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A Conceptual Cognitive Architecture for Robots to Learn Behaviors from Demonstrations in Robotic Aid Area

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***Abstract*—This paper proposes a conceptual hybrid cognitive architecture for cognitive robots to learn behaviors from demonstrations in robotic aid situations. Unlike the current cognitive architectures, this architecture puts concentration on the requirements of the safety, the interaction, and the non-centralized processing in robotic aid situations. Imitation learning technologies for cognitive robots have been integrated into this architecture for rapidly transferring the knowledge and skills between human teachers and robots..**

I. Introduction

ROBOTS are designed to help human beings, as expected by researchers and the general public. Currently, a new generation of robots, named cognitive robots, is developed to interactively help humans to complete certain tasks in certain areas, which integrates perception, action, learning, decision-making, and communication, is to generate human-like intelligence and behaviors for robots[1].

After the birth of humanoid robots, researchers expected that these robots can be placed into the human existing environment. Schaal[2] proposed that the imitation learning could be a possible solution to train humanoid robots to learn complex behaviors from human teachers. In the imitation learning, behaviors are learned from examples or demonstrations, which are provided by human or robot teachers. After observing examples, robots can generate reasonable and similar solutions to solve similar problems.

The application of the imitation learning for robots in the robotic aid area should have much stricter constraints[3] [4] [5]. The reason for using the imitation learning in the robotic aid area is that behaviors learned from human beings are ensured not harmful to humans[6].

Recently, the research on cognitive architectures has received broad attentions from robotics research community because it provides a kind of methods of using cognitive processes. Current cognitive architectures can be divided into four types: Reactive, Symbolic, Connectionist and Hybrid. A typical reactive architecture is Subsumption [7] which directly couples sensory-motor information. For symbolic type, some well-known architectures are: ACT-R[8], SOAR[9], and EPIC[10]. Typical connectionist type architectures include: BICS[11], Darwinism[12], and CAP2[13]. Hybrid type includes: RCS[14], JACK[15], and ISAC[16]. Billard [17] explained biological evidences of the existence of imitation learning in animals and argued it is reasonable to incorporate imitation learning in cognitive architectures.

The rest of this paper is organized as follows: Section II describes the system architecture, and the algorithms and the models in this cognitive architecture; Section III proposes a typical application of this cognitive architecture in the robotic aid area; Section IV discusses the advantage of this cognitive architecture and proposes possible problems in the future study. Section V summarizes the work in this paper.

II. System Architecture Design

The proposed architecture in this paper is based on the former research on ISAC cognitive architecture at Center for Intelligent Systems of Vanderbilt University[16].

A. Meta Management Agent (MMA)

In the MMA, the components are defined based on the motivations of the robots. All the components are designed in the Long time Memory (LTM).

--Behavior Motivation (BM)

This component stores the predefined goal of the robot, which is what this robot is expected to do to help humans, e.g. cooking, disabled assisting, and surgery assisting.

--Behavior Generation Memory (BGM)

The BGM stores methods of generating behaviors in the imitation learning. Several existing behavior generation methods, including Dynamic Motion Primitives [18] [19], Fuzzy Method [20], Lagrange method [21], Potential Filed Method [22], and Roadmap Method [23] were tested in our lab, and will be stored in this component. Mathematical Models representing behaviors are stored in the BGM. In our lab, Locally Weighted Projection Regression (LWPR)[24], Gaussian Process (GP)[25], and Linear Global Model (LGM)[26] were tested and will be used in this component.

--Behavior Learning Memory (BLM)

The BLM stores the evaluations of different methods of generating behaviors in different situations. Artificial Neural Network (ANN) [27] will be used to simulate the evaluation.

--Implementation

Triggered by the DA, the MMA finds suitable methods of generating behaviors by obtaining the motivation in the BM, searching behavior generation methods in the BGM, and obtaining the evaluation results from the BLM, and sends this information to Deliberation Agent.

B. Deliberation Agent (DA)

In the DA, robots use the evaluations from the BLM to determine which methods of generating behaviors should be used.

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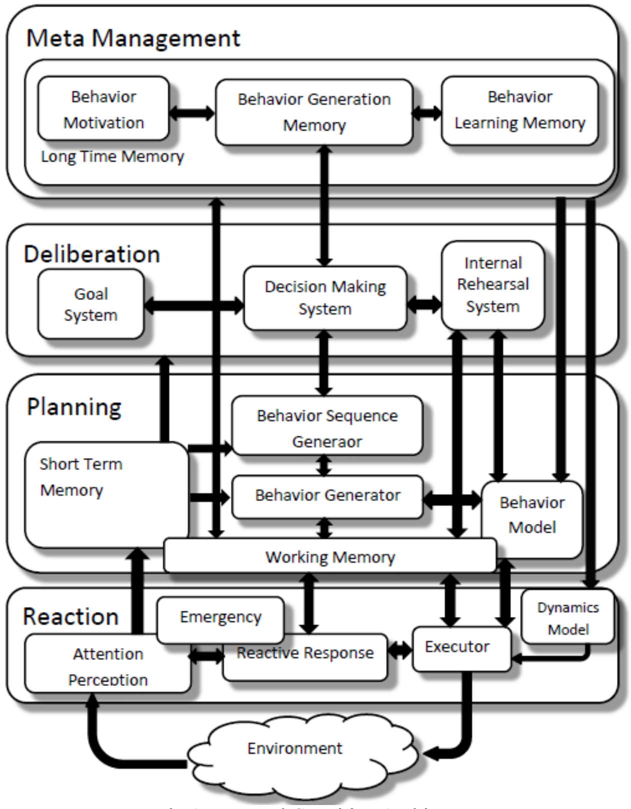

Fig.1 Proposed Cognitive Architecture

--*Goal System (GS)*

This component sets the goal in a given task which is related to a specific situation.

--*Decision Making System (DMS)*

The DMS receives the method of generating behaviors from the BGM in the MMA and sends the method to the Planning Agent for generating a behavior sequence. It also receives the results of executing the behaviors from the Planning Agent and sends to the MMA for evaluation of the methods. In an imitation learning task, the DMS receives the goal from the GS and evaluates the behavior sequence in the required situation using the Internal Rehearsal System.

--*Internal Rehearsal System (IRS)*

The IRS[28] evaluates the current behavior sequence and sends the evaluation results to DMS for final decision making. In IRS, a Robosim [29] based simulation model will be established to simulate the environment and the robot.

--*Implementation*

Given a goal of a task in a specific situation, the DMS receives the behavior generation methods from the BGM, sends the information to a Behavior Sequence Generator to generate a behavior sequence using a cognitive segmentation method, and evaluates result using the IRS. Results of executing the behaviors are sent from the Planning Agent to the BLM through the DMS for the evaluations.

C. *Planning Agent (PA)*

In the PA, robots collect the sensory information from environment and robotic body using the stored behavior models to generate required behaviors in the behavior sequence.

--*Short Time Memory (STM)*

The STM stores the environmental information.

--*Behavior Sequence Generator (BSG)*

The BSG receives the behavior generation methods from the DMS and generates behavior sequences to complete a goal in a given task which is related to a specific situation.

--*Behavior Model (BM)*

The BM stores behavior models which are learned through imitation learning. These behaviors are recorded using some mathematical models received from the BGM.

--*Behavior Generator (BG)*

The BG generates specific behaviors in the behavior sequences using learned behavior models and learned behavior generation methods received from the DMS. This generation is related to the information stored in the WM and the STM, and the results are sent to the Reactive Agent.

--*Working Memory (WM)*

The WM stores information which is directly related to the current task.

--*Implementation*

The BG receives behavior sequence information from the BSG, generates behaviors using received behavior generation methods from the DMS, task-Related information from the WM, and environmental information from the STM, and sends to the Reactive Agent.

D. *Reactive Agent (RA)*

In the RA, predefined reactive behaviors are stored in the 'Reactive Response' component. Robots rapidly execute the behaviors in the Reactive Response for simple situations. For example, robots can avoid the collision between itself and humans rapidly.

--*Executor*

Executor receives the information of behaviors in a behavior sequence and executes the behaviors using actuators. This is a typical sensory-motor control system.

--*Emergency*

In robotic aid domain, emergency events are significantly important. The Emergency collects the information from the environment and extremely rapidly affects Reactive Response component.

--*Attention-Perception (AP)*

The AP gathers information from the environment using stereo video signal[30] and an ANN model will be used to extract required information from several kinds of environmental information.

--*Reactive Response (RR)*

The RR stores the emergent responses. Receiving environmental information from the AP and the Emergency, the RR rapidly generates emergent behaviors and sends to Executor. A Subsumption [7] based sub-system will be used.

--*Implementation*

The Executor receives the information of the behaviors in a behavior sequence and executes the behaviors in a temporal order. If a command from the RR is received, the Executor executes them first.

III. A Conceptual Application in Robot Aid Domain

Fig.2 displays a robotic aid system developed at Vanderbilt University[31], which helps the disabled, patients and children. Currently, our research is to incorporate the imitation learning methods in this cognitive architecture to train a robot, named ISAC, rapidly learn skills from human teachers to help humans safely and interactively.

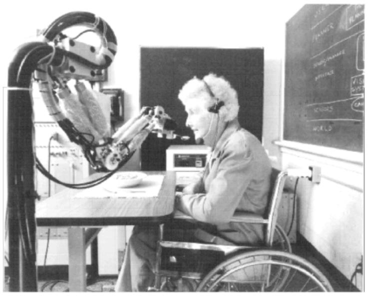

Fig.2 ISAC at Work (Year 1993)[31]

ISAC will be trained to help humans eat the food in the tray on the table. Therefore robots should learn how to move end-effector (a spoon) to the tray, get the food and move it to a position near the mouth of a human.

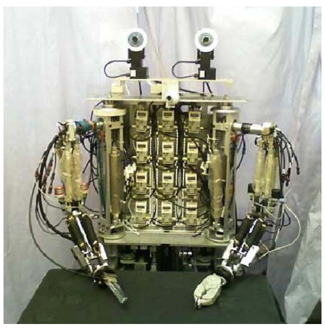

Fig.3 Pneumatic Driven Humanoid Robot: ISAC

This application is divided into 2 stages: Demonstration Learning and Imitation.

A. Demonstration Learning

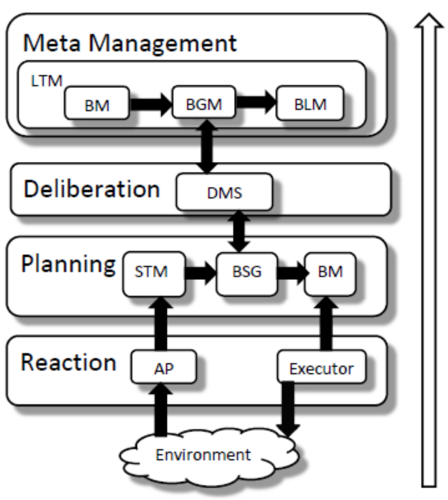

Fig.4 Demonstration Learning Flow Diagram

ISAC will be demonstrated the behavior of aiding human to eat the food by manually moving its right arm.

The demonstration will be learned using the cognitive architecture proposed in this paper and the used components and information loop are redrawn in Fig.4.

Demonstrations are sampled using the AP and segmented by the BSG using a cognitive segmentation method which is obtained from the BGM through the DMS. Segmented behaviors are stored in the BM as models for imitation. The behavior sequence and the behaviors are sent to the BGM for long time storage. The information flow is mainly bottom-up.

B. Imitation

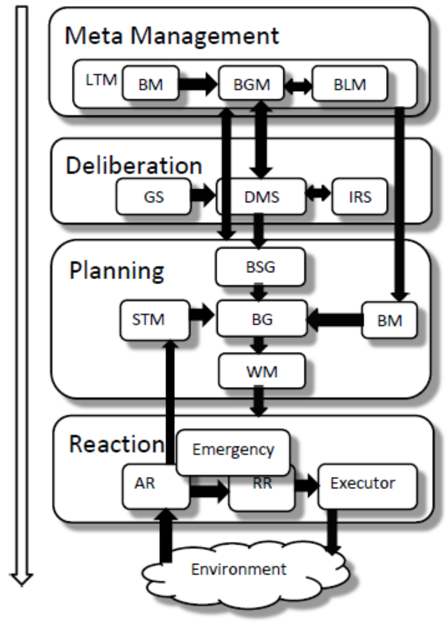

Fig.5 Imitation Flow Diagram

Given a new task, ISAC will use the AR to detect the position of the tray and the mouth of the human. The DMS analyzes the current situation and obtains the cognitive segmentation method, the behavior models, and the behavior generation methods in the BGM. Then a behavior sequence will be generated in the BSG to move the spoon to get the food and move it to the position near the mouse of the human. The behaviors in the behavior sequence will be generated in the BG using the behavior models in the BM. The WM receives the specific behavior information and sent to the RA. The Executor moves the arm of ISAC according to the behaviors. The execution results will be sent to the BLM in the MMA through the DMS for evaluations. The Emergency receives the information in the AR to affect the RR, in case of a collision between ISAC and the humans happens. The information flow diagram is shown in Fig.6. The information flow is mainly top-down.

IV. DISCUSSION AND FUTURE STUDY

This cognitive architecture provides a possible solution to improve the imitation learning to a more robust and flexible behavior generation method. In the future, robots are expected to learn complex behaviors in a dynamic environment and the analysis of cognitive processes can enhance the learning in a reasonable way. In a human-robot interactive situation, a robust architecture can help designers to improve the safety of the system. The main contribution of this cognitive architecture is that it combines the imitation learning and the cognitive architecture.

The long term goal is to train robots to generate behaviors autonomously in a dynamic human existing environment.

This paper proposes a cognitive architecture and an application of this architecture in robotic aid area. The next step is to implement this architecture on ISAC robot and carry out experiment in a real human existing environment to verify its effectiveness.

V. CONCLUSION

This paper proposes a cognitive architecture for imitation learning in robotic aid research area. The cognitive architecture is divided into several agents and algorithms or models are given for the components in each agent, and this method can be extended to other areas where imitation learning can be incorporated.

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