Online Knowledge Acquisition and General Problem Solving in a Real World by Humanoid Robots

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Abstract. In this paper, the authors propose a three-layer architecture using an existing planner, which is designed to build a general problem-solving system in a real world. A robot, which has implemented the proposed method, forms the concepts of objects using the Self-Organizing Incremental Neural Network, and then acquires knowledge, online and incrementally, through interaction with the environment or with humans. In addition, it can solve general-purpose problems in a real world by actively working with the various acquired knowledge using the General Problem Solver. In the experiment, the authors show that the proposed method is effective for solving general-purpose problems in a real world using a humanoid robot.

Keywords: Real World Intelligence, Humanoid Robot, Self-Organizing Incremental Neural Network, General Problem Solver.

1 Introduction

To enable humanoid robots to act intelligently in a real world, not only a control theory for robot motion or an information theory for robot intelligence, but also a close collaboration of various fields of study is needed. For the field of motion control of humanoid robots, many studies have been vigorously performed in private enterprises or research organizations, such as the study of an autonomy bipedal robot represented by ASIMO of Honda Motors, or the study of object-handling learning by a small humanoid robot [1]. However, on the other hand, in the field of intelligent information processing of humanoid robots, studies that can say "able to execute non-programmed operations autonomously" have not been reported so far. Therefore, this study proposes an architecture based on a keyword, that is, the intelligence of humanoid robots, specifically used for general-purpose problem solving in a real world.

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Designers have traditionally created intelligent robots by incorporating any possible situations and actions in advance. However, for a real world that continuously changes in a complex way, it is impossible to incorporate appropriate actions every time in advance. Instead of such a conventional method, there is an approach called Cognitive Developmental Robotics (CDR) [2] that focuses on robots' embodiment, in other words, it uses a process where the robots make contact with the environment through their own bodies, and then understand the information obtained from a real world. On the other hand, in terms of robot intelligence development, Weng and his followers have concluded that the following properties are required for a developmental system [3]:

I. The system is not specific to tasks.
II. The tasks are unknown to the system designers.
III. The system can generate approaches for unknown tasks.
IV. The system has an online learning ability.
V. The system has an open-ended learning ability.

An approach based on CDR could meet all the properties, except for property III because this property is obviously different from the others in terms of the intelligence level required. In particular, it demands not only the ability to "acquire" knowledge (solutions for tasks that are then expressed as knowledge), but also the ability to "generate" knowledge autonomously. To achieve this, in addition to the basic concept of CDR, a mechanism to generate new knowledge from existing knowledge is needed.

1.1 Purpose of This Study

The purpose of this study is to build a general problem-solving system in a real world that meets all the properties, including property III as defined by Weng. The proposed method is an architecture shown in Figure 1; a robot implemented using this architecture displays the following features:

- The robot forms the concepts of objects (symbols) from patterns obtained by seeing and hearing.
- The robot can acquire cause-effect relationships between actions and environmental changes in form of knowledge, both online and incrementally, through interaction with the environment or with humans.
- The robot can generate approaches for unknown tasks by combining existing knowledge.

2 Proposed Method

The architecture of the proposed method is shown in Figure 1. It is a three-layer architecture consisting of an Input Layer, a Pattern Memory Layer, and a Symbol Memory Layer. Among these, the Input Layer consists of three phases: a Symbol Grounding Phase, a Knowledge Acquisition Phase, and a Problem Solving Phase.

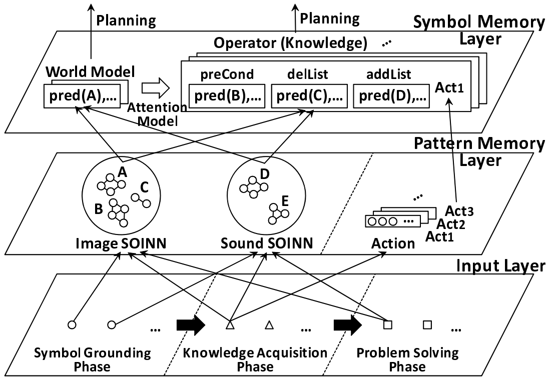

Fig. 1. Architecture of the proposed method. The black arrow in the Input Layer indicates the flow of processing. Arrows between each layer indicate the flow of data. A white arrow in the Symbol Memory Layer signifies the generation of operators (knowledge). In addition, a border in the Pattern Memory Layer means that the robot's movement information is kept in a space separate from the SOINN spaces.

In these phases, image and sound patterns are input from real environments. In addition, concept information added to each pattern in the Symbol Grounding Phase and the time-series data of the robot's joint angles (Act1, Act2, Act3 ...) in the Knowledge Acquisition Phase are input. In Figure 1, a circle, a triangle and a square in the Input Layer means that the type of each pattern is different by phases, as described. The Pattern Memory Layer stores patterns sent from the Input Layer, so that it functions as an interface for mapping a pattern to a symbol. The Symbol Memory Layer retains World Models and Operators, which include predicates (pred) that get symbols (A, B, ..) as arguments from the Pattern Memory Layer, which are used for planning.

1. Symbol Grounding Phase — In this phase, a robot forms the concepts of image and sound objects, which are used in later phases, using input patterns from real environments. This is realized by employing the Self-Organizing Incremental Neural Network (SOINN) [5]. The SOINN is capable of online incremental learning, that is, it can learn new input data without both storing all the previous ones and destroying the old learned knowledge. In this study, we prepare two SOINN spaces (Image SOINN and Sound SOINN) for image and sound patterns in the Pattern Memory Layer. A robot inputs each pattern to each SOINN along with the concept information provided by the experimenters.
2. Knowledge Acquisition Phase — In this phase, a robot acquires, both online and incrementally, cause-effect relationships in the form of knowledge from the changes to real environments that have been caused by its own actions. These cause-effect relationships are expressed, respectively, as one operator by the Attention Model. In particular, the Attention Model constructs an

operator by obtaining three elements necessary for its composition (a precondition (preCond), a deletion list (delList), and an addition list (addList)) from the changes to a real environment and then by combining these elements with taught movement information (Act).
3. Problem Solving Phase — In this phase, a robot solves general-purpose problems in real environments by working operators acquired in the Knowledge Acquisition Phase. This is achieved by employing the General Problem Solver (GPS) [4], which is a well-known planner for actively approaching working knowledge. First, a robot judges whether there are appropriate approaches for a task presented in a real environment. If such approaches exist, the robot chooses an approach according to a constant evaluation criterion, and then executes the approach in real environments. In this case, the robot repeats executing an operator and observing the changes to a real environment until it reaches a goal state.

3 Experiments

In this experiment, a robot acquires operators, both online and incrementally, as shown in Figure 2, such as, "If the robot raises its right/left hand, an apple/a bell will be put in his hand," "If the robot presses the bell, it will ring," and "If the robot makes a 'give me' gesture while the bell is ringing, the apple will move in front of it." We then presented tasks to the robot such as, "Put an apple in front of it when there is nothing on the table," which it had not directly experienced previously. As a consequence, as shown in Figure 3, the robot could perform the tasks by combining existing knowledge without direct teaching from the experimenters.

Fig. 2. An example of operators that the robot acquired

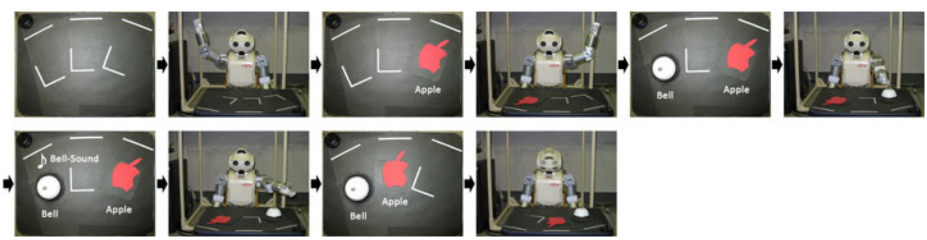

Fig. 3. An example of tasks that the robot performed. The last figure shows the robot nodding its head with satisfaction that it was able to reach a goal state.

4 Discussions

The proposed method meets all the properties, including property III as proposed by Weng, so that a robot implemented with it can act appropriately for tasks that it has not experienced directly, using actively acquired knowledge.

The SOINN is a key technology of the proposed method. Regarding only the symbolization of sense data, approaches using the Self-Organizing Map (SOM), the Recurrent Neural Network with Parametric Bias (RNNPB), or the Hidden Markov Model (HMM) are also conceivable (e.g., [6,7,8]). However, because it is generally necessary to define their internal structure beforehand, such as the number of nodes or states, they are not appropriate for online incremental learning. Although some of these approaches are, in principle, capable of online incremental learning, in fact, the performance of incremental learning using the SOM or RNNPB depends considerably on the number of nodes composing the network. Besides, since statistical methods such the HMM need a large amount of learning data, these methods are undesirable for robots in a real world from a practical standpoint. On the other hand, in an online incremental learning using the SOINN, not only it is unnecessary to define its size in advance, but also adaptation capability in a self-organizational way and high robustness to noise can be expected. These properties are essential to meet all the properties proposed by Weng.

Because it employs a layer structure that includes SOINNs, following are some superior aspects of the proposed method:

- It is capable of behaving robustly in the handling of unstable patterns in a real world. In addition, the concepts of objects can be also formed online and incrementally, which is necessary for knowledge acquisition and problem solving.
- It is capable of multimodal information processing required by robots, using multiple senses such as sight and sound. This study deals only with image and sound data, but in fact, other sensory data can be easily incorporated by preparing another SOINN space in the Pattern Memory Layer.
- A pattern set expressing the concepts of objects is not kept in individual operators but in the Pattern Memory Layer. Hence, concepts formed in the Pattern Memory Layer can be shared as a symbol from the Symbol Memory Layer, which results in significant savings in the memory capacity of operators in the Symbol Memory Layer.

5 Conclusion and Future Work

In this paper, the authors propose a three-layer architecture using an existing planner, which is designed to build a general problem-solving system in a real world. We consider this study as an important basis for the creation of humanoid robots that act intelligently in a real world. In terms of future studies, we will mainly focus on discussions of the following topics:

1. Automatic actions by getting used to tasks — In the current method, the more the number of operators acquired, the longer the time taken to plan. Namely, a robot that has a large amount of knowledge does not act at once when a task is presented to it. Therefore, by extending the architecture, we are now discussing a mechanism to cope automatically with the tasks that a robot has experienced before, without involving a planner.
2. Task instructions using languages — In the current method, task instructions are performed by presenting the goal states of tasks to a robot in real environments. However, it is paradoxical that we must prepare the goal states in advance of tasks that we want the robot to perform. Therefore, we are now discussing a mechanism to give the goal states of tasks to a robot using languages.

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