Robotic Body-Mind Integration: Next Grand Challenge in Robotics

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Abstract – The field of robotics has evolved from industrial robots in the 1960s to entertainment and service robots in the 2000s. During the last decade, major progress has been made in integrating a robotic body with sensors and AI-based software. In this paper, we describe our efforts to realize a next generation of intelligent robots called *cognitive robots*. Our work is embedded within a multiagent-based cognitive robot architecture with three distinctive memory systems: short-term and long-term memory structures for routine task execution and a working memory system (WMS) which is closely tied to learning and execution of tasks. The concept of WMS is relatively new in robotics and is expected to play a similar role of the prefrontal cortex (PFC) of our brain that performs cognitive tasks.

I. INTRODUCTION

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 [1] [2]. Many studies have shown the need for both, motivating work towards hybrid architectures [3]. While such an integration of robotic body and sensors offers the promise of robots which are fluent in routine operations, we hypothesize that responding to the full range of contingencies often present in complex tasks will require something more than the combination of these design approaches. Specifically, we see cognitive flexibility and adaptability arising from self-knowledge and processes that can analyze and modify the very mechanisms that support both reactive action and careful deliberation. We call this "robotic body-mind integration". 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 [4].

In this paper, we describe details of a cognitive robot architecture with three distinctive memory systems: short-term and long-term memories and a working memory system. We define short-term memory to be sensor-driven and typically lasts for minutes. Long-term memory can persist indefinitely and contains information such as skills and semantic knowledge. A working memory system (WMS) allows the robot to focus attention on the most relevant features of the current task and is closely tied to the learning and execution of tasks [5].

II. MULTIAGENT-BASED COGNITIVE ROBOT ARCHITECTURE

A humanoid robot is an example of a robot that may require intelligent behavior to act with generality in its environment and adapt its behaviors to accomplish tasks. As the complexity of an interaction grows, so grows the complexity of the software necessary to process sensory information and to control action purposefully. The development and maintenance of complex software systems can benefit from domain-specific guidelines that promote code reuse and integration. Information processing in our humanoid robot ISAC, is embedded within a multiagent-based software architecture called the Intelligent Machine Architecture (IMA) [6],[7],[8]. The IMA was designed to provide guidelines and allow for the development of subsystems capable of environmental modeling and robot control through the collections of IMA agents and associated memories, as shown in Figure 1.

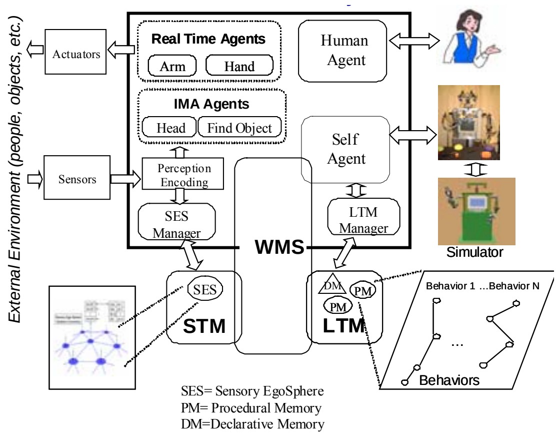
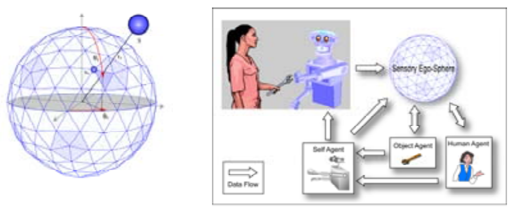


Figure 1: Multiagent-based perception, control and memory architecture.

III. ROBOT MEMORY STRUCTURE

A. Short-Term Memory: Sensory EgoSphere

ISAC's short-term memory (STM) resides in the Sensory EgoSphere (SES) [9]. The SES was inspired by Albus' egosphere concept [10]. It is defined as a geodesic sphere indexed by azimuth and elevation and centered at a robot's head. The SES stores a pointer to information about sensory data, its location in the environment, and the time at which it was registered. This pointer is connected to a vertex on the geodesic dome interface and to a record in the database. These vertices form nodes, like in a net, that approximate points in the environment for simple breadth-first searches. The SES operates asynchronously as an IMA agent. Figure 2 depicts the SES and its association with high-level agents [6].



(a) (b)

Figure 2: (a) Sensory EgoSphere and (b) SES association with high-level agents.

B. Long-Term Memory: Procedural and Declarative Memories

Long-term memory (LTM) in the brain stores information such as skills learned and semantic knowledge gained for retrieval in the future. The LTM consists of the Procedural Memory (PM) representing the former and the Declarative Memory (DM) representing the latter. Specifically, the PM holds information needed to generate actuator motions while DM holds information learned about objects in the environment.

Procedural Memory

The PM contains behaviors that can be combined to perform specific tasks. PM units are derived using the spatio-temporal Isomap method proposed by Jenkins and Mataric [11]. Figure 3 illustrates how it is used to generate behaviors [12].

Motion data such as *how to reach to a point* are collected from the teleoperation of ISAC. The motion streams collected are segmented into a set of motion segments. The central idea in the derivation of behaviors from motion segments is to discover spatio-temporal structure in a motion stream.

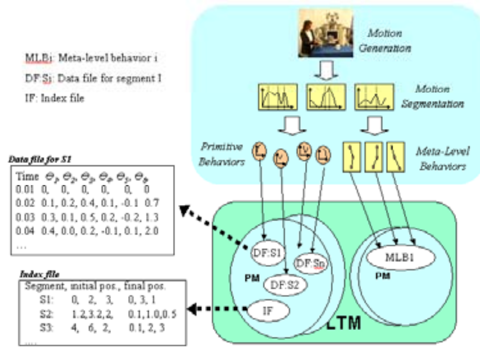


Figure 3: Derivation of PM through human-guided motion stream.

The interpolation method called the Verbs and Adverbs [13] is used to describe a motion (verb) in terms of its parameters (adverbs) that allows ISAC to generate a new movement based on the similarity of stored motions. Adverbs, or parameters, can be objective values which allow each set of motions to be interpolated in very different ways. This allows ISAC to be able to demonstrate new movements based on a small number of learned movements.

Figure 4 depicts a current representation of the PM data structure. At the top of this structure, meta-level behaviors will be stored which will allow us to identify what each behavior can contribute to solving a given task. Each entry in the meta-level behavior table will contain pointers to the underlying motion primitives.

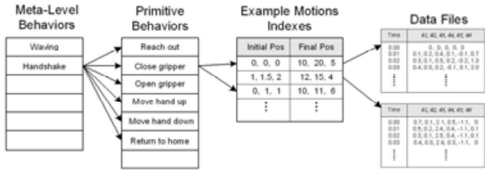


Figure 4: Structure of LTM database.

Declarative Memory

In his Animate Vision paper [14], Ballard states, "Animate vision systems can also use representations that are heavily *personalized* to achieve efficient behaviors." In developing the Declarative Memory (DM), we are following his arguments. For example, besides the name and type, we use the exemplar sensor data such as color, the last known location, and selected physical characteristics to be stored in the DM. This way, the WMS (See Section III.C) could bring in the minimum set of information from the DM to use to complete the task.

The Declarative Memory units consist of four fields: Name, Type, Physical Characteristics, and Recognition Information. The Physical Characteristics field contains information useful to cognitive processes, such as *can be picked up* or *fragile*. The Recognition Information field is a set of pointers to structures dealing with the sensor data taken in by ISAC. These structures, in turn, contain three fields: the filename of the raw data, the section of the data dealing with the object, and recognition information usable by the perceptual system such as color segmentation values or data for Lowe's Algorithm [15]. The Object Recognition nodes are not restricted to a single sensor modality. For example, if a Barney™ doll emitted a high-pitched squealing sound, this information could be stored in an indexed sound-based Object Recognition node. Figure 5 depicts a current representation of the DM data structure.

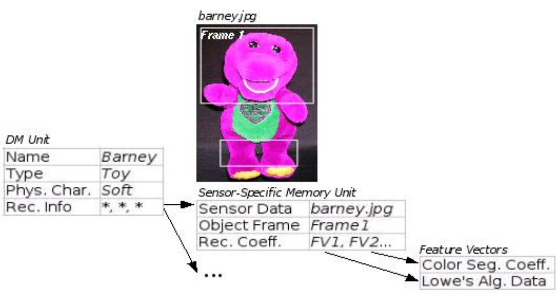


Figure 5: DM data structure.

C. *Working Memory System and Attention*

There is much evidence for existence of a working memory in primates. It is thought to be closely tied to the learning and execution of tasks, as it contributes to decision-making capabilities by focusing on essential task information and discarding distractions [16][17]. A well-known working memory test is the "Delayed Match to Sample", where a person is shown pictures of horses in sequence and asked if they are the same or different [18].

Inspired by this, we are currently developing a working memory system (WMS) model with the following objectives:

- reduce search space dramatically for cognitive task execution,
- provide learning ability for necessary "chunks" of information to be retained,
- change and generalize the context for novel situations through the use of artificial neural network, and
- provide the ability to supply task-specific "episodic" memory.

Figure 6 illustrates dataflow among the Cognitive Control (See Section IV.A), Working Memory System and Perceptive and Motor Memories in our implementation.

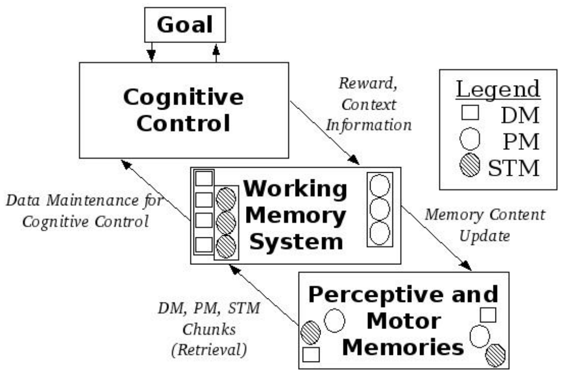


Figure 6: WMS dataflow.

IV. COGNITIVE CONTROL AND THE CENTRAL EXECUTIVE

A. Cognitive Control

Robots in the future are expected to exhibit robust performance in a wide variety of situations, requiring competencies ranging from efficient sensorimotor action control in routine situations to high-level *cognitive control* to handle new or difficult situations as shown in Figure 8 [19].

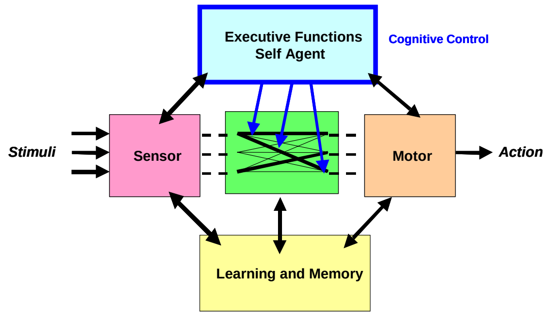


Figure 8: Concept of Cognitive Control [19].

Cognitive (or executive) control is the "ability of the brain to identify possible goals and figure out how to achieve them. It is also used to navigate complex situations and ignore the distractions and impulses that would derail our goal-directed efforts" [19].

In our case, it involves the control of behavior in situations when robot's sensorimotor-based routine action execution capabilities fall short of meeting task demands. Inspired by the work by Wolpert and Kawato [20], we are implementing the behavior choosing process using modular controllers that involves a central executive module and a working memory as shown in Figure 9.

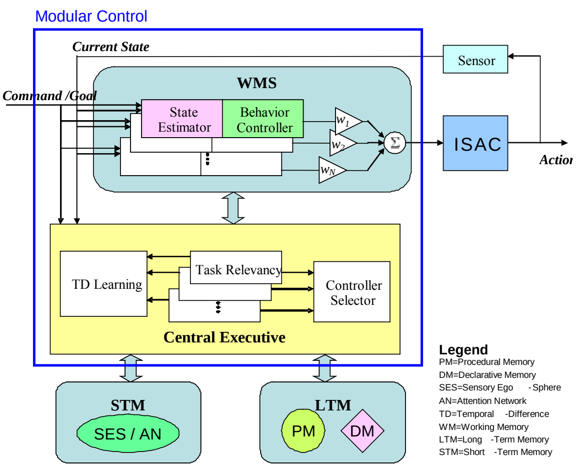


Figure 9: Central Executive and Modular Control.

B. Central Executive

Cognitive scientists have been developing cognitive architectures to model essential elements of human cognition. Soar [21] and ACT-R [22] are two of the well-known cognitive models using production rule systems.

Some cognitive architectures such as EPIC [23] suggest the concept of utilization of cognitive processor. A cognitive processor is a conjunction of human's working memory and executive functions. Under an NSF grant we are investigating one model of such executive functions called the Central Executive (CE).

The CE will be responsible for high-level executive functions such as:

- goal-directed action selection,
- regulation of working memory,
- control of the focus of attention, and
- manipulation of LTM.

Under current implementation, the CE is designed to carry out goal-oriented action selection. In order to select behaviors, each behavior is assigned an estimator and a controller, similarly to the concept of modular controller presented in [20]. The CE uses temporal difference (TD) learning [24] and task relevancy modules to choose appropriate behaviors.

TD learning allows the system to learn from past experiences based on a reinforcement signal in the form of an expected future reward in the current situation. The TD learning system loads a small set of behaviors into the WMS that it believes to produce positive rewards.

Consequently, only a limited number of behaviors are considered for execution at one time which allows the CE to rapidly execute tasks. Relevancy values will be used to compute weights for which will be assigned to each behavior during action execution.

During this process, the focus of attention of the environment is handled by the Attention Network [9] by putting focus on a particular location of the SES based on goal information.

The current status of the CE mostly regards the control of action based on skill information stored in the procedural memory section of the LTM. We are investigating to incorporate other knowledge information as a part of procedural memory similarly to production rules in ACT-R and EPIC. Strength of connections among production rules will be used in addition to the current calculation of task relevancies during action selection.

Figure 10 shows a simple two-behavior arm movement example to illustrate how behaviors are combined by finding the sum of vectors A and B with time-varying weights.

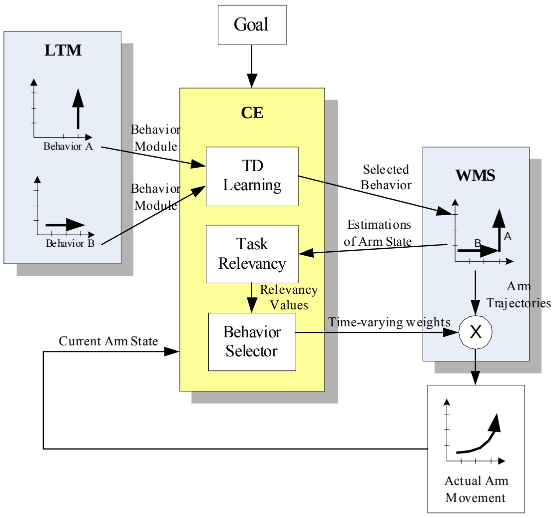


Figure10: Implementation of CE's goal-oriented behavior selection process.

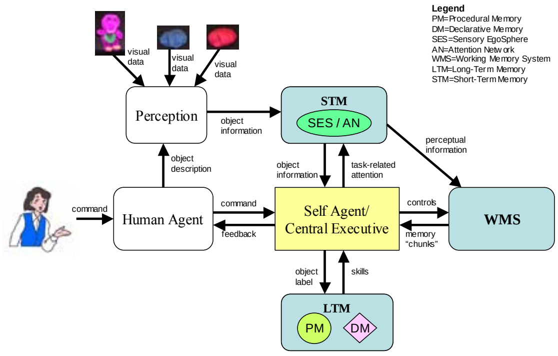
V. SYSTEM PERFORMANCE ANALYSIS

During computational modeling of sensorimotor processing for ISAC, we gained new insights about the modeling of the Central Executive and the Working Memory System.

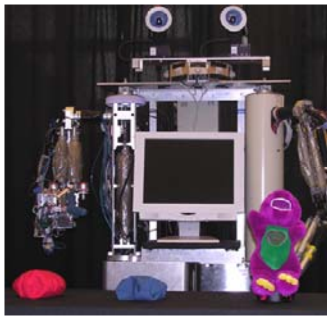
Key components within our cognitive robot architecture are being tested as shown in Figure 11 (a) using a set of evaluation tasks. These tasks are robotic analogs to some of the laboratory experiments that have been performed with monkeys [5]:

1. ISAC is trained to learn each object in turn by a human. (This task illustrates how ISAC associates words and features with objects and store the date into the STM.)
2. ISAC is asked to point to one of the objects learned. (This task illustrates how the Self Agent works with the STM and the Arm Agent to execute the command.)
3. Objects are shuffled and then ISAC is asked to point to one object. (This task demonstrates ISAC's perception-to-action mapping using the WMS as well as the ability to move the arm using modular control as shown in Fig. 11(b).)
4. One object is covered, ISAC is then asked to point to the object. (This step demonstrates the goal-oriented cognitive control for ISAC to recognize the absence of the object in its immediate sensory input and select appropriate actions.)

Results using the WMS will be compared to results in a current baseline system of ISAC without the WMS.



(a)



(b)

Figure 11: (a) System Performance Analysis and (b) Experiment environment.

VI. CONCLUSIONS

Realization of robots with human-level intelligence continues to be the dream of many robotic researchers. During the past decade, we have seen major advances in the integration of robotics, sensor technology and artificial intelligence, and expect this trend to continue. However, development of robots with human-level intelligence which we call cognitive robots will require further integration of advances in cognitive science, computational neuroscience and linguistics. This paper described our efforts towards this challenge.

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