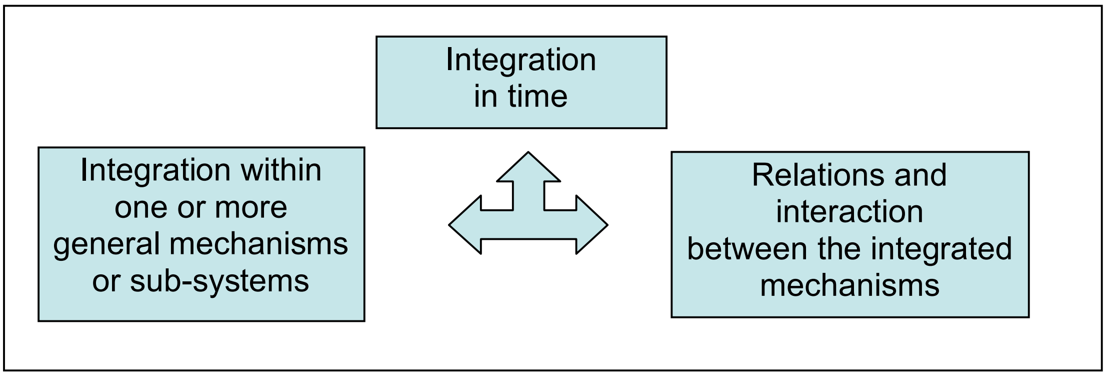
Figure 3-4. Table type 4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner

3.2 Integration dimensions

In order to analyze further the information provided in Tables 1-4 and the proposed integration, three integration dimensions are proposed (see Figure 3-5). They are discussed in detail in the following subsections.

Figure 3-5. Possible integration dimension



3.2.1 Integration in time

- Sequential:
    - Occur one after the other and the results of the first are used by the second

    - The mechanisms occur one after the other but the second is not directly related to the first but is mediated by another mechanism (memory retrieval, arousal etc.)
    - The first triggers/controls the second
- Parallel:
    - Are independent but the results from all of them are needed by a third mechanism
    - Compete and only the result of the winner is used
    - Cannot be separated and every mechanism uses the results from the others
    - Are related to different mechanisms: e.g. arousal of the system and decision making, emotion felt and retrieval from memory etc
- Overlapping
    - One of the processes must have started in order for the other to begin or/and one of the processes must have stopped in order for the second to stop

3.2.2 Integration within one or different general mechanisms

- One mechanism: e.g. top-down and bottom-up prediction mechanisms in attention
- Different mechanisms: e.g. an experienced emotion prepares the system to function more intensively and this facilitates another prediction mechanism like analogical transfer.

3.2.3 Direct and indirect interaction

- Direct:
    - One mechanism essentially uses the result from another (sequential) or
    - the results from two or more prediction mechanisms are needed for a subsequent (general or predictive mechanism to work) (parallel) or
    - The mechanisms work together and cannot be separated (e.g. experienced emotion gives energy for a symbolic operation)
- Indirect: The influence among predictive mechanisms are mediated by other general mechanisms

3.3 Integration questionnaire

In order to analyze further the information provided in Tables 1-4, an integration questionnaire was proposed. As the goal of this report is to evaluate the possible integration of anticipation mechanisms between the partners of the project it is expected that different relevant mechanisms were mentioned in the tables of type 1-4 (see Section 3.1). On the basis of this analysis, suggestions for integration had to be described and analyzed using integration dimensions given in Section 3.2.

3.3.1 Description of the selected mechanism taken from a partner

Describes the functionality and the intended use of the mechanisms by giving answers to the following questions:

1. What is this mechanism for: decision, attention, control, categorization, emotions …? Please give all that applies.
2. How will it change/affect the predictive/anticipatory behavior of your system?

3.3.2 Interaction of mechanisms

Explains how the mechanisms taken from a partner will interact with the existing ones (eventually based on the analysis scheme from Section 3.2) using the following questions:

1. What type of integration will be used? Will the integrated mechanisms be sequential in time or simultaneous and interacting
2. In which situation one mechanism will be used/will have priority instead of/over the other(s)?
3. How will conflicts be resolved when the two mechanisms try to get control priority?
4. In your system at which level this mechanism is situated (it will be useful if you provide some sort of schema depicting a global view of all the parts of your architecture/system and the connections between them).
5. How does it communicate/exchange information with the other levels/parts of your system?
6. Does it require a modification of the scenario (to make it simpler or more complex or impose additional constraints on it)?

3.3.3 Integration with the existing architecture

Describes how the integration of the mechanism in the current architecture is expected to happen and how well this new mechanism will fit/integrate with the current model. The explanation should be able to give answers to the following questions without being limited to them:

1. Will it add fundamentally new features to the system (emotions, curiosity, learning, perception, generalization, etc.)?
2. Will it extend/improve/modify already existing capabilities of the system?
3. Will it run in sequentially or in parallel?
4. What will be the influence (positive or negative) of its inclusion on other mechanisms of the system?
5. What are the intended effects on the most important capabilities/features of the system related to prediction and anticipation?
6. What are the expected effects on processing speed and resources use?
7. What is the importance of integration for the successful achievement of the goal in the scenarios?
8. What could be the negative effects of the integration?

3.3.4 *Evaluation of the resulting integration*

Describes the ways of evaluating the advantages of the suggested integration and answers the following questions without being limited by them:

1. Are there uncertainties about the performance of the integrated architecture at this moment?
2. What methods will you use to compare the new integrated architecture with the original one?
3. Should the new evaluation procedure (if a new one is needed) be different from the one to be used for evaluating a single mechanism (without integration)?

PART 2 – Deliverable Content

4 IDSIA

4.1 Integration of Mechanisms

IDSIA is interested in using UW-COGSCI's hierarchical methods and LUCS' context-sensitive reinforcement learning methods. However, particularly in the case of the combination of UW-COGSCI hierarchies with IDSIA intended inverse gradient modeling; it is not clear how it can be done and whether it will work.

IDSIA has very good reinforcement learning algorithms available which are based on neuro-evolution and is open to collaboration on this. Furthermore, IDSIA has available software for LSTM networks, which may be of use for any partner's anticipatory algorithm that uses some form of prediction (since LSTM predictive capability is pretty good).

4.1.1 General cognitive mechanisms

Table 4-1

General mechanism(s)	Use in the scenarios	Availability status	Partner
Selective attention (e.g. fovea)		Under development, almost finished	
Combined Bottom-up / Top-down hierarchies		Not yet available	UW-COGSCI
Context-Sensitive Reinforcement Learning		Available	LUCS
Neuro-evolution Strategies		Non available	

4.1.2 Predictive mechanisms

Table 4-2

Predictive mechanism(s) and type	Use in the scenarios	Availability status	Partner
RNNs / LSTM		Available	
Dyna-like models		Non available	

4.1.3 Anticipatory mechanisms

Table 4-3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Alvinn-like functionalities		Non available	RNNs/ LSTM	
Gradient Inverse Models		Non available	RNNs / LSTM	
Neuroevolution strategies		Non available	RNNs / LSTM	
Curiosity based reinforcement learning		Non available	RNNs / LSTM	

4.1.4 Integration

Table 4-4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner
UW combined hierarchical Bottom-up/Topdown approach with IDSIA Alvinn-like anticipatory mechanisms, with the predictive capabilities of RNNs (e.g. LSTM), and with Neuroevolution strategies, and with inverse gradient methods	Because IDSIA probably use RNNs in many of its algorithms, hierarchical RNNs might be an advantage in all of IDSIA algorithms	Same performance measure as for the basic non-hierarchical algorithms: it must perform better	UW-COGSCI
Context-sensitive reinforcement learning	Combine with alvinn anticipation and with LSTM in order to be able to handle time	Can LUCS reliably improve reinforcement learning in partially observable environments by taking context into	LUCS

		account from multiple time steps back in history?	

4.2 Mechanisms detailed description

4.2.1 UW-COGSCI's combined Hierarchical Bottom-up/Top-down approach

This involves a combined hierarchical approach, both top-down and bottom-up. The basic idea is that, based on levels of (un)certainty in either level, either top-down connections or bottom-up connections have more effect on the state of a particular layer of a (recurrent) neural network. The levels of uncertainty are determined by updating the system's predictive correctness at each level (think: Kalman Filters) as some previous research has already shown, this allows the entire system to produce better predictions at several levels of abstraction.

IDSIA considers this could be straightforwardly integrated into all or most of their RNN-based methods – as a tool - on the predictive side, or even the anticipatory side with the inverse-gradients method. The standard RNNs should be replaced with those hierarchical ones. In the case of gradient-inverse methods, IDSIA needs to think more on how to do integration – this is not straightforward.

4.2.2 LUCS Context-Sensitive Reinforcement Learning

IDSIA LSTM's predictive capabilities could be integrated with LUCS Context-Sensitive Reinforcement Learning, in order to be able to capture time – that is, context from several to (arbitrarily many) time steps away. This integration could take the form of value approximation, where LSTM would be functioning as the approximation mechanism of the value and context functions in Q-learning catered to Context-Sensitive Reinforcement Learning. IDSIA will probably put LSTM within LUCS' Ikaros framework for brain modeling, in order to improve cooperation and integration.

5 IST

5.1 Integration of Mechanisms

5.1.1 General cognitive mechanisms

Table 5-1

General mechanism(s)	Use in the scenarios	Availability status	Partner
Vision, attention selection and object recognition	Access the external environment and object search. Distinguish a ball from other objects.	Non available	IDSIA, LUCS
Robot motor control (Cognitive??)	Move through the environment.	Non available	IST
Planning	Make some plan on how to search the room for the ball.	Under development	IST, ISTC-CNR, NOZE
Knowledge representation	Mental model of the room and its contents	Under development	IST, ISTC-CNR
Deliberative model with emotion	Deliberation biased by emotion. Emotion *hijacking*.	Under development	IST, ISTC-CNR
Emotion coping and action tendencies	Agent an internal emotional state visible through agent's behavior. Believability.	Under development	IST
Etologicaly-based behavior	Action selection and believability.	Under development	IST

5.1.2 Predictive mechanisms

Table 5-2

Predictive mechanism(s) and type	Use in the scenarios	Availability status	Partner
Low-level predictors and feeling generators (Emotivectors)	AIBO uses this mechanism to monitor its perceptions and predict the next state. Based on this and actual read values it generates *feelings* (pre-emotions) (like surprise, positive, negative, etc.)	Available	IST

5.1.3 Anticipatory mechanisms

Table 5-3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Emotions	Resulting from perception and action. Surprise.	Available	Emotivectors	IST, ISTC-CNR
Emotions	Biasing behavior.	Available	Deliberation	IST, ISTC-CNR
Emotions	Emotions as goals	Available	Planning and deliberation	IST, ISTC-CNR

5.1.4 Integration

Table 5-4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner
Vision and Selective attention (fovea)	Use for vision perception filtering. Integration with the emotivector mechanism.	Improve performance by focusing resources. Increase believability by adding nature inspired mechanism surprise and attention driven behavior.	IDSIA
Model of the Environment		Under study	UW-COGSCI IDSIA

5.2 Mechanisms detailed description

5.2.1 Vision and Selective Attention

IDSIA's fovea mechanism provides a way for simplifying visual data so it can be linked with the emotivector mechanism or other low-level prediction mechanism. This way surprise and attention/curiosity drives can appear at the perception level providing anticipatory behavior.
With this nature replicating mechanism we can improve the desired believability. The agent will try to center the attention object with the focus of the fovea and can only recognize an object in this position. This reaction in anticipation of the desired "goal" or curiosity is very recognized in humans and animals.

Fovea's outer vision is reduced in detail so it requires less resources and this way we could link this "blurry" vision to prediction mechanisms, in particular the emotivector mechanism, as that trigger surprise our another curiosity driving sensation and influence behavior seeking recognition of interesting objects.

6 ISTC-CNR

6.1 Integration of Mechanisms

6.1.1 General cognitive mechanisms

Table 6-1

General mechanism(s)	Use in the scenarios	Availability status	Partner
1. A deliberative mechanism to choose an intention	The cognitive system should be able to choose in a deliberative ways between concurring options on the basis of salient beliefs and previous commitments.	Under development	ISTC-CNR, NOZE
2. A planning mechanism	The cognitive system should be able to identify the best means to achieve its current intentions. The planner should also be able to construct plans at different level of abstractions.	Under development	ISTC-CNR, NOZE
3. A Schema mechanism	The cognitive system should be able to operate in a real dynamic environment by means of sensory-motor interactions.	Under development	ISTC-CNR. Possible collaboration with UW-COGSCI, NOZE and OFAI
4. A Knowledge representation system	A mechanism to update and revise on the basis of current input the knowledge base of the cognitive system. The model of the environment is already coded.	Under development	ISTC-CNR
5. An Emotion Reasoner	A mechanism able to trigger different kind of emotions in relation to current input, expectations and their relationships.	Under development	ISTC-CNR
6. A Routine-based Perception	A set of routines to manage the low level interactions with sensors and effectors fully integrated with the simulator providing a more high	Under development	ISTC-CNR, NOZE

	level data format.		
7. A system that learns autonomously a repertoire of sensorimotor actions	Modification of body-environment relationships in robotic arms (pointing, postures, etc.).	Under development	ISTC-CNR

6.1.2 Predictive mechanisms

Table 6-2

Predictive mechanism(s) and type	Use in the scenarios	Availability status	Partner
Knowledge based prediction	The dynamics of the environment, of the consequences of the plans, and of other agents' behaviours is inferred using a declarative knowledge and memory. For example, the cognitive system, while patrolling around the house, can infer from its KB the predictive belief that during the day rooms having windows will be floodlit.	Under development	ISTC-CNR, NOZE
Prediction based on forward model	The forward models are part of the schema mechanism allowing the prediction of the next event (i.e. next sensory input as low-level consequences of actions).	Under development	ISTC-CNR, NOZE
Prediction with multiple paired forward models	To select, monitor and adjust the action, a mechanism managing multiple schemas doing different predictions is adopted. The schemas predict the outcomes of alternative courses of actions at the same time.	Under development	ISTC-CNR, NOZE
Anticipated body-environment states as desired states (goals)	Internal representations of states as conditions that will take place only if agent acts in suitable ways	Under development	ISTC-CNR
Prediction of other agents'	The cognitive system should be able to recognize an agent's plan by observing its	Under development	ISTC-CNR

actions through Plan recognition	actions. In this way it will know the next course of actions of the agent.		

6.1.3 Anticipatory mechanisms

Table 6-3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Anticipatory behavioural control	Actions are selected and fine-tuned exploiting their success in prediction as a measure of their appropriateness.	Under development	Multiple forward models based on schema mechanism	ISTC-CNR Possible collaboration with UW-COGSCI, NOZE and OFAI
Action selection by predictive reinforcement learning	The more successful schemas are linked to situational cues so that their future availability in similar circumstances is raised. The situational cues become then possible triggers of action schemas.	Under development	Schema mechanism	ISTC-CNR Possible collaboration with NOZE and UW-COGSCI
Goals and plans selection by explicit expectations	Once an intention is created, the cognitive system selects the most appropriate goal and plan using the prediction of their mid and long-term effects. This strategic mechanism is used to discover long term conflicts between goals and to reason about alternative anticipated course of actions.	Under development	Planner	ISTC-CNR, NOZE
Surprise	The cognitive system should be able to elicit a	Under development	Schema mechanism	ISTC-CNR, NOZE

	surprise reaction when a relevant mismatch is detected. Surprise should be possible both from mismatches at sensory-motor level and knowledge level expectations.		and Knowledge representation system	
Surprise-based shift between deliberative and automatic control of action	When surprise is not manageable by automatic action tuning, the control of action is shifted at the higher deliberative levels.	Under development	Schema mechanism and Knowledge representation system	ISTC-CNR, NOZE
Desired body-environment states (goals) as central organising elements of sensorimotor actions	The system uses desired body-environment states to organise and guide learning of sensorimotor actions in robotic arms	Under development	Anticipated desired states allow the system to chunk fine movements in order to build sensorimotor schemes (actions). These actions will be assembled as building-blocks to produce more complex behaviours.	ISTC-CNR
Reliance, help, obstacle, delegation and trust, both for competition and cooperation, by anticipating other's	The cognitive system behaves in terms of anticipated world states, distinguishing between positive and negative social interferences. This permits the cognitive system to understand opportunities or obstacles in the environment and to act in	Under development	Prediction of other agents' actions through Plan recognition	ISTC-CNR

behaviour	cooperation or competition			

6.1.4 Integration

A note: some parts of the system ISTC-CNR uses are developed in collaboration with NOZE; ISTC-CNR does not consider them for the sake of integration, even if there are two partners involved.

Table 6-4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner
Perception and concept formation	The cognitive system could be provided with a more sophisticated mechanism able to extract perceptual information from raw data to abstract high level frames on the basis of low-level sensory motor contingencies. Currently only a conceptual high level representation of data is adopted.	Conceptual knowledge will be extracted or based on learning; less and less knowledge will be predefined at design time by the programmer.	OFAI IDSIA LUCS
Learning a model of the environment	An adaptive mechanism that is able to build from scratch a map of environment on the basis of its interactive experience.	The system will be able to manipulate both pre-existing and learned information. Its model will be better for moving in the environment, e.g. being more attuned to its dynamics.	UW-COGSCI IDSIA
Selective attention and saliency maps	A mechanism to filter (both in a top-down and in a bottom-up fashion) relevant information in the environment on the basis of context effects	Input filtering will enhance performance and speed.	LUCS IDSIA

	and anticipation of informational gain.		
Optimal mechanisms for statistical learning	The cognitive system should predict at real time adopting optimal algorithms to obtain inductive generalizations.	Statistical learning will enhance the predictive capabilities of the system.	IDSIA OFAI
Visual identification of objects or relevant aspects of objects	Identification of targets and obstacles to allow a robotic arm to reach targets or assume postures in space	Successful eye-hand coordination in tasks that require reaching, or assuming postures in space, with respect to targets and/or obstacles	LUCS IDSIA

6.2 Mechanisms detailed description

6.2.1 Perception and concept formation

ISTC-CNR architecture mainly operates on a set of conceptual representations, and it adopts a set of routines for interacting with sensory data. This means that the anticipatory mechanisms manipulate data having a different format from sensors and effectors; data are manipulated by routines and the system is provided with a higher level conceptual representation. ISTC-CNR wants to integrate a mechanism permitting to treat directly perceptual information, in order to embed lower-level anticipatory capabilities, mostly related to sensory-motor activity. The work of LUCS and IDSIA can be thus integrated.

Another possibility is to allow the system to learn new concept by only manipulating an initial repertoire of actions, as done by OFAI; knowledge will be extracted (e.g. new Schemas or new beliefs to be used for planning) from raw data and new concepts formed by the means of sensory-motor interactions.

Classification of the integration type:
The percept/concept formation mechanism can be put in a sequence; it will provide input to many mechanisms, including the Schema mechanism and planning, in a direct way.

6.2.2 Learning a model of the environment

ISTC-CNR architecture manipulates explicitly represented knowledge, such as maps and models of the environment. ISTC-CNR wants to integrate a mechanism permitting to learn a predictive model of the environment by interacting with it, as it is done by IDSIA and UW-COGSCI.

Another interesting possibility is to integrate on-the-fly pre-existing knowledge (such as a map of the environment) with dynamic and more updated knowledge acquired by sensory information during exploration. Epistemic actions (such as search for, or look a specific place) can be performed in order to fill in incomplete maps or to obtain missing/wrong information.

As a result, the system will be able to reason about its (lack of) knowledge and to perform exploratory behaviour as a result of a need for information. Since most of the information contains predictive elements, the system will be biased to explore actions which consequences are not fully known, thus behaving in a curiosity-driven way; this is similar to what is done by IDSIA.

Classification of the integration type:
Pre existing and new knowledge can be integrated both in a sequential and overlapping way; it will be a direct interaction.

6.2.3 Selective attention and saliency maps

The selective attention mechanism will be used for filtering perception, in order to extract from the environment only the most salient features. For example, the "fovea" mechanism developed by IDSIA can be used in order to focus perceptual resources only on a limited and informative portion of the environment. In a similar way, saliency maps developed by LUCS can provide a pre-processing of information.

However, in ISTC-CNR architecture saliency is defined mostly in a goal-oriented way: what is most salient depends on system's current tasks and goals, which are explicitly represented. Thus, in order to successfully integrate a selective attention/saliency map mechanism into ISTC-CNR architecture, it will develop specialized mechanisms representing goal-oriented influences; in this way the selective attention mechanisms will receive a feedback from the higher level modules (such as the current active goal).

The feedback is intended to direct selective attention in a goal-driven way. For example, the feature extracted from the environment will be evaluated and only those relevant for the current tasks and goals will be retained. Or, epistemic actions can be used for orienting the perceptual mechanism towards the most relevant features.

As an alternative, a goal-driven feature extraction algorithm and a more bottom-up perceptual mechanism can be put in competition, letting the system arbitrate between different kinds and different sources of information.

Classification of the integration type:
The attentional mechanisms can either be placed first in a sequence, providing input to other modules, or in parallel with them. There will be direct or indirect or direct interaction, depending on the presence of feedback.

6.2.4 Optimal mechanisms for statistical learning

ISTC-CNR adopts many sources of prediction, including statistical learning, reasoning, plan recognition, etc. ISTC-CNR is interested in adopting the most accurate and effective statistical learning algorithms, that are already implemented by other partners such as IDSIA and OFAI.

Statistical learning and induction will be integrated into the Schema mechanism, permitting to realize better prediction for dealing with real time situations.

This mechanism will work either in parallel or in competition with the other predictive mechanism we adopt. In the case of parallel mechanism, an integration mechanism will be provided that fuses information depending on their reliability; in the case of competition, a selection mechanism will be developed that will select the most reliable predictor.

Classification of the integration type:

Statistical learning mechanisms can enhance the predictive capabilities of the system, possibly in a parallel way; they will be used both for the Schema mechanism and for planning, in a direct interaction.

6.2.5 Visual identification of objects or relevant aspects of objects

ISTC-CNR will conduct a research to build a controller capable of autonomously learning a repertoire of actions to be used as building blocks to produce more complex behaviours. The controller will allow a robotic arm (simulated and real) to reach different target points in space with the tip of its last segment (“hand”), and/or to assume different postures in space (complex versions of the task will involve the presence of obstacles), mainly based on proprioception. The integration might involve the addition of a camera to this system, and additional controllers developed at IDSIA and LUCS on vision and attention, to allow it to identify targets, and to identify eventual obstacles “in the way”, while reaching targets or assuming postures. Vision and attention modules might be used in conjunction to the controller of the robotic arm developed at ISTC-CNR to study the problem of the formation of repertoires of actions in an eye-hand coordination domain.

7 LUCS

7.1 Integration of Mechanisms

LUCS is interested in testing many of the anticipatory and predictive mechanisms available from the other partners as a component in their tracking system. If the technical difficulties of combining these sometimes very different mechanisms to be solved, it will allow many of the mechanisms to be compared within a common framework.

The nature of the tracking system which can use both symbolic and sub-symbolic representations makes it possible to combine it with many different types of architectures.

7.1.1 General cognitive mechanisms

Table 7-1

General mechanism(s)	Use in the scenarios	Availability status	Partner
Adaptive bottom-up attention system	Needed generally to find visual targets	Available	
Predictive tracking system	Used in all tracking tasks where there is a delay	Available	
Context-sensitive reinforcement learning/associations	General mechanism to add contextual information to associative systems	Available	
Path-planning system	Needed for mobile robots	Available	
Template-based object recognition system	Needed generally for target detection	Preliminary implementation available	
Event detection and event association	Used as world model	Preliminary implementation available	
Emotional conditioning model	Used for evaluation of potential targets and cues	Available	
Context integration	Used to form	Available	

model	codes of sequences of events or stimuli		

7.1.2 Predictive mechanisms

Table 7-2

Predictive mechanism(s) and type	Use in the scenarios	Availability status	Partner
Event associator	Used as associative world model	Available	
Kalman filter predictor	Used as predictor in tracking systems	Simplified implementation available	
Knowledge based prediction	Will be used for more advanced prediction from previous examples in tracking tasks	In implementation	ISTC-CNR, NOZE
Hierarchical prediction	As above	Non-available	UW, IDSIA
LSTM	Used for contextual information that is not local in time	Available	IDSIA

7.1.3 Anticipatory mechanisms

Table 7-3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Surprise based shift between deliberative and automatic control of action	Used during learning and control in tracking and mobile robots	In implementation	Event associator & Knowledge based prediction	*IST_CNR, NOZE*
Artificial Immune Systems	Will be used for more advanced prediction from	Under development	Event associator & Knowledge	*OFAI*

	previous examples in tracking tasks		based prediction	
Anticipation by analogy	Will be used for more advanced prediction from previous examples in tracking tasks	In reimplementation	Event associator & Knowledge based prediction	*NBU*

7.1.4 Integration

Table 7-4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner
Artificial immune systems	The predictive/anticipatory part of our tracking system can potentially be replaced by any of a number of mechanisms that will allow these systems to be compared. It is unclear to what extent the representations used will be suitable for all models, however.	Comparison with system based on other mechanisms	OFAI
Knowledge based reasoning			ISTC-CNR, NOZE
Classifier systems			UW-COGSI
System for analogy making			NBU

7.2 Mechanisms detailed description

7.2.1 LSTM

The context model developed by LUCS is limited to code events that occurred close in time to an event that they influence. By adding an LSTM network to LUCS current model, LUCS hopes to be able to design a more competent context system. It remains to be seen if this more advanced system is able to solve some of the tasks where our current system fails.

7.2.2 Mechanisms for prediction and anticipation

It is the general goal of LUCS to integrate different mechanism for prediction and anticipation with the systems LUCS has available. Although this appears possible in principle, it is not certain that the different mechanisms can be combined in a straight forward way. Some of the integrations listed above may not be realistic for practical reasons.

Since many of the game room scenarios include a tracking component and our tracking system allows the integration of symbolic reasoning methods and more control directed approaches as well as neural network models, it appears that this will be a suitable domain for comparison between different mechanisms. A consequence of this approach is that the same performance measures can be used in all cases.

8 NBU

8.1 Integration of Mechanisms

8.1.1 General cognitive mechanisms

Table 8-1

General mechanism(s)	Use in the scenarios	Availability status	Partner
1. A mechanism to supply the model with input and a goal	The robot must know the goal during the execution of any actions and the information coming from perception must be internalized and influence the reasoning processes	Available	
2. Retrieval of past episodes from memory	A mechanism to "recall" past episodes which look like current one at some degree. For example: The robot sees several cubes and has to make the prediction on the basis of analogical transfer that the object looked for is behind these cubes /analogy with a previous similar episode in order to obtain more information about the current one/	Available	
3. Learning and Knowledge base(s) management	A mechanism to manage and update the KBs of the robot. Modification of weights among agents (learning) and automatic coding of new episodes which come from observation, prediction, generalization (as the last stage of analogy) etc. The generation of predictions on the basis of analogy is based on evaluation of the predicted outcome. At the same time assessment of the "quality" of the learned information is needed (e.g. based on reinforcement learning).	Non-available	UW-COGSC ISTC-CNR
4. Perception *vision* – sensors: camera, sonar *hearing* -	Process the information from the sensors (active perception) of the robot and code and relate them in the symbolic form used by AMBR	Non-available	ISTC–CNR, NOZE, IDSIA, LUCS

microphone *tactile feedback* – bumpers, hands	(constructive perception). Very important is the recognition and encoding of relations as they are essential for the knowledge representation base and its use. The successful implementation of such learning mechanisms is related to the implementation of Mechanism 2.		Navalpakkam Laurent & Itti, Vision Research 45 (2005) 205–231
5. Action(s) mechanism and motor control	AMBR needs a mechanism for planning, action, and action monitoring.	Non-available	UW-COGSCI, IDSIA Needed from other partners: A mechanism for generating a plan and running it with constant action monitoring
6. Decision making	Judgment and decision making mechanisms must be included in AMBR in order to give the robot (real or simulated) the possibility to evolve in the scenarios' environment making judgments and decisions based on prediction (anticipation).	Non-available	UW - COGSCI JUDGEMAP (a model of judgment based DUAL/AMBR), other models for judgment/decision making
7. Emotions	Emotions are an important mechanism that can be used to implement prediction/anticipation (see D2.1, subsection 4.3). They can be integrated in AMBR as a low level mechanism, related to global changes in the system (resource allocation, activation mechanism, capacity of the WM etc.) or as a selection mechanism in analogy making (episodes related to the current emotion 'experienced' by the robot		ISTC – CNR, IST

	can be more likely to retrieve). Thus including emotions can lead to a more adapted behavior of the robot and serve as a basis for integration of emotion and analogy based anticipation mechanisms.		

8.1.2 Predictive mechanisms

Table 8-2

Predictive mechanism(s) and type	**Use in the scenarios**	**Availability status**	**Partner**
Transfer	When an episode similar to the current one is retrieved from LTM, part of this episode's knowledge should be transferred to the new one. Permitting direct prediction of various properties of the current scene. E.g.: Spatial relations prediction - predicting the location of an object; Environment evolution prediction – predicting the changes in the environment by using knowledge from one domain and transfer it to another domain.	Available	
Generalization	The architecture should be able to generalize on the basis of specific episodic knowledge.		
Selective attention	Tracking, recognition and prediction of salient characteristics of the scene, filtering the data processed by the higher level mechanisms. Should involve the existing AMBR WM focus of attention (as a top-down mechanism).	Non-available	LUCS
Schemas with condition-action-prediction part	AMBR needs a set of mechanisms to select and correctly perform the actions needed for the completion of a task.	Non-available	UW-COGSCI, IDSIA

	This could be achieved by means of a special type of situations which are basically schemas that include a condition part, an action part and a prediction part. This new type of situation must be subject to learning based on experience. The learning mechanism must account for the success of the task completion. The latter should influence the future use of the perception-action-prediction schema via reinforcement or by additional symbolic encoding (e.g. like ACT-R).		

8.1.3 Anticipatory mechanisms

Table 8-3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Combination of emotion and transfer	Emotions eliciting preparatory behavior can lead to changes in some global mechanisms in AMBR like increase of the activation, narrowing of the working memory etc. which influence the process of analogical mapping and thus the transfer (which is the main predictive mechanism in AMBR). The elicited emotion, already represented by the system can be a seed for retrieving episodes related to similar emotions and thus relevant for the situation at hand. Theoretically this can be a chain mechanism: emotion → episode →emotion → …, leading to a series of predictions.	Non-available	Transfer is the main predictive mechanism in DUAL/AMBR	ISTC-CNR, IST

8.1.4 Integration

Table 8-4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner
Selective attention at the perception may introduce anticipatory behavior	Selective attention as a bottom-up process can be integrated with top-down (based on spreading of activation) mechanisms already available in DUAL/AMBR. Such a mechanism can be used in scene recognition, search and creation of internal maps. Selective attention can direct the perception of the robot and thus will influence the process of episode retrieval and analogical transfer.	Improving performance by more efficient information acquisition resulting in shorter task completion times.	LUCS
Emotions	Anticipation based on emotion can be advantageously combined with anticipation based on analogy by altering the retrieval and transfer process. Emotions can influence some global parameters of DUAL/AMBR such as working memory capacity, activation levels etc.	Faster reaction times based on the fact that emotions set the system an appropriate state. More precise episode retrieval due to the emotional context and thus better performance.	ISTC-CNR, IST
Condition-action-prediction schemas	They can represent a new conceptual structure in DUAL/AMBR instantiated in different	Improved planning, much better action monitoring which	UW-COGSCI

	'episodic' schemas. They can be retrieved from memory due to the activation in WM of any of their parts – condition, action or prediction. The same would be true for the transfer of parts of such schemas. Thus, this mechanism can be used for many purposes: action and motor control, prediction of the action results, understanding of the action based on transferred action part or even of the conditions which have led to the present action or results of it.	will result in an amelioration of the overall performance. Also the possibilities to restate the goals and plans "on the fly"; during action execution will possibly provide more efficient way of handling the tasks.	

8.2 Mechanisms detailed description

8.2.1 Selective attention

The selective attention mechanism will bring anticipatory behavior at the perception level and will perform a first stage categorization (selection of important features and relations) of the perceived environment. This preliminary work will reduce the information that will be used by the main anticipatory mechanism thus not only reducing the information to be processed but also filtering out information irrelevant to the current task. This integration should speed up the anticipatory processes and make them more reliable.

This mechanism should work in parallel with the main anticipatory mechanism (analogical transfer). If the prediction resulting from analogical transfer is used to direct attention two mechanisms of selective attention will be available – a bottom-up and a top-down one. The interplay between these two mechanisms must be further explored.

Classification of the integration type:
Parallel and competing attentional mechanisms with indirect or direct interaction depending on the competing mechanism.

8.2.2 Emotions

The integration of emotions may bring a different level of anticipatory mechanism in AMBR. Emotions may influence the way AMBR agents get activation by modeling various kinds of emotions that have different global effects on AMBR such as slowing or accelerating the computing speed of the system, modifying the size of the working memory etc. In the latter case emotions can be thought of as 'experienced' by the system.

Emotions can become part of the description of an episode and thus participate in mapping and transfer. In the former case they will influence retrieval and transfer (prediction) and in the latter they will be transferred (predicted). In both cases emotions will influence the action planning in DUAL/AMBR.

Classification of the integration type:
'Experienced' emotions will be parallel to and influence the standard mechanisms of DUAL/AMBR.

Emotions which are represented and anticipated lead to retrieval of episodes related to a similar emotion. This can influence the process of retrieval and thus of reasoning and analogy based anticipation. The two mechanisms are overlapping and are related to the same general mechanisms – retrieval and reasoning.

9 NOZE

9.1 Integration of Mechanisms

9.1.1 General cognitive mechanisms

Table 9-1

General mechanism(s)	Use in the scenarios	Availability status	Partner
A deliberative mechanism to choose an intention	The cognitive system should be able to choose in a deliberative ways between concurring options on the basis of salient beliefs and previous commitments.	Under development	ISTC-CNR, NOZE
A planning mechanism	The cognitive system should be able to identify the best means to achieve its current intentions. The planner should also be able to construct plans at different level of abstractions.	Under development	ISTC-CNR, NOZE
A Routine-based Perception	A set of routines to manage the low level interactions with sensors and effectors fully integrated with the simulator providing a more high level data format.	Under development	ISTC-CNR, NOZE
An extensible cross language protocol	The need for a standard interchange language (i.e. like KIF – Knowledge Interchange Format) to share information across different architectures	Under development	NOZE; Possible collaboration with ISTC-CNR, NBU
A concurrency mechanism	A mechanism able to create non-deterministic concurrency between any kinds of module in the integrated architecture.	Available	NOZE; Possible collaboration with ISTC-CNR, NBU
A computational resources controller	A mechanism able to control, to dispatch and to plan computational resources usage (cpu, time, memory) in order to use them to optimize its own goals fulfilling.	Available	NOZE; Possible collaboration with ISTC-CNR, NBU

9.1.2 Predictive mechanisms

Table 9-2

Predictive mechanisms and type	Use in the scenarios	Availability status	Partner
Knowledge based prediction	The dynamics of the environment, of the consequences of the plans, and of other agents' behaviours is inferred using a declarative knowledge and memory. For example, the cognitive system, while patrolling around the house, can infer from its KB the predictive belief that during the day rooms having windows will be floodlit.	Under development	ISTC-CNR, NOZE
Prediction based on forward model	The forward models are part of the schema mechanism allowing the prediction of the next event (i.e. next sensory input as low-level consequences of actions).	Under development	ISTC-CNR, NOZE
Prediction with multiple paired forward models	To select, monitor and adjust the action, a mechanism managing multiple schemas doing different predictions is adopted. The schemas predict the outcomes of alternative courses of actions at the same time.	Under development	ISTC-CNR, NOZE
Prediction based on different models	A meta model should take into account effects or dynamics of predictions produced by different modules with different predictive mechanisms and capabilities.	Under development	NOZE; Possible collaboratio n with ISTC-CNR, NBU

9.1.3 Anticipatory mechanisms

Table 9-3

Anticipatory mechanism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Goals and plans selection by explicit expectations	Once an intention is created, the cognitive system selects the most appropriate goal and plan using the prediction of their mid and long-term effects. This strategic mechanism is used to discover long term conflicts between goals and to reason about alternative anticipated course of actions.	Under development	Planner	ISTC-CNR, NOZE
Surprise	The cognitive system should be able to elicit a surprise reaction when a relevant mismatch is detected. Surprise should be possible both from mismatches at sensory-motor level and knowledge level expectations.	Under development	Schema mechanism and Knowledge representation system	ISTC-CNR, NOZE

Goals and plans selection by explicit expectations	Once an intention is created, the cognitive system selects the most appropriate goal and plan using the prediction of their mid and long-term effects. This strategic mechanism is used to discover long term conflicts between goals and to reason about alternative anticipated course of actions.	Under development	Planner	ISTC-CNR, NOZE
Surprise-based shift between deliberative and automatic control of action	When surprise is not manageable by automatic action tuning, the control of action is shifted at the higher deliberative levels.	Under development	Schema mechanism and Knowledge representation system	ISTC-CNR, NOZE

10 OFAI

10.1 Integration of Mechanisms

10.1.1 General cognitive mechanisms

Table 10-1

General mechanism(s)	Usage in the scenarios	Availability status	Partner
Artificial Immune Systems (AIS)	General multilayered architecture that develops over time	Under development	OFAI
Prediction Fractal Machines (PFM)	Deviate an environmental “grammar” based on fractal machines	Under development, existing prototype	OFAI

10.1.2 Predictive mechanisms

Table 10-2

Predictive mechanism(s) and type	Usage in the scenarios	Availability status	Partner
Artificial Immune Systems (AIS)	Predictions at different levels of abstraction based on the short term expectations related to (virtual) sensor inputs Extraction of primitive laws of the procedures in the agent’s environment.	Under development	OFAI
Prediction Fractal Machines (PFM)	Predicting the future of discrete sequences from fractal representations of the past.	Under development, existing prototype	OFAI

10.1.3 Anticipatory mechanisms

Table 10-3

Anticipatory mechanism(s)	Usage in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Artificial Immune Systems (AIS)	The predictive capabilities of AIS are used to form a large interactive anticipatory framework of different abstraction levels. The expectations are also used in terms of a larger temporal scale and complexity.	Under development	Artificial Immune Systems (AIS)	OFAI

10.1.4 Integration

Table 10-4

Integrable anticipatory mechanism(s) from other participants.	Possible integration	Evaluation of the resulting integration	Partner
Selective attention & vision	Usage as input for the (virtual) sensor pool	Under development	LUCS
Any sensory filter (especially vision) modules and mechanisms	Usage as input for the (virtual) sensor pool	Under development	All Partners
Integration of sensory flow via prediction	Categorisation	Under development	ISTC-CNR
Integration of sensory flow at multiple levels	Hierarchical categorisation	Under development	ISTC-CNR

of time abstraction			
Qualitative decision making (Logics)	- Surprise - Interpretation of the next stimulus via abductive processes	Under development	ISTC-CNR
Emotion Module	Introduction of emotions and complex drives to the artificial immune system	Under development	ISTC-CNR?

10.2 Mechanism detailed description

10.2.1 Artificial Immune System

One of the basic and most relevant ingredients for OFAI Artificial Immune System will be the filtered sensor modalities that are used by the system to describe the significant parts of antigens, namely epitope, as well as the corresponding antibody's paratopes and further idiotopes. As described in deliverable 2.2 OFAI will use a so called "sensor pool" for the extraction and integration of any sensory information, and the AIS will furthermore just try to gather its information out of that pool without directly accessing raw sensory data.

The "sensor pool" will consist of a collection from less to more processed raw sensor data, virtual sensor information based on raw or processed sensor data, or any other relevant information about the environment. The sensor pool may even include such abstract sensor information as, e.g. "a pink object is present", "there is something in front of the robot", or "there is a high-level sound nearby".

As ingredients for this pool OFAI will need any sensor processing mechanisms that are available from the partners in the consortium (e.g. the selective attention and vision mechanisms developed by partner LUCS, but any other sensor processing and in particular visual processing mechanisms will be of great use).

In this context the anticipatory mechanisms "integration of sensory flow via prediction" and furthermore "integration of sensory flow at multiple levels of time abstraction" from partner ISTC-CNR can also be regarded as perceptual abstraction filters which OFAI may be able to integrate within this sensor pool.

Additionally at this point of time OFAI is thinking of integrating ISTC-CNR's "qualitative decision making (logics)" into its system. It should run in parallel to the artificial immune system and induce surprise to the system. This system could be seen as an integrated but external (in terms of integration into the immune system processes) observer, that may influence the behaviour and structures of the immune system by external regulation mechanisms. Something quite similar may also be introduced to enable to robot using more sophisticated drives and even emotions.

10.2.2 Interaction with the other mechanisms

In terms of interaction the emotion and surprise modules are planned to be run in parallel to the artificial immune system architecture. They will be able to influence the system by modifying system parameters and therefore steering the behaviour of the system into certain directions. Permanent interaction of the AIS and the external modules will guarantee that emotions are able to influence the behaviour of the system as well as the goal that it is engaged on (e.g. anger may lead to other goals, as affection).

The artificial immune system will always stay in control of the robotic agent, but be influenced by emotion and surprise modules when choosing the actions it takes and goals it performs.

The additional sensor filters and modules are integrated into a common sensor pool. The integration has to be performed following certain protocols in terms of interaction and maintenance. As long as the filters are well programmed and the interfaces are well specified no side effects to the system should occur, nor – because of the strict separation between control system and perception system – should any sensor filter be able to affect the artificial immune system directly in any way.

For an overview see Figure 9-1.

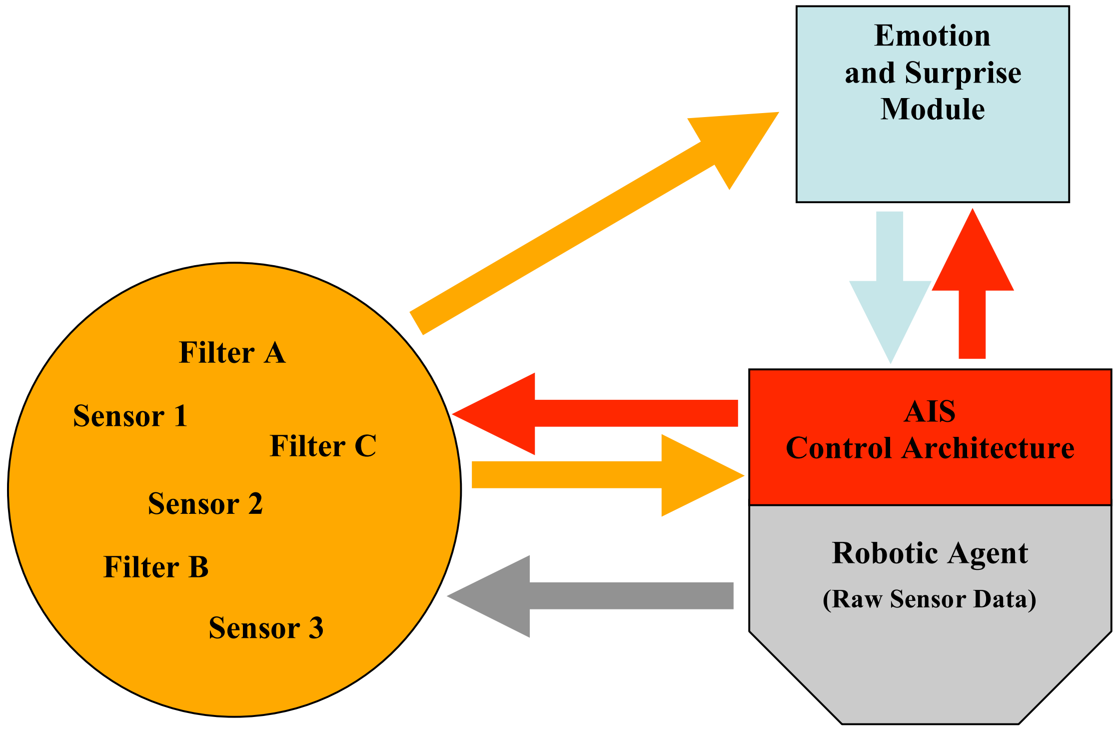


Figure 9-1. Schematic overview of the artificial immune system architecture (red) controlling the robotic agent (grey) which perceives raw sensor data and sends this to the sensor pool (orange). The sensor pool consists of several sensor filter and abstraction mechanisms which then are used as an input for the AIS control architecture in modeling the antigens and antibodies. Finally the emotion and surprise module (blue) influences the AIS control architecture by modifying some of its system parameters.

10.2.3 Integration

As said before, since the basic artificial immune system architectures OFAI dealt with before did not contain modalities which allowed influence by emotion or surprise mechanisms, the integration of such mechanisms, which induce some kind of external drives to the system, will be a major goal within the project.

Such an "emotion module" which runs in parallel to the artificial immune network and gathers information from the filter pool, as well as from observing the activities and operations of the artificial immune system will introduce a lot of new features including emotional reactions, new more complex drives and new problem solving abilities. Further, when allowing the "emotion module" to have influence on internal mechanisms of the system (e.g. controlling the rate of mutation, the selection and removal of antibodies, etc.) even the "anticipational power" of the AIS will be influence and enhanced.

As negative effects one may mention the negative effects that the introduction of emotion capabilities always has to a system: decrease of predictability by an external observer, introduction of more instability to the system. But of course these negative effects can also be seen as advantages, particularly in relation with artificial immune systems and in terms of evolutionary diversity which may lead out of local minima the system may have run into.

Filter mechanisms from other partners (e.g. "selective attention and vision" from LUCS) that are integrated into the filter pool, will have no negative side effects on the system, as long as the interfaces to the pool are well defined and maintained.

Of course as already mentioned these new perceptual mechanisms are of great help to broaden the agents' sensory horizon. With every new sensor filter the abilities of the system in terms of modelling its environment by antigens will rise and allow dealing with it much more efficiently. Therefore of course also the goal solving behaviour will be improved with those sensor enhancements.

10.2.4 Evaluation of the resulting integration

As described before the use of several different virtual sensors and especially sensor and abstract filters is inevitable as an input for the artificial immune system's environmental and internal representation mechanisms. Therefore the integration of any new mechanism in this correlation will lead to increasing power of the system. The comparison of systems using different sensory mechanisms will be performed by running several test using different sensor filter configurations from inside the sensor pool while the robotic agent tries to reach one and the same goal, and afterwards measured and compared by statistical means.

11 UW-COGSCI

11.1 Integration of Mechanisms

11.1.1 Predictive mechanisms

Table 11-1

Predictive mechanism(s) and type	Use in the scenarios	Availability status	Partner
Sequential prediction	Necessary in various scenarios to be able to predict continuous and abrupt changes that obey certain sequences. For example, to recognize the object permanence in the rolling ball problem or to predict the path of the marble in the marble game.	Several potential systems are available but not integrated: LSTM is good in sequential processing but not so good in symbolic processing. XCS and ACS2 may have more potential in the latter part of the integration.	UW-COGSCI, IDSIA; OFAI; ISTC-CNR
Change prediction	Change is another form of prediction that has partially been applied in several systems but requires further investigations. Essentially all scenarios require the accurate prediction of change or progress in the environment to behave optimally.	LSTM is a change predictor in some sense. ACS2 as well as artificial immune systems are as well. However, the representation of change prediction may be changed and optimized.	UW-COGSCI, IDSIA, OFAI, ISTC-CNR and others
Hierarchical predictions	Several scenarios require the representation of objects implying also the	Non-available	UW-COGSCI,

	learning of permanence of objects. Other scenarios require solving abstract sequential tasks. Both tasks may be solved by implicit object representations. However, a more appealing alternative seems to be a hierarchical, increasingly abstract representation of actual visual input. Since the tasks require accurate abstract (potentially sequential) reasoning, a hierarchical representation that suitably abstracts over simple sensory input would come in very handy.		IDSIA

11.1.2 Anticipatory mechanisms

Table 11-2

Anticipatory mecha-nism(s)	Use in the scenarios	Availability status	Connection with predictive mechanisms	Partner
Anticipatory object recognition	Several scenarios require the manipulation of objects – which, of course, requires the capability of object recognition – either learned or pre-wired. However, also other scenarios that do not require immediate object recognition require the successful prediction of object location (essentially another form of object interaction).	A big challenge	The capability of general (change-) predictions is a prerequisite to be able to predict object behavior (in some sense a restricted change prediction).	UW-COGSCI; IDSIA, OFAI, ISTC-CNR, and others
Use of context information	Context information may be used in several scenarios to improve predictions as well as control and decision making. Moreover, motivations may be seen as currently desired context information.	LUCS has a context processing system. The hierarchical systems of Rao/Ballard may be used as well.	Context information is seen as a preset for predictions and control, essentially changing the prior probabilities in	UW-COGSCI; LUCS

			a Bayesian sense. Thus, predictions are required and will be improved by using context information efficiently.	
Goal-oriented action triggering	Many scenarios require changing goal pursuit, in which essentially a simple reinforcement learning approach is inappropriate. Goal-oriented action triggering is a valid alternative.	UW is working with associative networks that link start state, goal state, and actions and allow a bidirectional network activation	Predictions need to be available that predict goal outcomes given current state and actions. The inverse model of these predictions can then be used to trigger actions and control given state and goal.	UW-COGSCI
Integration of motivations	To be able to make the adaptive system move by itself, goal states need to be provided or internally generated. To accomplish an internal generation, motivations seem necessary that induce the generation of desired goal states.	Only few reinforcement learning mechanisms are available. General motivations, associations to goal states and their triggering of goal states and resulting, emerging activity that leads towards that goal state are Non-available.	One key aspect seems to be that goal states need to be associated with actions that lead to these goals. Thus, goal-oriented action triggering remains another challenge to accomplish.	UW-COGSCI; IDSIA, OFAI; NBU
Integration of emotions	Emotions may bias motivations to improve the	Some approaches	Without motivations and	UW-COGSC

	balance between different motivations in action. Several tasks require the accomplishment of multiple goals in which such a bias seems important.	from NBU as well as ISTC-CNR.	related predictions emotions cannot be integrated from the perspective described.	I, NBU; ISTC; IST

11.2 Mechanisms detailed description

11.2.1 Sequential prediction

Many of the predictive learning system in the project are episodic and not as much sequential. For example, the XCS classifier system as well as the ACS2 system learns iteratively from each problem instance but they do not predict successive states (episodic nature of learning). Although ACS2 actually predicts the next state, the prediction is hardly used to improve learning of sequences. Moreover, both systems are not suitable to solve non-Markovian tasks – those, tasks in which the current state information is not necessarily sufficient for optimal decision making. Thus, it is apparent that sequential predictive capability – that is, predictions that form chunks of successive state changes (or gradual changes in state) – need to be improved. Other labs including the predictive fractal machines as well as the LSTM have internal states and thus non-Markov capabilities. Potential combinations need to be investigated further.

Clearly, the long-short term memory network appears very capable in predicting gradual changes seeing its strong capability in (1) learning context-sensitive grammars, and (2) chaotic functions. The recently published Evolino system (Wierstra, Schmidhuber, Gomez, 2005) showed that LSTM-based networks are very good sequence learning tools. However, LSTMs are network structures with pre-wired, restricted expressive capabilities and initial biases. The Evolino architecture improves on these restrictions by combining an evolutionary structural learning mechanism, which structures the lower-layer LSTM units, with a gradient-based (pseudo inverse) optimization mechanism yielding highly and long-term accurate sequential predictions.

The combination of the LSTM and the XCS mechanism promises to yield several new system advantages. (1) The capability of online learning and iterative rule-structure improvement. (2) The enhancement of XCS capabilities to also serve as a non-Markovian learning system. (3) To combine the symbolic, rule-based XCS representation with the sequential but sub-symbolic, neural representation of the LSTM system. The Evolino system has shown that a combination of evolutionary structural learning with gradient-based predictive learning is fruitful and worthwhile The XCS/LSTM combinations may enhance these capabilities even further offering a bridge between symbolic and subsymbolic representations.

11.2.2 Change prediction

Despite many insights in (mainly cognitive) visual processing but also video compression, most predictive systems available in our project are systems that predict next states and not the changes that lead to those next states. LSTM is one exception to this since LSTM combines predictive change with predictive states using its multiplicative gating mechanism. However, there still seems to be room for improvement in this respect as well. XCS and ACS2, on the other hand, predict next states and not the change to next states.

In cognition, the question whether humans are actually predicting next states or the change to next state remains an open question (most likely they do both with an emphasize on either one dependent on the task and the task-related representation available). However, the task-relatedness is the crucial point here and remains to be shown when the one or the other type of prediction applies.

This observation leads to the suspicion that task-relatedness plays a crucial role as well as the available task-related representation. For example, in a predictive task in which visual input is continuously shifting from one side to the other and back, a predictive system is expected to do best which is able to predict such visual shifts (directed activity transitions). On the other hand, if a visual input simply changes in brightness, it is the intensity which changes. Thus, intensity changes and simple linear changes are most likely the most effective change representations. If the scene consists of combinations of the former, both predictive capabilities in parallel are expected to be most effective. However, also clearly nonlinear changes are necessary sometimes – for example, when the camera reaches its most extreme tilt and needs to turn back, or when the image (like the monitor) reached maximum brightness and can only decrease in brightness. Thus, abrupt changes in the progressing stream require non-linear representations.

Besides general visual changes, such changes may be restricted to a current object in the scene or a general particular area. To account for this, object recognitions are necessary that restrict potential changes to the object-restricted area or that exclude the object area, etc.

Thus, it remains a highly important part of the MindRACES project to differentiate and evaluate different predictive capabilities of the different available systems and then to combine those systems that have capabilities required for the predictive and anticipatory tasks in consideration.

11.2.3 Anticipatory object recognition

The former paragraph already mentioned the required object recognition for accurate change prediction (in scenes in which objects are involved). Since this is also the explicit task in various scenarios defined in the MindRACES project, the accomplishment of an object-based predictive representation may be one of the big challenges in the project.

To accomplish this endeavor, we intend to combine the symbolic capabilities of XCS, as mentioned above, with the long-short term principles (that is, the memory cells) in the LSTM network. Essentially, a classifier may be enhanced to have an internal state that increases and decreases dependent on multiplicative units. A big challenge is the combination of the two – how strong should the influence of the multiplicative units be? How should they be initialized? To investigate these concerns, several combinations will be investigated.

In particular, in simpler predictive tasks such as the rolling ball or a simpler version of the marble game, it might be interesting to combine also the principles of context information processing with XCS and LSTM. In fact, higher-level layers in a hierarchical XCS-like (or LSTM-like) architecture can be expected (dependent on how they are structures) to predict changes in lower layer activity (see also below). Thus, they essentially provide context information with respect to the continuous changes. Such context information may represent a barrier in the marble game as well as the current movement of the relevant object in the game.

Thus, context may be tagged to an object, which, for example, is moved (or is moving) forward. Or, context may influence the tagged object, which, for example, reaches a barrier and thus changes its velocity vector. The available systems promise great potential in achieving highly capable predictive units that distinguish between objects and their behavior.

11.2.4 Use of context information

Clearly, predictive capabilities for their own sake are without much use. For a successful realization of anticipatory behavior, predictive capabilities need to be utilized for improving (a) further learning of more accurate predictions themselves, (b) integration of these predictions in visual (search) tasks, (c) integration of these predictions in predictive control, (d) integration and utilization of predictive capabilities for decision making.

In the previous section UW-COGSCI already proposed to integrate context information for improving predictions in several ways. Object-oriented context information may be utilized to predict visual change in several ways (object movement, barriers…). Moreover, context information may actually also stem from the control side. That is, context information may indicate that the robot is currently moving forward – which then in turn can pre-activate (or bias activation) towards those rules or neurons that indicate a visual shift towards a certain direction (visual expansion). Thus, different context information is expected to pre-activate different predictive units dependent on the available information.

Besides using control signals as context information, predictive capabilities may be combined with actual sensory feedback to stabilize and improve control. Given a current goal state and the actual state, UW is currently working on different schemes that use the difference vector or the actual state vector of the two information codes to improve and stabilize robot arm control. The capability of various systems available to the MindRACES partners to also express the confidence in certain predictions and thus the actual reliability of feedback information gives the control task another advantage.

There is one more form of context, which may be described as the motivational context, which leads to actual decision making. This context is discussed in a subsequent section.

11.2.5 Goal-oriented action triggering

Besides goal generation itself, discussed in the next section, it is important to integrate mechanisms that are capable of converting goals into actions that lead to such goals. In control as well as in cognitive psychology, such models are often termed inverse models – models that produce actions or action gradients given current sensory input and desired goal state (or goal state properties). There are several systems that use such mechanisms including Hebbian learning models that generate bidirectional associations as well as several others investigated by Haruno, Wolpert, and Kawato and others (Haruno et. al, 2001, 2003; Jordan and Wolpert, 1999). UW is investigating its own system developed for robot arm control (Herbort, Butz, Hoffmann 2005) as well. These mechanisms may be enhanced to the hierarchical, predictive and anticipatory mechanisms discussed.

Moreover, it seems essentially necessary that such goal-oriented action triggering is accomplished in hierarchical representations because abstract goal representations most likely cannot be directly associated with, say, goal coordinates. Translations dependent on the current sensory input and environmental context seem necessary. Moreover, transitions from abstract to (currently possible) concrete goal states are necessary. Also a goal might not be immediately reachable so that intermediate sub-goals may need to be activated and distinguished. Also, sub-goal generations seem to be most appropriate in a hierarchical predictive architecture.

Haruno, M., Wolpert, D. M., & Kawato, M. (2001). Mosaic model for sensorimotor learning and control. Neural Computation, 13 (10), 2201-2220.

Haruno, M., Wolpert, D. M., & Kawato, M. (2003). Hierarchical mosaic for movement generation. In T. Ono et al. (Eds.), Excepta medica international coungress series (Vol. 1250, p. 575-590). Amsterdam, The Netherlands: Elsevier Science B.V.

Oliver Herbort, Martin V. Butz, & Joachim Hoffmann (2005). Towards the advantages of hierarchical anticipatory behavioral control. KogWiss 2005.

Jordan, M. I., & Wolpert, D. M. (1999). Computational motor control. In Gazzaniga (Ed.), The cognitive neuroscience. Cambridge, MA: MIT Press.

11.2.6 Integration of motivations

Besides the important considerations of using predictive capabilities to improve model learning, visual processing, as well as immediate action control, the final points to design an actual cognitive system is to give it the opportunity to make decisions on its own. That is, a cognitive system should have certain, pre-wired motivations (such as the need to retrieve red objects as energy resources…) in order to generate currently desired goal states.

Thus, it is necessary to endow our predictive systems with a motivational module (most likely) using homeostatic variables that require certain actions or object interactions (such as object retrieval) to lead to satisfaction. The higher the difference between the actual state of a motivational variable and its base state the stronger its influence on decision making.
Homeostatic variables should be associated with goal states that lead to the (previously experienced) satisfaction of the variables. The higher the current difference in the variable, the larger the stimulation of the goal states and thus, the larger the drive to accomplish these goal states (matching the internal, desired goal state with actual sensory feedback).

To accomplish the successful implementation of such a scenario it seems important that the initially tested scenarios should be sufficiently simple. That is, only few motivations exist that may be accomplished with relatively simple actions. If this is accomplished, the architecture may then be enhanced to higher capacity and more challenging tasks and associated goals.

11.2.7 Integration of emotions

The simple task, however, may also serve as an interesting environment to study competitive scenarios in which emotional influences might play an important role. Hereby, we interpret emotions as biasing the strength of different motivations.

For example, there might be two motivations: One to search and retrieve food and another for being safely hidden in some cave providing shelter. The combination of the two may work fine usually leading to the search and retrieval of food (for example, in the multiple room environments) and the search for shelter once hunger and storage motivations are satisfied. However, if the environment changes to, for example, a bad day or the apparent presence of predators, the motivational influences may change in that more food is currently not as important as the need for shelter. Thus, it is the motivational bias that is changed by emotions. Several other scenarios come into mind in which such capabilities might be investigated: Such as dangerous rooms, etc.

Emotions may thus be interpreted as predictive motivational biases that bias the importance of motivations with respect to the current environmental context. Motivations certainly do that also themselves but emotions may be interpreted as a more general priority bias, that is, a multiplicative weighting of actual motivations and their influences on current behavior.

11.2.8 Hierarchical predictive representations

All above predictive and anticipatory capabilities require suitable representations. Most likely it will be a very important point throughout the project (and beyond) to consider many alternative sensory representations and encodings and find the best one for the learning mechanism at hand (and vice versa).

For many of the more challenging scenarios in the project, flat architectures neither provide the flexibility nor the speed to achieve challenging anticipatory behavior patterns in real time. Goals need to trigger actions not by specifying the exact required sensory inputs but rather a (sub-) set of goal properties. These properties do usually not denote actual sensory input but abstract sensory patterns. Only hierarchical structures can extract and process abstract sensory patterns effectively. This seems obvious from a neuroscience and cognitive psychology perspective, however, also in computer science, research in reinforcement learning showed that hierarchical representations are mandatory to solve challenging real-world tasks (and even much simpler symbolic tasks) effectively. Thus, hierarchical predictive representations await strong research effort in cognitive science in general and in the MindRACES project in particular.

From the anticipatory perspective in the project, higher levels should be used in a contextual sense providing expected activity to the lower input, biasing the activity patterns in the lower levels (changing priors in a Bayesian perspective). With an additional estimate of the accuracy (or importance) of these top-down expectations (or desired states), the influence can be weighted and compared to actual input to reach a consequent internal state estimate. Such hierarchical representations are intended to have not only an emergent internal representation of abstract environmental properties but also to have an immediate influence on sensory (and other) processing in the lower layers in an anticipatory way.

11.2.9 Selective attention

As the last point in UW-COGSCI future work perspective stands the issue of selective attention. The more complicated an environment becomes – with all its simple and interdependent changes – the more difficult it becomes to actually predict all currently observed changes. This leads us to the importance of selective attention and essentially the prediction of only parts of the actual incoming sensorial information – or, more generally, the prediction of different parts of the environment with different levels of accuracy. In this general interpretation of attention, attention is not a winner-takes all algorithm or a visual spot that completely ignore parts of the visual input but rather a gradual change of importance (more or less focused) that increases importance of some parts of the environment and decreases the importance of other parts.

Thus, attention is assumed to be predictive influencing the continuous predictive processing stream emphasizing the importance of sub-streams of sensory input. Two challenges arise when considering selective attention. (1) How selective attention may be integrated into a predictive system and (2) how to make the decision on which inputs to pay attention to.

There are several groups interested in attention represented mainly by our colleagues at LUCS. Attention, however, is so far not integrated into other systems of interest including the XCS system, the ACS2 system, as well as the LSTM system. The integration of attention-related processing capabilities poses an imminent challenge to the project.

The second part is more related to the motivational parts of our cognitive system. Essentially, motivations may be linked to several potential goal states that possibly even contradict each other. Only selective attention can choose between potential goal states, most likely considering the current potentials of achieving each of them and then directing visual processing and control towards the important factors to achieve the most promising state properties.

12 Conclusion

The possible collaborations identified at this stage of the project are summarized in Table 12-1. The next stage in WP6 will be to analyze in depth the possible integrations and implement the most promising ones.

Table 12-1. On each row the first column points out the participant that wishes to collaborate, the following columns show the intended collaboration with the others participants.

	IDSIA	IST	ISTC-CNR	LUCS	NBU	NOZE	OFAI	UW-COGSCI
IDSIA				Context-sensitive reinforcement learning methods				Combined hierarchical Bottom-up / Top down approach
IST	Vision, attention selection and object recognition; Model of the Environment		Planning; Knowledge representa-tion; Deliberative model with emotion; Emotions	Vision, attention selection and object recognition		Planning		Model of the Environment
ISTC-CNR	Perception and concept formation; Learning a model of the environment; Selective attention and saliency maps; Optimal mechanisms for statistical learning; Visual identification of objects or relevant aspects of objects			Perception and concept formation; Selective attention and saliency maps; Visual identification of objects or relevant aspects of objects		A Schema mechanism; Anticipatory behavioural control; Action selection by predictive reinforcement learning	Perception and concept formation; Optimal mechanisms for statistical learning; A Schema mechanism; Anticipatory behavioural control	Learning a model of the environment; A Schema mechanism; Anticipatory behavioural control; Action selection by predictive reinforcement learning
LUCS	Hierarchical prediction; LSTM		Knowledge based prediction; Surprise based shift between deliberative and automatic control of action		Anticipation by analogy	Knowledge based prediction	Artificial Immune Systems	Hierarchical prediction; Classifier systems

	IDSIA	IST	ISTC-CNR	LUCS	NBU	NOZE	OFAI	UW-COGSCI
NBU	Schemas with condition-action-prediction part; A mechanism for generating a plan and running it with constant action monitoring	Emotions; Combination of emotions and transfer	Learning and Knowledge base(s) management; Emotions; Combination of emotions and transfer	Selective attention at the perception level				Learning and Knowledge base(s) management; Condition-action-prediction schemas; Decision making; Schemas with condition-action-prediction part; A mechanism for generating a plan and running it with constant action monitoring.
NOZE			An extensible cross language protocol; A concurrency mechanism; A computational resources controller; Prediction based on different models		An extensible cross language protocol; A concurrency mechanism A computational resources controller; Prediction based on different models			
OFAI			Integration of sensory flow at multiple levels of time abstraction; Qualitative decision making (Logics); Emotion Module	Selective attention & vision				

	IDSIA	IST	ISTC-CNR	LUCS	NBU	NOZE	OFAI	UW-COGSCI
UW-COGSCI	Hierarchical predictions; Sequential prediction; Change prediction; Anticipatory object recognition; Integration of motivations	Integration of emotions	Sequential prediction; Change prediction; Anticipatory object recognition; Integration of emotions	Use of context information; Selective attention	Integration of motivations; Integration of emotions		Sequential prediction; Anticipatory object recognition; Integration of motivations	