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Robotic Body-Mind Integration:
Next Grand Challenge in Robotics

K. Kawamura, S. M. Gordon and P. Ratanaswasd

1. Introduction

During the last thirty years, the fields of robotics, cognitive science and neuro-science made steady progress fairly independently with each other. However, in a quest to understand human cognition and to develop embedded cognitive artifacts like humanoid robots, we now realize that all three fields will benefit immensely by collaboration. For example, recent efforts to develop so-called intelligent robots by integrating robotic body, sensors and AI software led to many robots exhibiting sensorimotor skills in routine task execution. However, most robots still lack robustness. What, then, would be the next challenge for the robotics community? In order to shed light on this question, let's briefly review the recent history of robotic development from design philosophy point of view.

In recent years, design philosophies in the field of robotics have followed the classic dialectic. Initial efforts to build machines capable of perceiving and interacting with the world around them involved explicit knowledge representation schemes and formal techniques for manipulating internal representations. Tractability issues gave rise to antithetical approaches, in which deliberation was eschewed in favor of dynamic interactions between primitive reactive processes and the world [Arkin, 1998] [Brooks, 1991].

Many studies have shown the need for both, motivating work towards hybrid architectures [Gat, 1998]. The success of hybrid architecture-based robot control led to wide-ranging commercial applications of robotics technologies. In 1996, a panel discussion was held at the IEEE International Conference on Robotic and Automation (ICRA) Conference to identify the grand research challenges for The Robotics and Automation Society for the next decade.

Figure 1 shows three grand challenges identified by the panel and the progress made in the last decade in each area.

Such an integration of robotic body, sensor and AI software led to a wide variety of robotic systems. For example, Sony's QRIO (see Figure 1) can dance and play a trumpet. The da Vinci robotic surgical system by Intuitive Surgical Inc. (www.intuitivesurgical.com) can assist surgeon in laparoscopic (abdominal) surgery.

- **The 1996 ICRA panel discussion**

  (IEEE Robotics and Automation Magazine, 3(4), Dec 10-16,1996)

    - Human-Robot Interface (HRI)
    - Modularity
    - System Integration

      Sony's QRIO

- **Much progress has been made since then**

    - Human-Robot Interface ➜ Vision, Voice, Gesture, Haptic, EMG, etc.
    - Modular / Evolutionary ➜ Multi-Agent Systems, BBDs
    - System Integration ➜ Integration of Body and Sensor

BBDs - Brain-Based Devices

Figure 1. Grand Challenges for Robotics and Automation.

Such robots are fluent in routine operations and capable of adjusting behavior in similar situations. We hypothesize, however, that robustness and flexibly responding to the full range of contingencies often present in complex task environments will require something more than the combination of these design approaches. Specifically, we see human's perception and cognitive flexibility and adaptability should be incorporated in the next generation of intelligent robots. We call this "robotic body-mind integration" in this paper. Thus, a fully cognitive robot should be able to recognize situations in which its reactive and reasoning abilities fall short of meeting task demands, and it should be able to make modifications to those abilities in hopes of improving the situation. These robots can be classified as *cognitive robots*.

Recently several national and international research programs were initiated to focus on "cognitive agents" [EU, 2004; DARPA, 2005; Asada, et al., 2006]. At ICAR2003 in Coimbra, Portugal, we proposed a cognitive robotic system framework (Figure 2) [Kawamura, et al, 2003a].

In this chapter, we will give details of our cognitive robot architecture with three distinctive memory systems: short-term and long-term memories and an adaptive working memory system will be described. Short-term and long-term memories are used primarily for routine task execution. A working memory system (MWS) allows the robot to focus attention on the most relevant features of the current task and provide robust operation in the presence of distracting or irrelevant events.
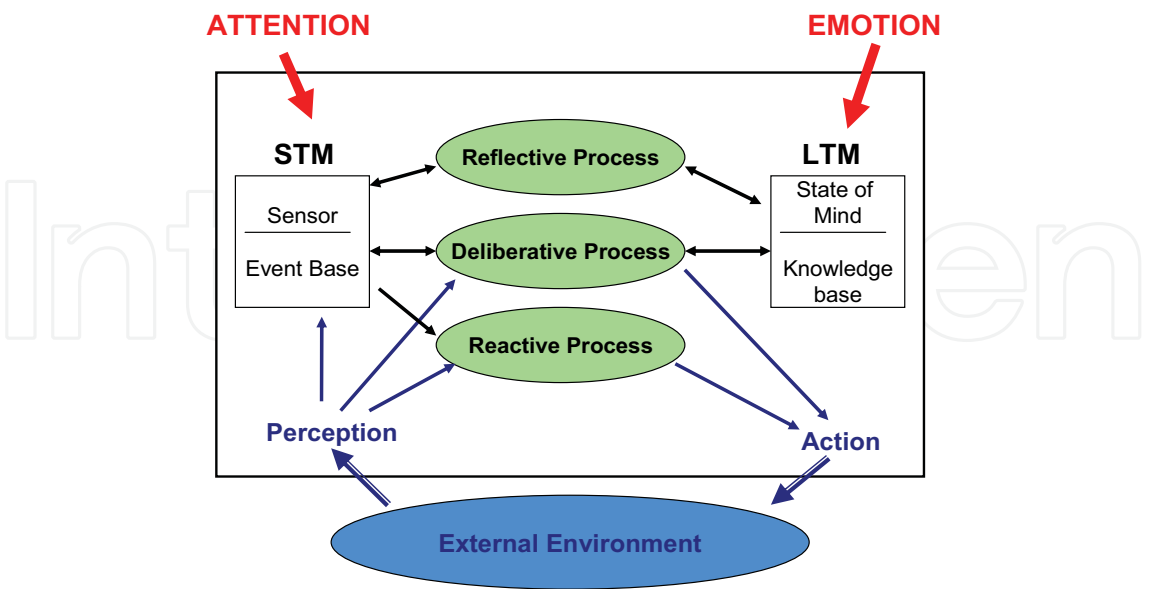
Figure 2. Framework for a cognitive robotic system.

2. Representative Cognitive Architectures in the US

Field of cognitive science has been interested in modeling human cognition for some time. Cognitive scientists study human cognition by building models that help explain brain functions in psychological and neuroscience studies. Over the last decades, many different cognitive architectures and systems have been developed by US cognitive scientists to better understand human cognition. In the following, we will briefly describe three of them. The first two were chosen for their popularity in the US and their generality. The third was chosen as an exemplary system to incorporate human perceptual and motor aspects in more specific ways to analyze complex cognitive tasks such as aircraft cockpit operation. All three have inspired our work.

2.1 ACT-R

ACT-R (Adaptive Character of Thought-Rational) [Anderson and Liebiere, 1998] is a cognitive architecture using production rules to be applied to problems of human cognitive and behavior modeling. It is based on The ACT-R theory of cognition. Within this architecture, one can develop ACT-R models for different cognitive tasks [Lovett, et al, 1999]. It includes multiple modules that correspond to different human cognitive functions, i.e. perception, motor and memory. Figure 3 shows (a) the functional structure of ACT-R and (b) how it works. "One important feature of ACT-R that distinguishes it from

other theories in the field is that it allows researchers to collect quantitative measures that can be directly compared with the quantitative measures obtained from human participants." [ACT-R, 2006] Successive versions of ACT-R have seen wide-spread applications to problems of cognitive and behavioral modeling. Anderson's group is extending the ACT-R architecture to show how visual imagery, language, emotion, and meta-cognition affect learning, memory and reasoning under the DARPA BICA (Biologically Inspired Cognitive Architecture) Program [DARPA, 2005].
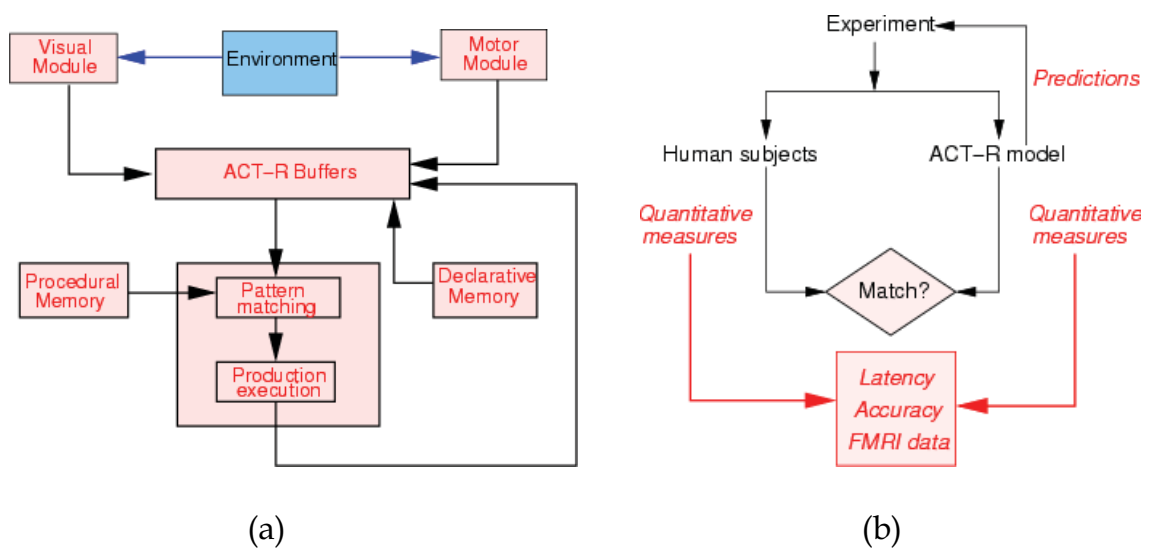

Figure 3(a). ACT-R architecture (b) How ACT-R works [ACT-R, 2006].

2.2 SOAR

Soar is a general purpose architecture designed as an unified theory of cognition by John Laird, et al [Laird, et al, 1987]. It is a production rule-based system based on the simple decision cycle – elaboration of state, selection of operator, and actions. Soar represents all cognitive activity by states. It has been applied commercially by Soar Technology Inc. Like the working memory system in our robot architecture, Soar's functional account of working memory emphasizes the important role of learning. Figure 4 shows the high-level description of the Soar Cognitive Architecture. Laird's group is now enhancing the Soar architecture by incorporating a comprehensive memory and learning system that includes the three types of human memory: procedural, semantic and episodic and emotion under the DARPA BICA (Biologically inspired Cognitive Architecture) Program [SOAR, 2006].

Learning in Soar is a by-product of impasse resolution. When an impasse is encountered, Soar creates a state space in which the goal is to resolve the impasse. Once the impasse is resolved, information about the resolution is trans-

formed into a new production rule. This new rule can then be applied whenever Soar encounters the situation again. The process of encoding and storing the newly learned rules is called "chunking". However, Soar's chunking is different from the term "chunk" used by cognitive neuroscientists when referring to human working memory. Soar's chunking is a learning method used to process information already present in the working memory for storage in the long-term memory. On the other hand in our architecture, as in human working memory, chunks refer to the arbitrary pieces of information stored in the long-term memory. (See Section 5.3.2 for details)
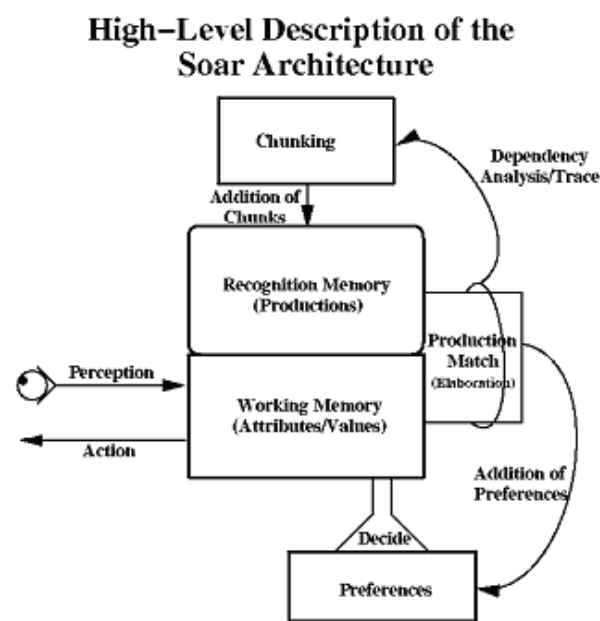

Figure 4. SOAR architecture adopted from [Wray, 2005].

2.3 EPIC

EPIC (Executive-Process/Interactive-Control) is a cognitive architecture designed to address the perceptual and motor aspects of human cognition [Kieras and Meyer, 1995]. It is designed to model human cognitive information processing and motor-perceptual capabilities. EPIC also uses a production system. EPIC has three types of simulated sensory organs: visual, auditory and tactile. Long-term memory consists of declarative and procedural memories. The cognitive processor populates working memory with procedural memory and actions are executed according to the production rules whose conditions are met. EPIC (Figure 5) was especially constructed for modeling complex cognitive activities associated with skilled perceptual-motor performance in task situations such as aircraft-cockpit operation and air-traffic control [Kieras, et al, 1999].

Figure 5. EPIC architecture [Meyer & Kieras, 1997].

3. Multiagent Systems

3.1 Multiagent Systems

In robotics, the term 'agent' is commonly used to mean an autonomous entity that is capable of acting in an environment and with other agents. It can be a robot, a human or even a software module. Since Minsky used the term 'agent' in *Society of Mind* [Minsky, 1985], the term 'multi-agent system' (MAS) – a system with many agents - is becoming more and more popular in artificial intelligence (where is better known as distributed artificial intelligence) [Ferber, 1999] and mobile robot communities (where it is often called multi-robot system). We adopted a multi-agent based system for our humanoid in the 1990s for its ease of modular development as we added more sensors and actuators and the need to integrate both the human and the robot in a unified human-robot interaction framework [Kawamura, et al, 2000].

3.2 Holons and Holonic Manufacturing Systems

In 1989, Japanese Government proposed a global collaborative program called the Intelligent Manufacturing Systems (IMS) [IMS, 1996] IMS was designed to advance a technical and organizational agenda in manufacturing to meet the challenges of global manufacturing in the 21st century. In 1996, we joined the Holonic Manufacturing System (HMS) project as a member of the US team within IMS. A holonic manufacturing system is a system having autonomous but cooperative components called holons [Koestler, 1967]. A holon can comprise other holons while, at the same time, being part of another holon. This gives rise to a holarchy where all holons automatically manage their component holons and simultaneously allow themselves to be managed within the holarchy [van Leeuwen, 1998]. The concept of holon and holarchy is similar to that of agent and agency [Minsky 1985]. Our goals within the HMS project were to develop a holonic system for batch manufacturing tasks [Saad, 1996] and to develop a control architecture for an prototype assembly holon (Figure 6), i.e. a humanoid robot [Shu, et al, 2000] using the Intelligent Machine Architecture described below. Unfortunately due to the lack of support from the US Government, we withdrew from IMS in 1999.
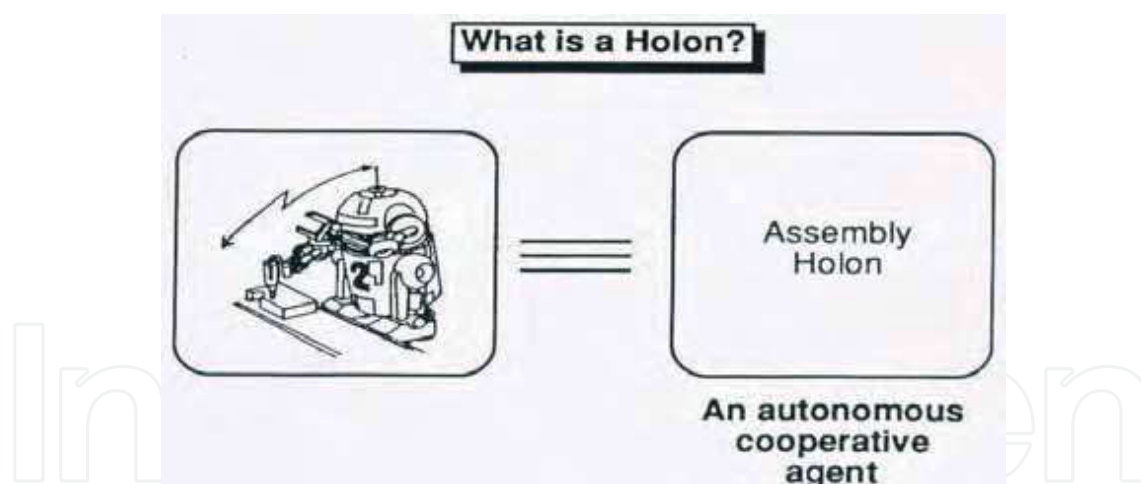

Figure 6. An assembly holon [Christensen, 1996]

3.3 Intelligent Machine Architecture

A humanoid robot is an example of a machine that requires intelligent behavior to act with generality in its environment. Especially in interactions with humans, the robot must be able to adapt its behaviors to accomplish goals safely. As grows the complexity of interaction, so grows the complexity of the software necessary to process sensory information and to control action pur-

posefully. The development and maintenance of complex or large-scale software systems can benefit from domain-specific guidelines that promote code reuse and integration. The Intelligent Machine Architecture (IMA) was designed to provide such guidelines in the domain of robot control [Kawamura, et al, 1986; Pack, 1998]. It is currently used to control ISAC. [Olivares, 2004; Olivares, 2003; Kawamura, et al, 2002].

IMA consists of a set of design criteria and software tools that supports the development of software objects that we call "agents". An agent is designed to encapsulate all aspects of a single element (logical or physical) of a robot control system. A single hardware component, computational task, or data set is represented by an agent if that resource is to be shared or if access to the resource requires arbitration. Agents communicate through message passing. IMA facilitates coarse-grained parallel processing. The resulting asynchronous, parallel operation of decision-making agents simplifies the system model at a high level. IMA has sufficient generality to permit the simultaneous deployment of multiple control architectures. behavior can be designed using any control strategy that most simplifies its implementation. For example, a simple pick and place operation may be most easily implemented using a standard Sense-Plan-Act approach, whereas visual saccade is more suited to subsumption, and object avoidance to motion schema.

IMA works very well to promote software reuse and dynamic reconfiguration. However, the large systems built with it have experienced scalability problems on two fronts. First, as the system exceeds a certain level of complexity it is difficult for any programmer to predict the interactions that could occur between agents during actual operation. This level seems to be higher than for a direct, sequential program. But that level has been reached in the development of ISAC. The other scalability problem may or may not be a problem with IMA itself but may be an inevitable consequence of increasing complexity in a system based on message passing. The asynchronous nature of message passing over communications channels with finite bandwidth leads to system "lock-ups". These occur with a frequency that apparently depends on the number of agents in the system. It may be possible to minimize this problem through the use of system-self monitoring or through a process of automatic macro formation. For example, the system could, through a statistical analysis, recognize the logical hierarchies of agents that form repeatedly within certain tasks or under certain environmental conditions. A structure so discerned could be used to "spin off" copies of the participating agents. These could be encapsulated into a macro, a compound agent that optimizes the execution and inter-process communications of the agents involved. For such an approach to be most useful, it should be automatic and subject to modification over time frames that encompass several executions of a macro.

4. ISAC Cognitive Architecture

IMA encapsulates the functions of hardware, low-level controllers, and basic sensory processing into independent, reusable units. This abstraction of details away from control loops, image operators, signal processing algorithms, and the like, enables programming to occur at the level of purposeful actions and environmental features. Actuators are supplanted by actions. Raw sensory data are replaced by features. These abstractions are the keys of ISAC's abilities and are implemented using IMA agents. The functions of actuators are encapsulated within control agents. Each agent interfaces to its corresponding hardware resource and provides control interface to other agents. In the current system, there are two arm agents, two hand agents, and a head agent. ISAC's perceptual system includes a number of sensors. Each sensor is assigned an IMA agent that processes the sensory inputs and stores the information based on the type of perception. For visual inputs, there are visual agents that perform perception encoding, such as color segmentation, object localization and recognition, motion detection, or face recognition. Other inputs include sound localizations and sound recognition agents. Each of the individual tasks is encapsulated by an atomic agent, such as find-colored-object, reach-to-point, and grasp-object agents. At the higher level, ISAC's cognitive abilities are implemented using two compound agents: the Self Agent which represents ISAC's sense of self, and is responsible mostly for task execution, and the Human Agent which represents the human who ISAC is currently interacting.

Memory structures are utilized to help maintain the information necessary for immediate tasks and to store experiences that can be used during decision making processes. Sensory processing agents write data to the Sensory EgoSphere (SES) which acts as a short-term memory (STM) and interface to the high-level agents [Peters, et al., 2001]. The long-term memory (LTM) stores information such as learned skills, semantic knowledge, and past experience (episodes) for retrieval in the future. As a part of LTM, Procedural Memory (PM) holds motion primitives and behaviors needed for actions, such as how to *reach to a point* [Erol et al, 2003]. Behaviors are derived using the Spatio-Temporal Isomap method proposed by Jenkins and Matarić [Jenkins & Mataric, 2003]. Semantic Memory (SM) is a data structure about objects in the environment. Episodic Memory (EM) stores past experience including goals, percepts, and actions that ISAC has performed in the past. The Working Memory System (WMS) is modeled after the working memory in humans, which holds a limited number of "chunks" of information needed to perform a task, such as a phone number during a phone- dialing task. It allows the robot to focus attention on the most relevant features of the current task, which is closely tied to the learning and execution of tasks. Figure 7 depicts the key IMA agents and the memory structure within the ISAC cognitive architecture.
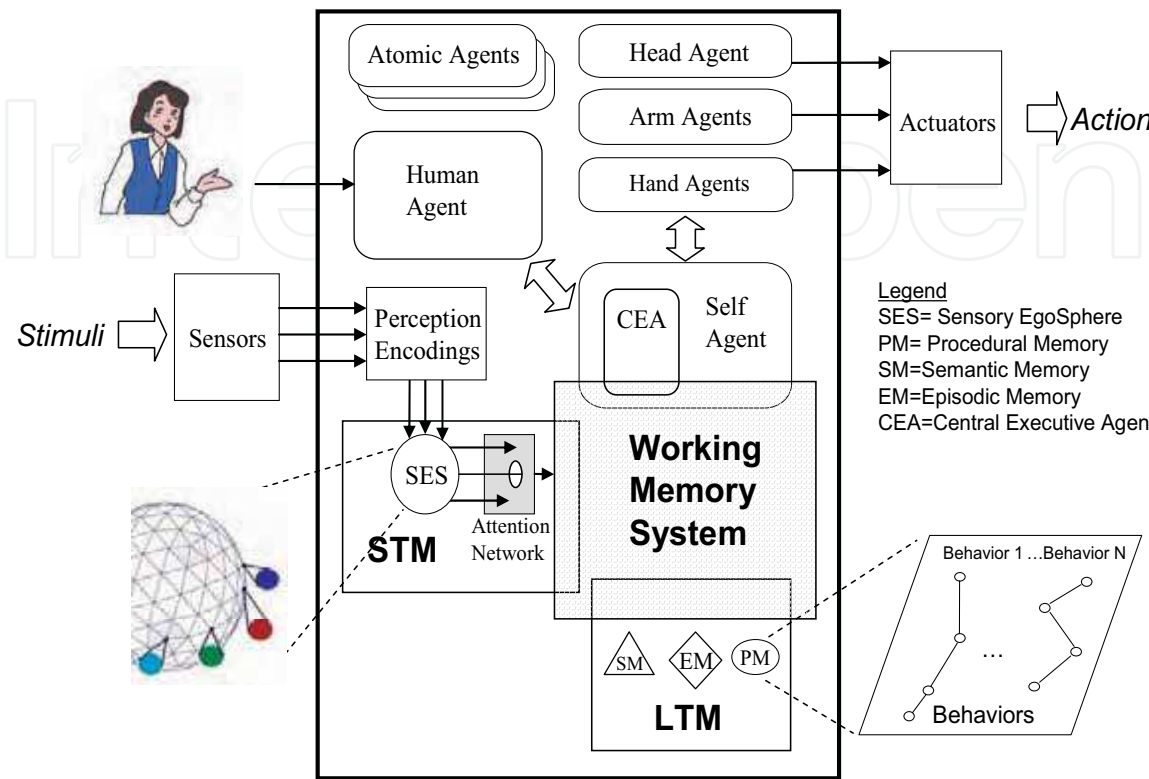
Figure 7. Multiagent-based cognitive robot architecture.

4.1 Self agent

According to Hollnagel and Woods, a cognitive system is defines as "*an adaptive system which functions using knowledge about itself and the environment in the planning and modification of actions*" [Hollnagel, 1999]. Key words here are *knowledge about itself*. In our architecture, the Self Agent (SA) represents robot itself. It is responsible for ISAC's cognitive activities ranging from sensor signal monitoring to cognitive or executive control (see Section 6.1 for detail discussions on cognitive control) and self reflection. "Cognitive control is needed in tasks that require the active maintenance and updating of context representations and relations to guide the flow of information processing and bias actions." [Braver, et al, 2002] Figure 8 is a diagram of the Self Agent and the associated memory structure. The Description Agent provides the description of atomic agents available in the system in terms of what it can or cannot do and what is it doing. The First-order Response Agent (FRA) selects the humanoid's actions according to (1) the percepts in the environment and (2) the commands/intentions of the person with whom the robot is currently interacting. The intentions are supplied by the Human Agent (see Section 4.2 for details) and interpreted by the Intention Agent. The Emotion Agent keeps

track of robot internal variables that will be used during action selection, attention and learning. The Activator Agent invokes atomic agents to handle temporal integration for the selected actions. The Central Executive Agent (CEA) working closely with the Working Memory System and the other SA agents provides cognitive control functions for ISAC. CEA is described in detail in Section 6.2.
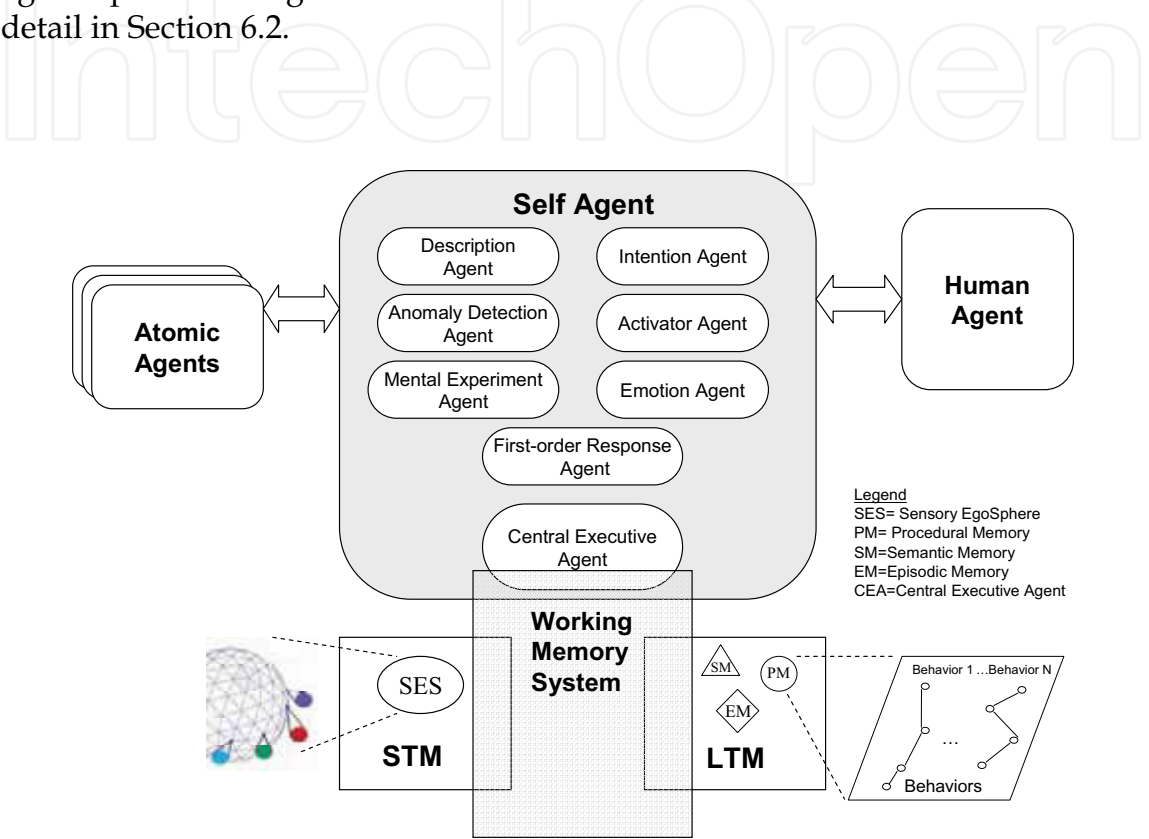

Figure 8. Self Agent and associated memory structure.

A key function of any cognitive robot must be is *self-reflection*. Self reflection will allow the robot to reason its own abilities, cognitive processes, and knowledge [Kawamura, et al, 2003b]. As part of an initial effort to incorporate self-reflective process into ISAC, we are proposing two agents: the Anomaly Detection Agent (ADA) and the Mental Experimentation Agent (MEA) within the Self Agent. ADA will monitor the inputs and outputs of the atomic agents in the system for fault detection. And when an impasse is raised and if the CEA fails to find an alternative solution, MEA will conduct a search through the space of control parameters to accomplish the task in "simulated mode" The concept of self reflection is closely related to that of self awareness (Fig. 9) and machine consciousness [Holland, 2003].
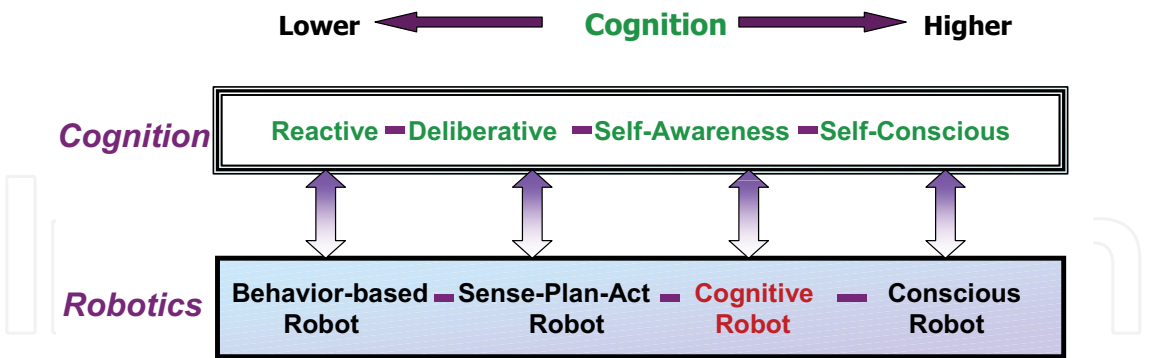
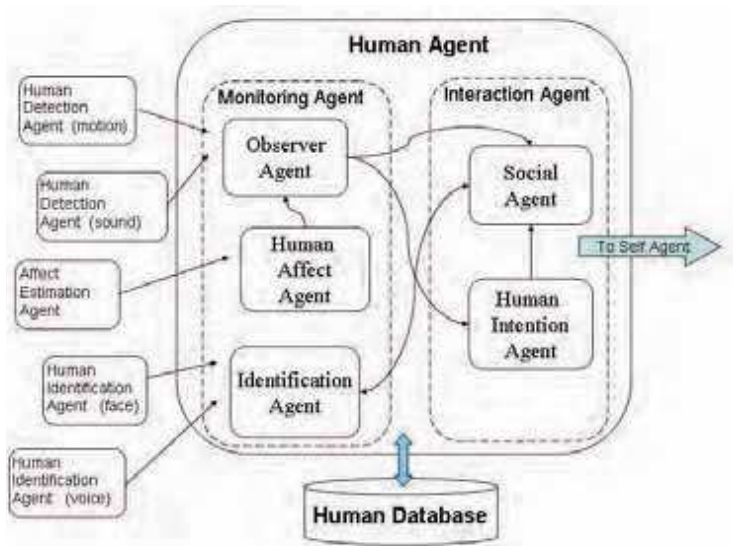Figure 9. Spectrum of cognition in robotics.

4.2 Human agent

The Human Agent (HA) comprises a set of agents that detect and keep track of human features and estimate the intentions of a person within the current task context. It estimates the current state of people interacting with the robot based on observations and from explicit interactions (Figure 10 a and b) [Rogers, 2004]. The HA receives input from various atomic agents that detects physical aspects of a human (e.g., the location and identity of a face). The HA receives procedural information about interactions from the SA that employs a rule set for social interaction. The HA integrates the physical and social information with certain inferred aspects of the cognitive states of interacting humans, such as a person's current intention.

The HA processes two types of human intentions. An expressed intention is derived from speech directed toward ISAC, e.g., greetings and requests from a human. Inferred intentions are derived through reasoning about the actions of a person. For example, if a person leaves the room, ISAC assumes it means that the person no longer intends to interact, therefore, it can reset its internal expectations.

The Human Agent's assessment of how to interact is passed on to the SA. The SA interprets the context of its own current state, e.g. current intention, status, tasks, etc. This processing guides ISAC in the selection of socially appropriate behaviors that lead towards the ultimate goal of completing tasks with (or for) humans.

(a)

(b)

Figure 10. (a) ISAC interacting with humans and (b) Human Agent and associated atomic agents.

5. Memory Structure

ISAC's memory structure is divided into three classes: Short-Term Memory (STM), Long-Term Memory (LTM), and the Working Memory System (WMS). The STM holds information about the current environment while the LTM holds learned behaviors, semantic knowledge, and past experience, i.e., episodes. The WMS holds task-specific STM and LTM information and streamlines the information flow to the cognitive processes during the task.

5.1 Short-term memory: The Sensory EgoSphere

Currently, we are using a structure called the Sensory EgoSphere (SES) to hold STM data. The SES is a data structure inspired by the egosphere concept as defined by Albus [Albus, 1991] and serves as a spatio-temporal short-term memory for a robot [Peters, et al, 2001; Hambuchen, 2004]. The SES is structured as a geodesic sphere that is centered at a robot's origin and is indexed by azimuth and elevation.

The objective of the SES is to temporarily store exteroceptive sensory information produced by the sensory processing modules operating on the robot. Each vertex of the geodesic sphere can contain a database node detailing a detected stimulus at the corresponding angle (Figure 11).
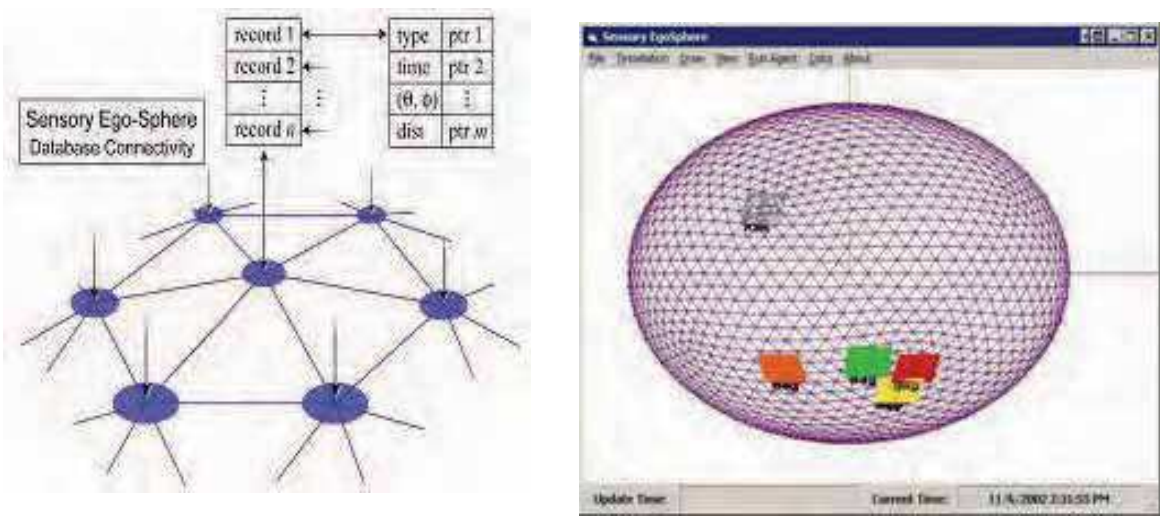

Figure 11. Mapping of the Sensory EgoSphere and topological mapping of object locations.

Memories in the SES can be retrieved by angle, stimulus content, or time of posting. This flexibility in searching allows for easy memory management, posting, and retrieval.

The SES is currently being used on ISAC (Figure 12a), and was installed on Robonaut (Figure 12b) at NASA's Johnson Space Center in Houston several years ago by members of our research group.
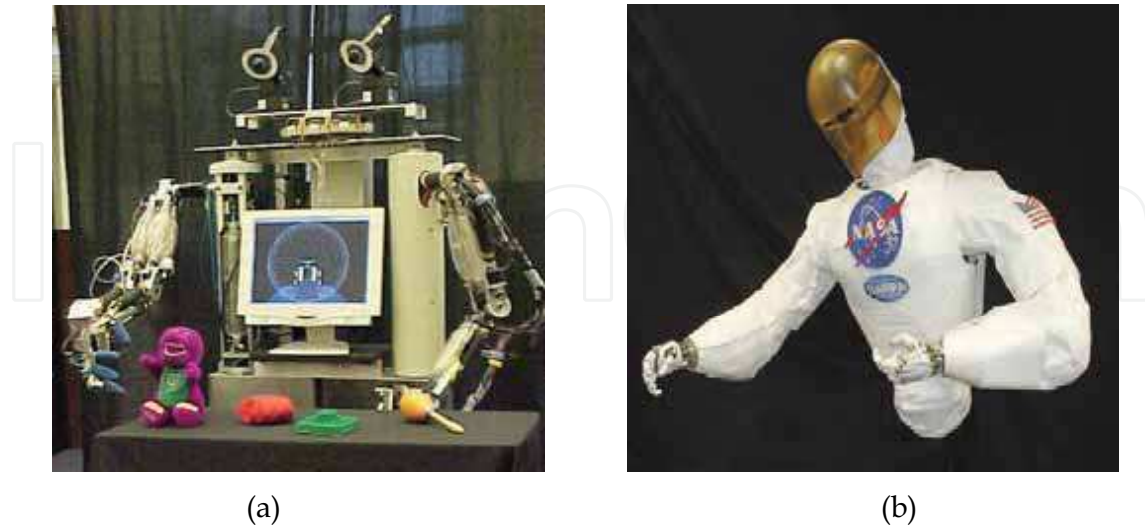
<center>(a)   (b)</center>

Figure 12(a). ISAC showing SES screen, (b) NASA's Robonaut.

5.2 Long-Term Memory: Procedural, Semantic and Episodic Memories

LTM is divided into three types: Procedural Memory, Semantic Memory, and Episodic Memory. Representing information such as *skills, facts learned* as well as *experiences gained* (i.e. *episodes*) for future retrieval.

The part of the LTM called the Procedural Memory (PM) holds behavior information . Behaviors are stored in one of two ways: as motion primitives used to construct behaviors or as full behavior exemplars used to derive variant motions.

Using the first method, stored behaviors are derived using the spatio-temporal Isomap method proposed by Jenkins and Mataric [Jenkins, et al, 2003]. With this technique motion data are collected from the teleoperation of ISAC. The motion streams collected are then segmented into a set of motion primitives. The central idea in the derivation of behaviors from motion segments is to discover the spatio-temporal structure of a motion stream. This structure can be estimated by extending a nonlinear dimension reduction method called Isomap [Tenenbaum, 2000] to handle motion data. Spatio-temporal Isomap dimension reduction, clustering and interpolation methods are applied to the motion segments to produce Motion Primitives (Figure 13a). Behaviors are formed by further application of the spatio-temporal Isomap method and linking Motion Primitives with transition probabilities [Erol, et al, 2003].

Motions recorded using spatio-temporal Isomap are stored in a separate manner as shown in Figure 13(b). At the top of this structure, behavior descriptions will be stored which will allow us to identify what each behavior can contribute to solving a given motor task. Each entry in the behavior table will contain pointers to the underlying motion primitives.
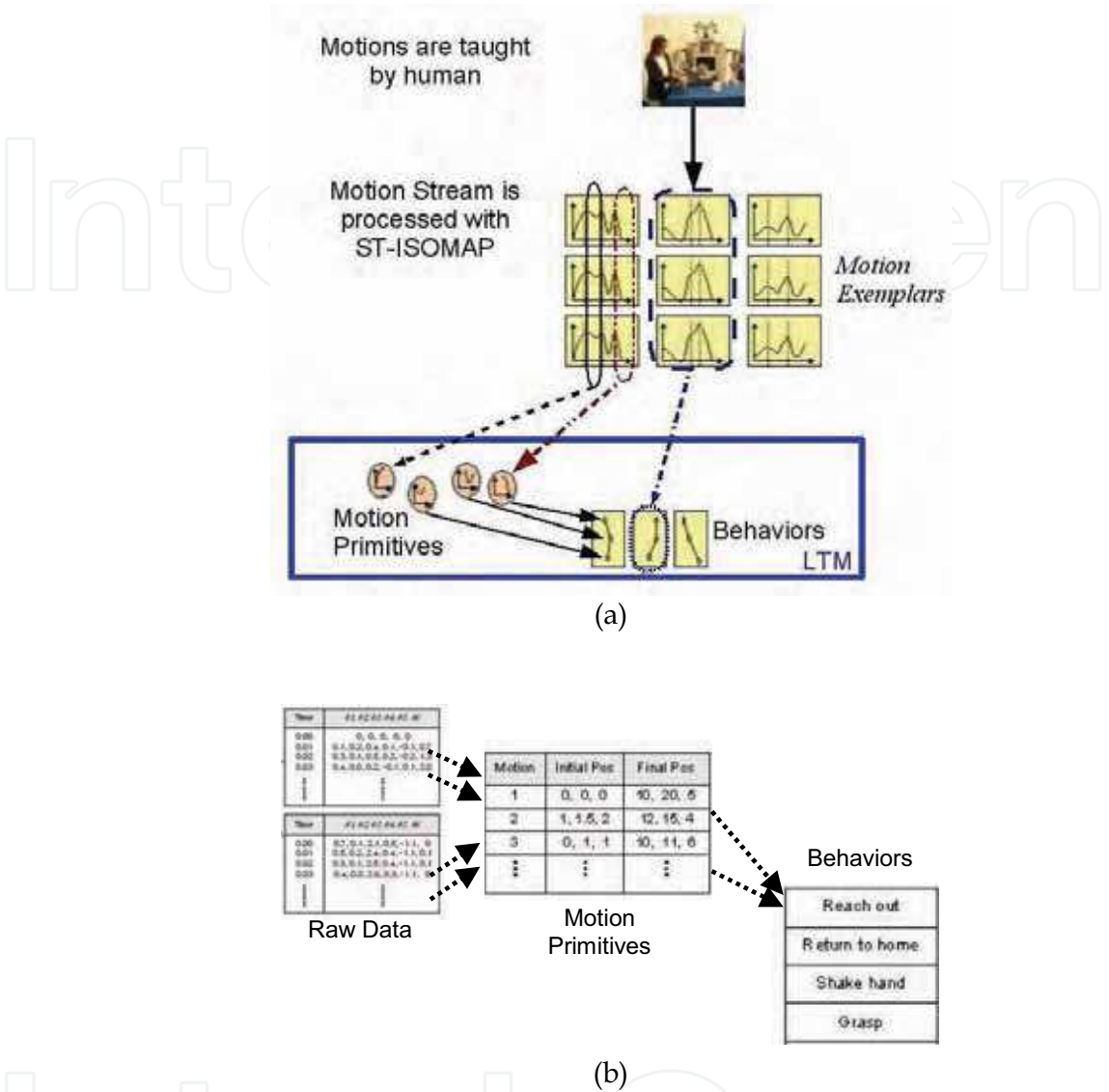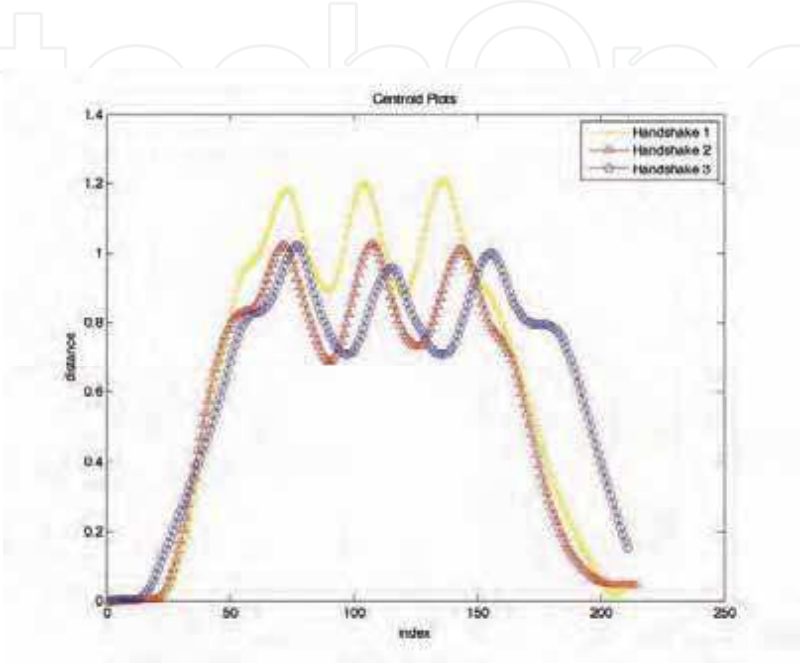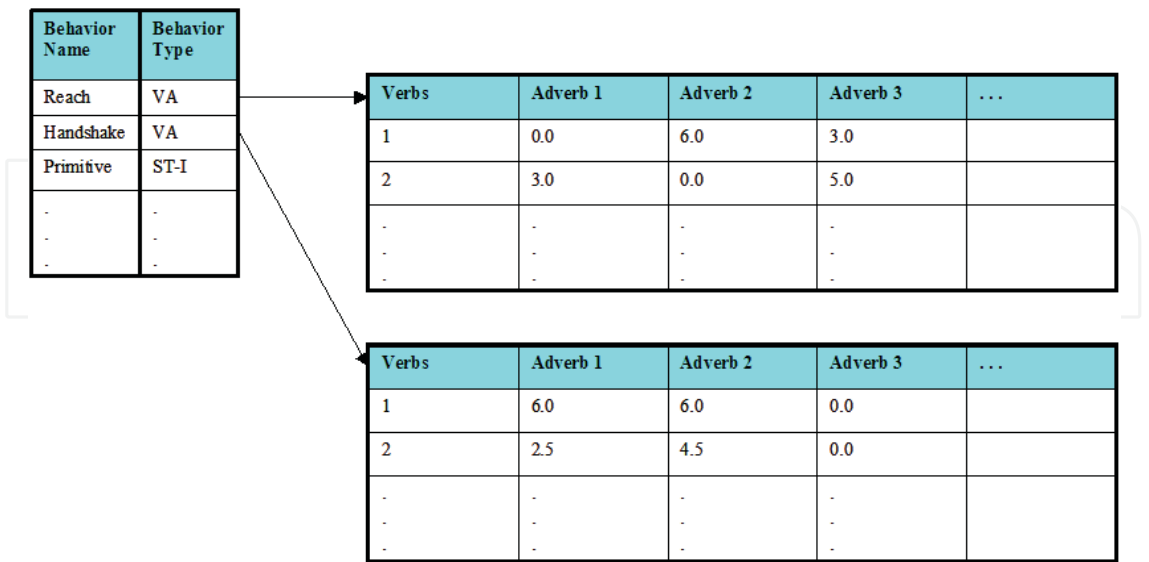
(a)

(b)

Figure 13(a). Derivation of Procedural Memory through human-guided motion stream and (b) Structure of Procedural Memory data unit.

The latter method stores behaviors using the Verbs and Adverbs technique developed in [Rose, et al, 1998]. In this technique, exemplar behavior motions are used to construct *verbs* while parameters of the motions are termed *adverbs*. An important aspect in storing and re-using a motion for a *verb* is the identification of the *keytimes* [Spratley, 2006; Rose, et al, 1998] of the motion. The keytimes represent significant structural breaks in the particular motion. For the Verbs and Adverbs technique to function properly individual motions for the same verb must have the same number of keytimes and each keytime must have the same significance across each motion. Figure 14(a) shows keytimes for three example motions. The example motions are recording of the same motion, three different times. This information is used to create the verb, *hand-*

shake. The keytimes in this example are derived by analyzing the motions using a technique called Kinematic Centroid [Jenkins, et al, 2003]. The x-axis represents the normalized point index for each motion. The y-axis represents the Euclidian distance of the kinematic centroid of the arm from the base of the arm.

(a)

(b)

Figure 14 (a). Example motions and their keytimes [Spratley, 2006], (b) Structure of PM data representation for Verbs and Adverbs.

Each verb can have any number of adverbs, each of which relate to a particular space of the motion. For example, the verb *reach* could have two adverbs: the first related to the direction of the *reach* and the second related to the distance from ISAC's origin that the particular motion is to extend. Extending this example, adverbs could be added to include features from any other conceivable space of the motion, such as the strength of the motion or the speed of the motion. Stored in the LTM are the verb exemplars and the adverb parameters for each verb. New motions such as *reaching*, or *handshaking* are interpolated by ISAC at run time using the new (desired) adverb values.

Figure 14(b) depicts the manner in which behaviors are stored in LTM using Verbs and Adverbs. For each entry in PM, the motion and storage types are recorded. The next entry holds pointers to the verb information and the final entries hold the adverb values.

5.3 Attention and the Working Memory System

5.3.1 Attention

Attention is a sensory/cognitive mechanism to limit the amount of information needed to be manipulated by the brain for task execution. It "allows the brain to concentrate only on particular information by filtering out distracters from a desired target object or spatial location by amplification of the target representations." [Taylor and Fragopanagos, 2004] Attention can be goal-oriented during task execution such as searching for an object or it can be reactive in salience events such as when hearing a loud sound.

Attentional function in ISAC is implemented using the Attention Network which monitors both task relevant sensory data and unexpected yet salient sensory data on the Sensory EgoSphere (SES) [Hambuchen, 2004]. As sensory processors report all exteroceptive events to the SES, the direction of attention to external sensory events are also available through SES nodes (Figure 15). As multiple events are registered in a common area, activation increases around a central node. Nodes that receive registration from task- or context-related events have their activations increased by the Attention Network. The Attention Network selects the node with the highest activation as the focus of attention. Sensory events that contributed to this activation are selected and those that fall within a specified time range of each other are passed into the working memory.

Besides level of activation, the Attention Network also pays attention to percepts on SES with high emotional salience. When a percept is assigned high emotional salience, the Attention Network selects the percept as the focus of attention. Emotional salience is provided by the Emotion Agent, a part of the Self Agent. Its implementation, including attention based on emotional salience is described in Section 7.2.
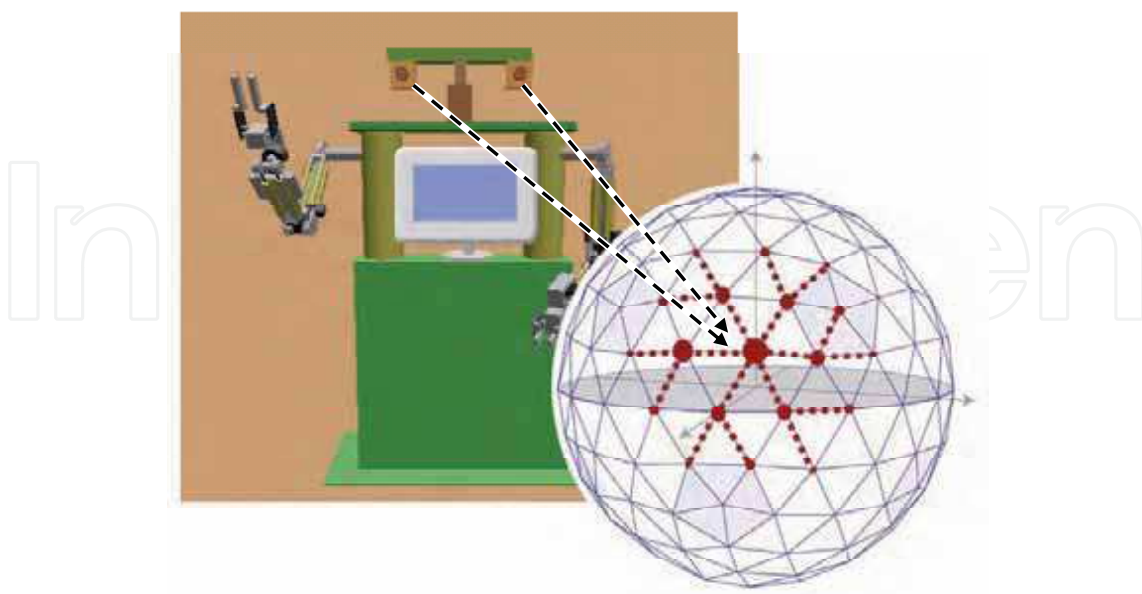
Figure 15. The attention network's assignment of FOA at the center node among events registered in a common area on SES [Hambuchen, 2004].

5.3.2 Working memory system

There is much evidence for the existence of working memory in primates [Funahashi, et al, 1994; Miller, et al, 1996]. Such a memory system is closely tied to the learning and execution of tasks, as it contributes to attention, learning and decision-making capabilities by focusing on task-related information and by discarding distractions [O'Reilly, et al, 1999; Baddeley, 1986; Baddeley, 1990]. The working memory in humans is considered to hold a small number of "chunks" of information needed to perform a task such as retaining a phone number during dialing.

Inspired by the working memory models developed in cognitive science and neuroscience, the Working Memory System (WMS) in robots was designed to provide the embodiment necessary for robust task learning and execution by allowing ISAC to focus attention on the most relevant features of the current task [Gordon & Hall, 2006].

WMS in our cognitive architecture was implemented using the Working Memory Toolkit (WMtk) based on the computational neuroscience model of working memory [Phillips, 2005]. This toolkit models the function of dopamine cells in human brains using a neural net-based temporal difference (TD) learning algorithm [Sutton, 1988]. The toolkit has a function to learn to select and hold on to "chunks" of information that are relevant to the current task based on future expected reward from processing these chunks. These chunks include behaviors, current percepts, and past episodes. Figure 16 illustrates the current WMS structure and associated system components. A simulated delayed saccade task using WMtk was reported by Philips and Noelle [Philips,

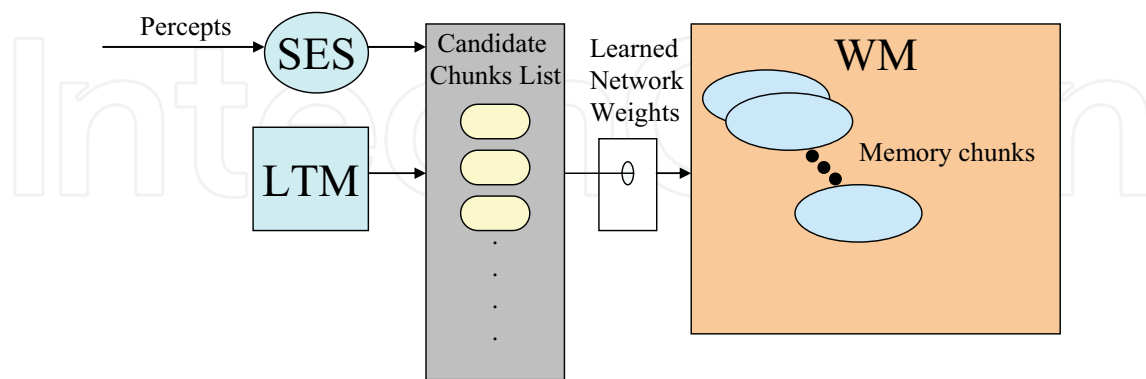2006]. Section 7.1 in this chapter details working memory training and task learning conducted on ISAC.

Figure 16. Structure of the working memory system.

6. Cognitive Control and Central Executive Agent

6.1 Cognitive Control

Cognitive control in humans is a part of executive functions (such as planning and abstract thinking) within the frontal lobes in the human brain [Stuss, 2002]. Cognitive control is "the ability to consciously manipulate thoughts and behaviors using attention to deal with conflicting goals and demands" [O'Reilly, et al, 1999] [MacLeod and Sheehan, 2003]. As levels of human activities range from reactive to full deliberation, cognitive control allows humans to inhibit distractions and focus on the task at hand including task switching. According to researchers in neuroscience, human cognitive control is performed through the working memory in the pre-frontal cortex (PFC) [O'Reilly, et al, 1999; Braver and Cohen, 2000; MacDonald et al., 2000]. Cognitive control during task execution/switching requires the brain to perform executive functions including:

- Focus attention on task-related information
- Maintain and update goal information
- Inhibit distractions
- Shift between different level of cognition ranging from routine actions to complex deliberation
- Learn new responses in novel situations

Cognitive robots, then, should have the ability to handle unexpected situations and learn to perform new tasks. Also, cognitive control is expected to give

flexibility to the robot to reason and act according to stimuli under conflicting goals in dynamic environment. Realization of cognitive control functions for ISAC is currently pursued through the maintenance of task-related information in the working memory system through gating of information that could be passed into the decision-making mechanism called the Central Executive Agent discussed in Section 6.2.

Attention and emotions are known to play an important role in human' decision and task execution[Arbib, 2004]. Therefore, we are now adding attention and emotion networks to realize cognitive control for robots as shown in Figure 17 modified from [Miller, 2003].
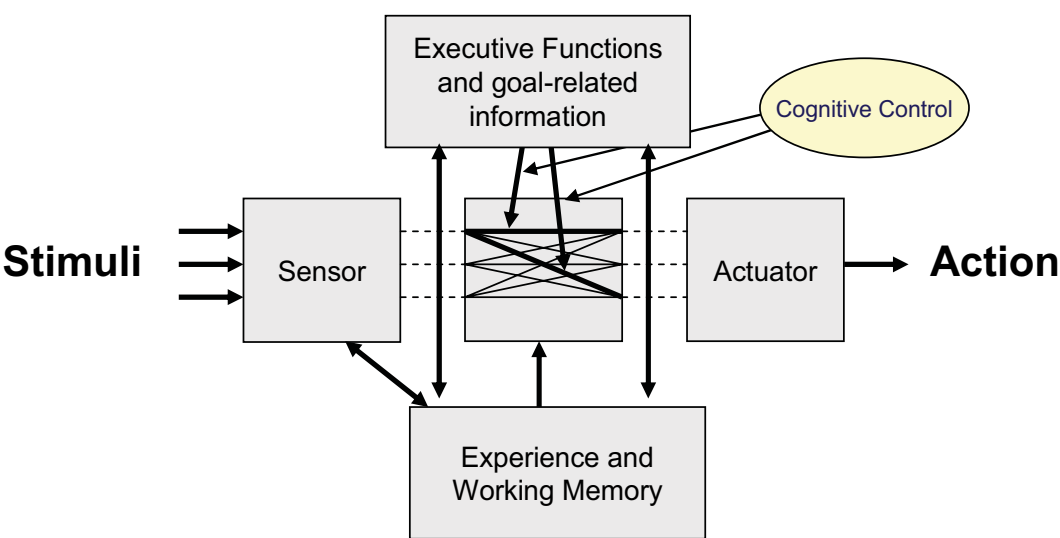

Figure 17. Concept of cognitive control modified from [Miller, 2003].

6.2 Central Executive Agent

ISAC's cognitive control function is modeled and implemented based on Baddeley and Hitch's psychological human working memory model [Baddeley, 1986]. Their model consists of the "central executive" which controls two working memory systems, i.e., phonological loop and visuo-spatial sketch pad (Figure 18).
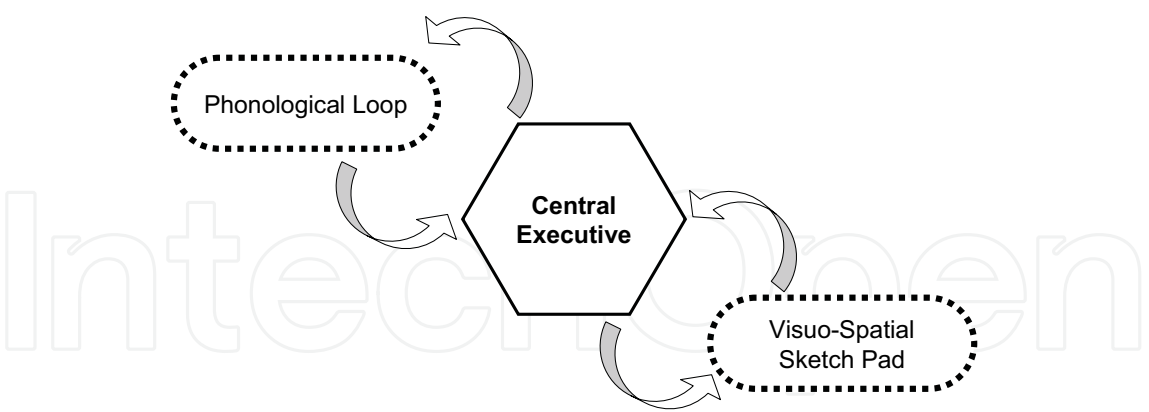
Figure18. A schematic Diagram of a multi-component model of working memory [Baddeley & Hitch, 1974].

In our cognitive architecture, an IMA agent called the Central Executive Agent (CEA) is responsible for providing cognitive control function to the rest of the system. It interfaces to the Working Memory System (WMS) to maintain task-related information (or "chunks") during task execution. Under the current design, CEA will have the four key functions: 1) situation-based action selection, 2) episode-based action selection, 3) control of task execution, and 4) learning sensory-motor actions. Each function will be realized through interaction between CEA, other IMA agents, and various memory systems as shown in Figure 19.
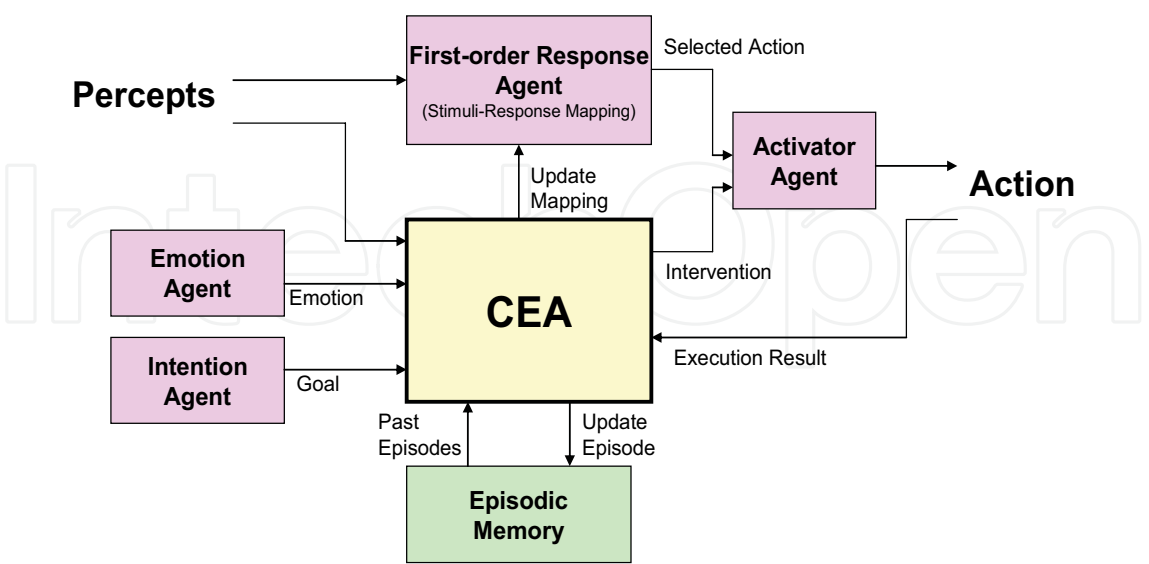

Figure 19. CEA's interactions with other processes.

Sensory inputs, stimuli and/or task commands, are encoded into percepts and posted on the SES. Only those percepts that have high *emotional salience* will

receive attention from the Attention Network and will be passed to WMS. These percepts, if not intervened, will cause corresponding actions to be selected according to embedded stimuli-response mapping. On the other hand, CEA selects actions using the combination of two paradigms. CEA will retrieve past episodes that are relevant to these percepts from the Episodic Memory. These past episodes contain actions used in past execution and results. The results of invoked actions from stimuli-response mapping could be a part of these episodes. CEA determines if the action to be executed is likely to produce a negative result. If so, CEA will intervene by suggesting a different action based on the current state of ISAC, current percepts, and action. Once the action is executed, CEA will update the stimulus-response mapping according to the execution result and the current task is then stored as a new episode in the Episodic Memory.

7. Experimental Results

7.1 Working Memory Training Experiment for Percept-Behavior Learning Tasks

The working memory system (WMS) is used to manage ISAC's memory focus during task execution. For simple tasks, WMS holds a small number of chunks of information related to the task. Typically on ISAC, the number of chunks loaded into WMS ranges from 2 to 4. For example, if ISAC were to be asked to "*reach* to the red bean bag", WMS would be responsible for loading two chunks of information: one chunk for the *reach* behavior and another chunk for the red bean bag percept. For more complex tasks (i.e. those that require more than 4 chunks of information) the tasks must be broken into simpler tasks and WMS is responsible for handling each simple task in turn as well as maintaining ISAC's focus on the long-term goal, the completion of the complex task.
WMS is not the tool that decomposes complex tasks into simple tasks. In the future, another agent such as CEA (section 6.2) must do this job. WMS, given the current state of ISAC, solely determines which chunks from LTM and STM to load into the system, in essence focusing ISAC on those pieces of information. Experiments utilizing WMS in this manner have already been conducted [Gordon, et al, 2006].
Current work with ISAC's WMS is centered on training a variety of different WMS for different types of tasks, such as::

- *Object Interaction* – Simple object interactions such as *reaching, pointing, tracking*, etc.
- *Human Interaction* – Performing such behaviors as *face tracking, greeting, handshaking, waiting for commands*, etc.

Figure 20 shows the architecture being used to train each these WMS.

Figure 20. Control architecture used during working memory training.

During training, a reward rule is used to inform WMS how well it is performing. The reward rule captures whether or not the current chunks could be used to accomplish the task and how well the task has been accomplished.

7.1.1 Experimentation and Trials

Using the architecture shown in Figure 20, an initial experiment was designed for to test object interaction using working memory. Steps for this experiment are as follows:

1. ISAC is given certain initial knowledge (i.e. embedded ability and/or information)

   a) ISAC's perceptual system is trained to recognize specific objects. The information is stored in the semantic memory section of the LTM.
   b) Using the Verbs and Adverbs algorithm, ISAC is taught a small set of motion behaviors including how to *reach*, *wave*, and *handshake*.
   c) Figure 21 demonstrates ISAC performing these behaviors. This information is stored in the procedural memory section of the LTM.

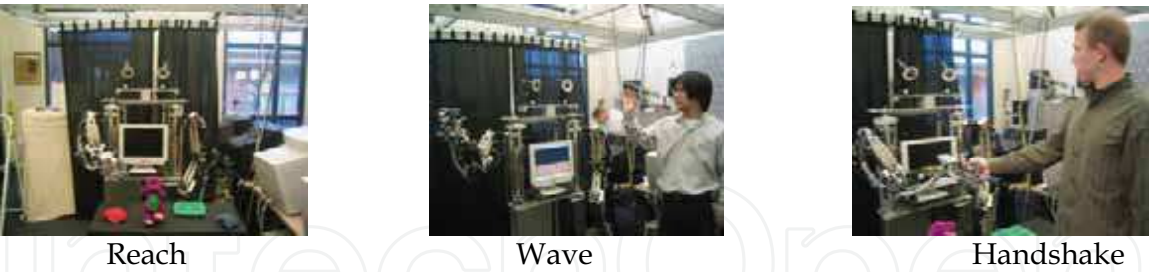Reach   Wave   Handshake

Figure 21. Sample configurations for reach, wave, and handshake.

2. Two bean bags are placed on a table as shown next in Figure 22.a.
3. ISAC is asked to "reach to the bean bag", although a specific bean bag is not specified.
4. ISAC's perceptual system will recognize the bean bags and post the information to SES.
5. WMS will focus on "chunks" of information necessary for accomplishing the task.
6. A reward is given based upon how well the action is completed.
7. Over time, ISAC learns the appropriate chunks to focus on from the SES and LTM.
8. Once ISAC has demonstrated that it has learned the most appropriate chunks to load into WMS (Figure 22.a), bean bags are rearranged (Figure 22.b) and ISAC is given the command "reach to the bean bag".
9. Real-time experiments were conducted after initial simulation trials (Figure 22.c).

When the bean bags are rearranged, ISAC should not necessarily reach to the same bean bag as before but should choose the *bean bag percept* from the SES that is the most appropriate. For this task the most appropriate bean bag is the nearest one. The combination of percept and behavior, or "chunks", will be loaded into the working memory and used to execute the action.

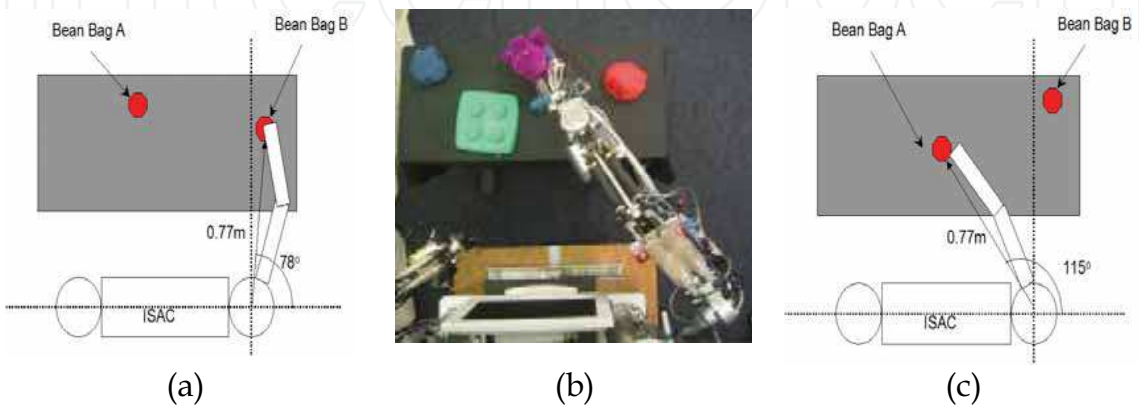(a)   (b)   (c)

Figure 22 (a, b). Sample configurations for reaching and (c) actual experiment view.

The reward rule for this experiment is based on three criteria:

1. What is the degree of success for the behavior WMS chose to load?
2. How well did the object chosen by WMS meet the task criteria? e.g., focusing on any bean bag *vs.* focusing on another object.
3. How well is SAC able to act upon the object? e.g., in this experiment, could ISAC reach the bean bag?

In order to measure Reward Criterion #3, the reward was given based on the inverse proportion of the distance from ISAC's hand to the object. Reward Criteria #1 and #2 gave a discrete positive valued reward if the system chose appropriately. No preference (i.e., reward of 0) was the result if the system did not choose correctly. The values for the overall reward typically fell in the range of 0 – 400. Since it was desired to give negative reward to the system when it did not act appropriately, a negative weighting factor of –200 was added to the final reward to "tilt" the low values into the negative range.

Note that when using these reward criteria, it is possible to incorrectly reward the system for performing the task in less than an optimal manner. For example, if the system performs the behavior *handshake* or *wave* while focusing on the appropriate bean bag and if this action happens to bring the hand very close to the bean bag, then the system would receive a positive reward. In order to avoid this undesirable situation, more rules or knowledge are needed.

Initial trials for this experiment were performed off-line, in simulation, to speed-up the initial testing phase of the system. This simulation was set-up to remove the time-bottleneck of generating and performing motions. For the simulation, when ISAC needed to act on an object within the workspace, the motion was assumed to have been performed properly (Reward Criterion 3).

The action taken by ISAC was determined by what WMS currently believed was the best choice. In other words the action that WMS believed would yield the greatest reward. This system also contained an exploration percentage, specified as a part of initial knowledge that determined the percentage of trials that WMS chose a new or different action. This enabled WMS to always continue learning and exploring.

During initial research trials, simulation was not allowed to choose the same action more than twice. This constraint enabled a much quicker simulation time. Once the system finished exploration, the system was restarted with the learned information and given the task to "*reach* to the bean bag". For each arrangement (Figures 22a,b) the system chose appropriately to reach towards the correct bean bag, i.e. the nearest one. Table 1 shows the contents of ISAC's short-term and long-term memory systems during the training portion of the simulation.

SES	LTM
1. bean bag: location = (Figure 22.b), type = A	1. *reach*
2. bean bag: location = (Figure 22.a), type = B	2. *handshake*
3. blank	3. *wave*

Table 1. Memory contents during simulation training.

	Working Memory Contents			
Trial #	1	2	3	4
Chunk 1	bean bag A	bean bag B	*wave*	*handshake*
Chunk 2	*reach*	bean bag A	bean bag B	bean bag A
Random	NA	*handshake*	NA	NA
Reward	203.4	-20.5	-197.7	2.3

Table 2. Working memory contents during simulation training.

In these trials, WMS was allowed to choose two "chunks" from the short- and long-term memory systems to accomplish the task. However, the working memory was not restricted to choosing exactly one object and one behavior. If the working memory chose to focus on two objects or two behaviors, then respectively a behavior or object was chosen at random. This ensured that an action was still performed. The reasoning behind this was so that the system did not learn to simply choose combinations that lead to no reward, a situation that could be preferred if WMS was consistently getting negative reward for its choices. Table 2 shows samples of the contents in the working memory in these trials.

To evaluate system performance further, a third task was developed. For this task ISAC was again given the command to "*reach* to the red bag", however this time the *reach* behavior was deleted from the initial knowledge limiting the behavior choices to *handshake* and *wave*. The working memory had to choose the *next best* behavior. For each of the arrangements shown previously (Figures 22a,.b), WMS chose to perform the *handshake* behavior. This behavior was chosen because it allowed the arm to get closest (Reward Criterion 3) to the bean bag (Reward Criterion 2) and thus, best accomplished the goal task.

7.1.2 Trials on ISAC

After the initial training and experimentation, ISAC was allowed to perform the generated motions (Figure 22.c). Two new objects (a green Lego toy, and a purple Barney doll) were added to the table, at random positions. ISAC's vision system was trained (Step 1) to recognize each new object and recorded the type of object as well as some simple descriptive information (color=green,

purple; toy type=Barney doll, Lego). ISAC was given tasks (Step 3) such as "*reach* to the bean bag" or "*reach* to the toy". Each of these tasks did not specify to which bean bag or toy ISAC was to *reach*. ISAC recognized the objects (Step 4). WMS focused on "chunks" of information from the SES and LTM in order to accomplish the task (Step 5). ISAC was allowed to explore the space of possible actions receiving reward each time (Steps 6 and 7). After this was accomplished, the objects were rearranged in a variety of different positions (Step 8) and ISAC was given a command. The results (set of 20 commands) were that ISAC successfully performed the correct action on the nearest (easiest to reach) requested object.

For this system to properly choose the correct set of chunks to focus on, the system currently has to explore all the possibilities during training. Figure 23, shows an example learning curve for this system for the *reach* command. The graph shows the number of times each of the trained behaviors (see Figure 23) was chosen during each ten trial segment. When the system first begins training, it is required to explore each of the possible behaviors as well as try different percept/behavior combinations. As can be seen from this graph, it took approximately 20 trials to learn *reach* before the system determined that the *reach* behavior was the definite best.

Attempting to explore all possibilities in the future will lead to a combinatorial explosion if a large number of behaviors or percepts are added to the system. In order for this system to continue to operate properly in the future, improvements need to be made to the representational structures for behaviors and percepts used by the system. One method of improving this representational structure that we are considering is to store intentionality along with percepts (i.e. chairs are for *sitting*, tables are for *placing*, and bean bags are for *reaching* and *grabbing*). This, along with a method discussed in section 7.1.3 of pre-filtering chunks using Episodic Memory, will aid WMS to perform quick and accurate chunk selection and retrieval.
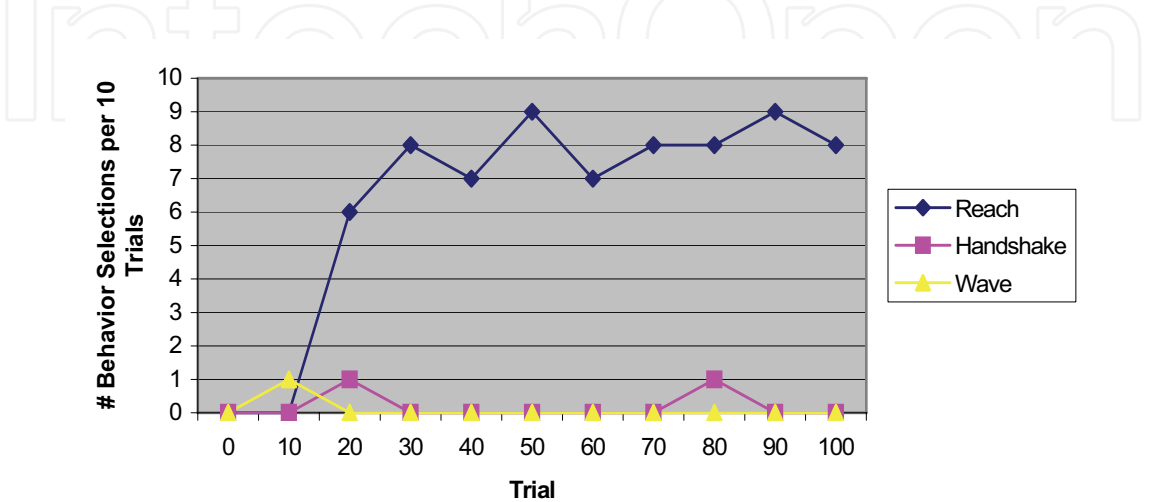

Figure 23. Learning Curve for *Reaching* Action.

7.1.3 Learning New Tasks Using Multiple WMS

A single WMS, if it were large enough and if it were trained extensively enough, could theoretically handle most, if not all, of the simple situations ISAC could encounter. However, due to the size of the state and chunk representations the computation time to select appropriate chunks and the training time to train a single WMS over all possibilities would be enormous. For this reason, separate WMS are being trained to handle different types of situations that ISAC may encounter. As stated earlier in this section, two differently WMS are currently in development: Object Interaction working memory (WM1) and Human Interaction (WM2).

When training WM1, the "Task Info" is set to the current command, such as "*reach* to the bean bag". When training WM2, however, the "Task Info" is kept blank. WMS in each case is responsible for learning which behavior chunks from LTM and which percept chunks from STM are appropriate for each situation. WMS is also responsible for learning "how well" certain chunks accomplish particular tasks. It is important that WMS learn which memory chunks best accomplish tasks and which other chunks could be used when, for some reason, the "best" ones are not available.

Using multiple WMS to accomplish the task of one monolithic WMS speeds up training time and decreases computation time. The idea behind training these separate systems is to enable ISAC the ability to continuously, smoothly, and appropriately interact with its environment. Each of these WMS, once trained, will be stored in the LTM and linked with the particular episode (see Episodic Memory, section 5.2 and 5.3).

Upon entering a new state, ISAC will pull from the Episodic Memory an episode that most closely matches the current state. Along with this episodic information will be the trained WMS that enabled ISAC to act appropriately in that situation. This WMS will be loaded into the system and used throughout the duration of the current state.

Episodic information also helps filter the list of candidate chunks presented to WMS. Figure 24 shows how Episodic Memory can be used to filter the candidate chunks list.

Pre-filtering the candidate chunks list also speeds up computation and selection time for WMS. This feature is especially important as ISAC's knowledge base grows. When no appropriately matching episode can be retrieved, ISAC can rely on the current state information (such as the presence of a task command, people to interact with, etc.) to determine which trained WMS is likely the most appropriate.

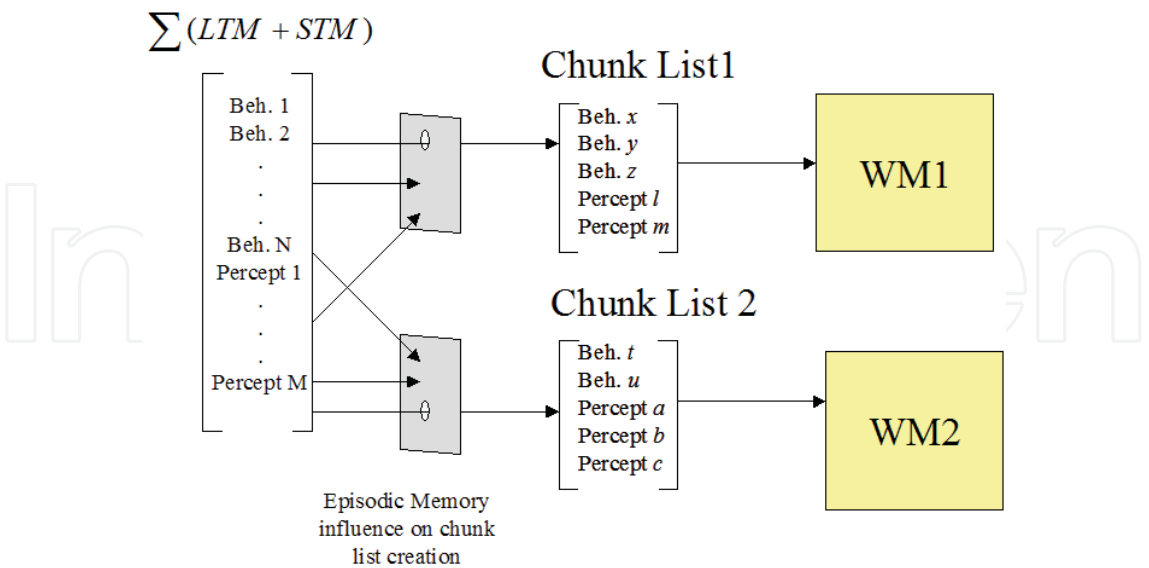No appropriate feature is in place to filter the candidate chunk list for ISAC for this scenario.

Figure 24. Pre-selection of candidate chunks based on past experience.

ISAC will be responsible for pouring through all stored, memorable information to complete the task. As ISAC's experience grows, however, the chunk list will begin to shrink as ISAC learns what types of information are most relevant. Once ISAC learns the information, an episode can be created and used to filter chunks for future scenarios.

7.2 Situation-based Stimuli Response Experiment

In order to test ISAC's decision-making functions under conflicting goals, a simulation experiment was conducted [Ratanaswasd, et. al., 2006]. In this experiment, ISAC first selects a set of percepts to pay attention to based on the emotional salience. ISAC then decides how to respond to each percept according to a situational change.

7.2.1 Experiment setup

System components use are Central Executive Agent, Attention Network, and Emotion Agent. Sound stimuli (i.e., music and alarm) are captured through a microphone and processed in Matlab. Mozart's Symphony No. 40 is used for "music," and a recorded sound of an actual fire alarm is used for "alarm." The initial state of ISAC's emotional level is to *dislike the alarm sound while liking the music*. This is accomplished through the emotion vectors shown in Table 3. ISAC is also trained to perform three actions, i.e., performing the requested task to fixate on the Barney doll, yelling "Alarm!", and performing a free-style dance.

Two types of situations were tested as shown in Figure 25:

Situation 1: (Salience-based Reactive Action Experiment))
Various sounds (a short piece of music, an alarm sound, human voices, and background noises) were presented to the system at different times while ISAC was idle, i.e. no task was conducted.

Situation 2: (Situation-Based Task Switching Experiment)
A task to fixate on the Barney doll was first given to the model. Then, the same sounds were presented during the task execution.
A feedback on the action selected was given by a human teacher as a part of supervisory learning..
The process was repeated until the model learned the proper response.

Figure 25. Overview of the experiment

7.2.2 Attention and Emotion

In our cognitive architecture, emotions are handled by the Emotion Agent (EA) [Dodd, 2005]. EA provides the emotional responses to the percepts in the environment. This response is currently represented in a pre-defined form of a vector called the *Emotion Vector*. Each element of the vector holds the level of a basis emotion that ISAC possesses toward the percept. Table 3 shows the Emotion Vector used in the experiment. The magnitude of this vector is sent to the Attention Network as the level of emotional salience for the given stimulus. The Attention Network then acts as a gating by allowing only the percepts with high emotional salience to go through and become candidate chunks for WM as shown in Figure 26.

Stimulus/Task-response	Emotion Vector			Emotional salience
	happy-sad	love-hate	alert-uninterested	
Alarm sound	0.1	-0.8	-0.6	1.01
Musical piece	0.7	0.5	0.1	0.86
Task command	0.1	0	0.6	0.61
Other human words	0.1	0.1	0.1	0.17

Table 3. Stimuli *vs.* Corresponding emotion vectors.

Figure 26. Focus of attention using the Attention Network.

7.2.3 Situation-Based Decision Making

If two or more percepts and/or commands are given to ISAC at the same time, ISAC must resolve the conflict. The Central Executive Agent (CEA) described in Section 6.2 is responsible for conflict resolution. For example, if a percept with a high emotional salience is detected while a task is being executed, CEA must make a decision how to respond to the newly acquired percept. The current situation is used by CEA for decision making. For this experiment, "a situation" can be translated from the change in perceptual information as follows: Let the set of all percepts in the Focus of Attention (FOA) at a given time be denoted by X. Members of X then comprise a combination of some known percepts from LTM. In a perceptual event, either a percept disappears or a new percept attracts the robot's attention, and the original set of percepts in FOA will change. For this experiment, "a situation" was considered to be *any change of specific members of X* as illustrated in Figure 24.
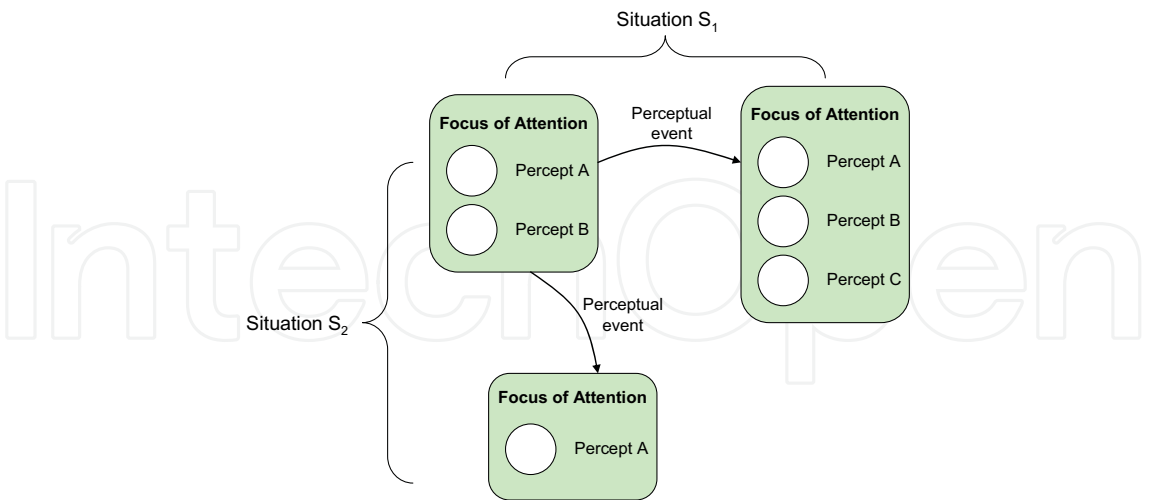
Figure 24. Relationship between changes in percepts in FOA and situations.

The probabilities $P[A_j^{(i)}]$, $j=1,2,...,N$, associated with the actions $A_1^{(i)}$, $A_2^{(i)}$ ..., $A_N^{(i)}$ and subjected to the constraint $\sum_{j=1}^{N} P[A_j^{(i)}]=1$, were computed by CEA using past history of the number of times the appropriate action was provided through supervised learning. That is, during the teaching phase, the human teacher provided the appropriate action $A_j^{(i)}$. CEA then kept track of the frequency that $A_j^{(i)}$ had been provided for S_i, and used it to update $P[A_j^{(i)}]$ accordingly. During the execution phase, when Situation S_i occurred, CEA selected an action as follows:

The unit interval [0,1] is partitioned into N regions, each with a width of $P[A_j^{(i)}]$. A uniform random number on the unit interval is generated, and the region j, $1\leq j \leq N$, in which it falls is determined. The associated action $A_j^{(i)}$ is then selected.
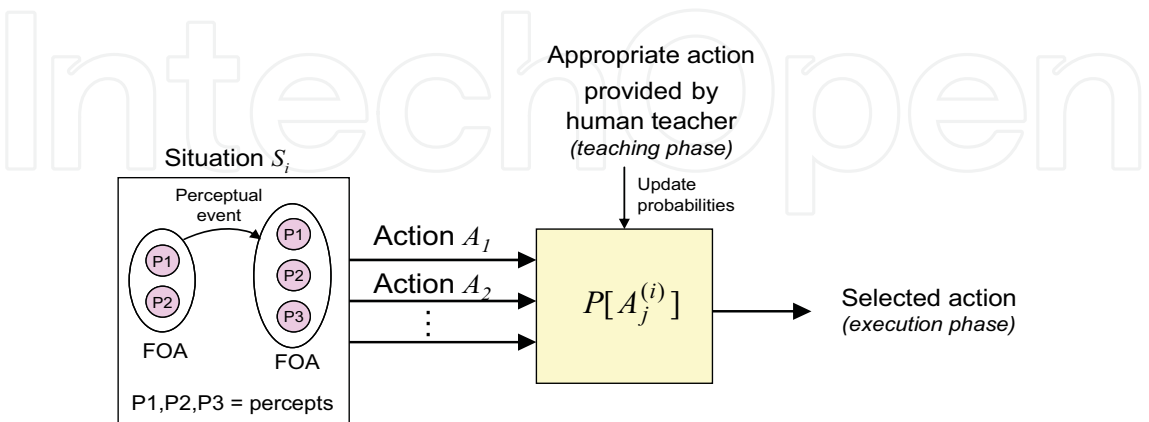

Figure 25. Decision making and learning.

By selecting an action probabilistically, the actions having higher probabilities are more likely to be selected. This enables continual exploration so that the

robot may respond to dynamic situations. The decision-making process is illustrated in Figure 25.

7.2.4 System Evaluation

In the first situation, only the musical piece and alarm sound caused the Emotion Agent to create the emotion vectors with a high emotional salience. Because no task (goal) was given, CEA selected the action based on the initial emotional state. This situation demonstrated the system's ability to focus attention to those percepts that cause a high emotional salience

In the second situation, a task to fixate on the Barney doll was given to the system prior to the presence of other stimuli. The changes in FOA then created two situations, i.e. "Music was heard during the task execution" and "Alarm was heard during the task execution". Using the probabilistic model of the situation as discussed above, CEA decided if it should pay attention to the stimuli or keep focusing on the task based on prior knowledge of the stimuli and situation. "Situation 2 (before learning)" in Table 4 summarizes the system responses.

FOA	Situation 1	Situation 2 (before learning)	Situation 2 (after learning)
Music	"Dancing"	Ignored the music	Ignored the music
Alarm	Yelled "Alarm!"	Yelled "Alarm!"	Ignored the alarm

Table 4. Stimuli Response Results.

Finally, the model was later taught to respond to Situation 2 differently from the initial knowledge. That is, the model entered the teaching phase again to learn a new appropriate response, which in this case was to ignore the alarm for Situation 2. 100 trials of teaching were performed and the results from learning are shown in Figure 26. This figure shows the number of times the model chose to ignore the alarm for every ten trials. In the beginning, the model did not ignore the alarm right away because of the strong association between the percepts and actions initially embedded in the model. After about 20 trials, the supervised learning changed the associated probabilities in the model enough so the model started to learn to ignore the alarm. With increasing trials, the system learned to select the correct response. However, as the selection was performed using a probabilistic method, it was still possible that the system selected incorrect action occasionally as seen in the graph. This allows the system to explore other possible actions in dynamic situations. Because the probabilistic model was updated for every teaching trial, the system was more likely to select the correct action as the number of trials increased. If

this number reached infinity, the system would then select the correct action 100% of the time.
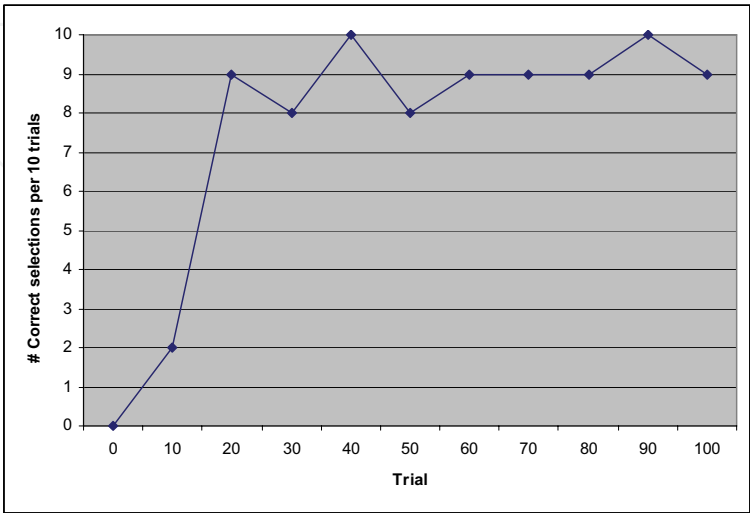

Figure 26. Learning curve for the response to the alarm in Situation 2.

This simple experiment was conducted to verify that the system did learn to select the appropriate action under supervisory learning [Mitchell, 1997] using attention and a set of "snapshot" state of emotions. As the next step, we are now working to develop a more realistic, dynamic model of emotion which will reflect the change in ISAC's internal states over time. The details of how this time-varying event-based model of emotion will influence action-selection process will be described in Section 8.

8. Future Integrated Experiment

Any cognitive robot should be able to use both external and internal stimuli to consciously organize their behaviors such as action selection, attention and learning. According to this, emotion could be one of main factors to mediate decision-making process. In order to make the attention- and emotion-based action selection process more realistic, we are now working to develop a time-varying event-based model of emotion reflecting the change in ISAC's internal states over time. In this type of action-selection process, the system does not necessarily perform the same action every time for the same set of external stimuli.

In ISAC's cognitive architecture, the Self Agent is responsible for meta-management of its internal states similar to that proposed by Sloman [Sloman, et al., 2005] as shown in Figure 30. We have used the fixed, embedded emotion level as a part of the Self Agent in the experiment. The Emotion Agent will

be modified to be more dynamic to better keep track of ISAC's internal state. The details of this work are described now.
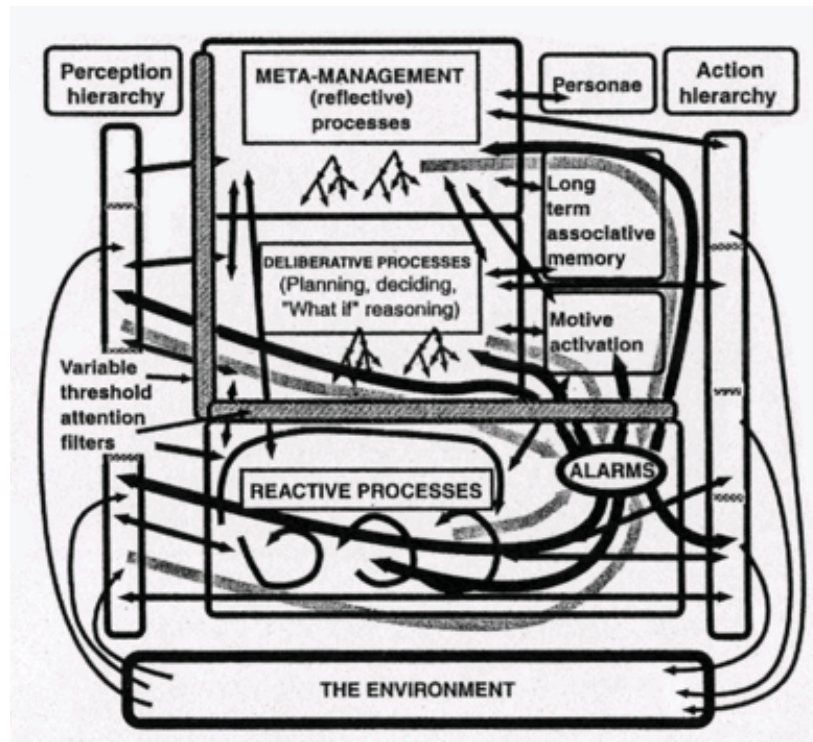

Figure 30. H-CogAff Architecture [Sloman, et al, p. 227, 2005]

8.1 System Integration

The incorporation of both internal and external stimuli in the architecture enables the system to be as dynamic as possible, gearing responses so that they are not a function of the external inputs alone. This creates a robot that can respond differently to the same situation based solely on the internal state of the robot. The internal stimulus that will be used for this experiment is the level of excitement of the robot. The excitement level will be a product of both ISAC's external environment and ISAC's other internal states (such as presence of command, joint activity, etc.)

It is important that ISAC's excitement or arousal to a given situation not be a static function, but rather a dynamic function of time. For the time being, ISAC's level of excitement is calculated using a first-order exponential decay function:

$$Excitement \ = \alpha(S) \cdot e^{-\beta(S) \cdot t}$$

The terms α(S) and β(S) are functions of the state, S, of ISAC and are designed in such a way that they can be learned or modified over time using standard reinforcement learning techniques. Therefore, a particular situation (or a change in state) S_i which may initially be embedded in ISAC as "very exciting" (i.e. $\alpha(S_i)$ returns a high value and $\beta(S_i)$ returns a low value) can, over time, adjust to reflect ISAC's experience with that particular state. Conversely, states initially embedded as "not exciting" can, based on experience, become exciting states. One final point to add is that the decay nature of the excitement function ensures that no state continues to excite ISAC indefinitely (i.e. ISAC will eventually get bored with even the most exciting event).

As ISAC's other cognitive processes learn, these processes in turn will utilize the current state of excitement when making decisions. This utilization will be a function of the excitement level as well as the internal and external states that have caused the current excitement level. As the stimuli that excite ISAC change over time, ISAC's decision-making process should reflect this change and summarily, ISAC should make different choices. The experiment is designed to teach ISAC this ability and then put ISAC in a situation in which multiple possibilities exist forcing the robot to make a decision. It is hoped that ISAC's cognitive architecture will allow it to make this decision.

8.2 Experimental Design

To demonstrate the use and effectiveness of utilizing both internal and external stimuli during action selection and task switching, an experiment has been designed that requires the principles of cognitive robotics discussed in this chapter. During this experiment, ISAC will be presented with a range of different scenarios and be forced to decide whether to continue with the present task or switch to another task. Close monitoring of ISAC's internal level of excitement or arousal will be the mechanism that that aids in making this decision.

Through habituation and learning, ISAC will develop an association between excitement levels and different percepts or tasks. In other words, based on experience, certain percepts will excite ISAC more than other percepts, and certain tasks will excite ISAC more than other tasks. These associations will begin as embedded knowledge, based on novelty, within ISAC. Over time and through experience and habituation, these correlations will change and ISAC will begin to develop its own sense of excitement/boredom.

he experiment steps are as follows:

1. Embed ISAC with knowledge that certain percepts and tasks are more exciting than others (i.e. faces are more exciting than bean bags, *dancing* is more exciting than *reaching*, etc.)

2. Train a small set of WMS to react to certain situations (see WM1 and WM2 from section 7.1)

   a) WM1 is trained to enable ISAC to interact with simple objects.

   b) WM2 is trained for interaction with people.

   c) WM3 is trained to enable ISAC to respond appropriately to sound stimuli.

3. Have a person enter the room and give ISAC a task.

4. Repeat step 3 several times in order to cause a change in ISAC's embedded excitement function (Section 8.1)

5. Have a person enter the room and give ISAC a task. During the task execution have music begin playing in the room.

6. Continue playing the music for several minutes.

Steps 1 and 2 of this experiment are the initial embedding of knowledge into the system. When a person enters the room and gives ISAC a command, this interaction should excite ISAC causing it to desire to engage with the person and complete the task. Through repetition of Step 3, this excitement level should continue to decrease with each repeated command. Over time, the excitement level associated with Step 3 should degrade to such an extent that ISAC essentially becomes unmotivated to perform the task. At this point, when ISAC hears music during the execution of the task (Step 5), the robot should choose to ignore the person and pay attention to the music instead. After the music plays for several minutes (Step 6), ISAC should eventually become bored with this as well (as discussed in section 8.1.). Once bored with the music, ISAC should transition back to the commanded task.

9. Conclusions

In the last forty years, industrial robots have progressed from the Plan-Sense-Act paradigm to more robust, adaptive/intelligent control paradigm [Kawamura, 2006]. In particular, the integration of body, sensor and AI-based software has produced not only advanced industrial robots, but non-industrial robots ranging from entertainment and home to a variety of health-related robots, we expect this trend to continue. This chapter introduced the next grand challenge in robotics, i.e. the integration of body and mind. In particular, the chapter described our efforts towards this challenge through the realization of a cognitive robot using cognitive control, attention, emotion, and an adaptive working memory system. In the last forty years, the field of industrial robotics and automation has also seen many innovations. As manufacturing becomes more distributed and sophisticated, realization of human-like robotic coworkers with cognitive skills will be a challenge not only to academia, but to manufacturing engineers as well.

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How to reference

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K. Kawamura, S. M. Gordon and P. Ratanaswasd (2006). Robotic Body-Mind Integration: Next Grand Challenge in Robotics, Industrial Robotics: Theory, Modelling and Control, Sam Cubero (Ed.), ISBN: 3-86611-285-8, InTech, Available from:

http://www.intechopen.com/books/industrial_robotics_theory_modelling_and_control/robotic_body-mind_integration__next_grand_challenge_in_robotics

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