Behavior Selection Method of Humanoid Robots to Perform Complex Tasks

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Abstract. This paper proposes a behavior selection method of humanoid robots to perform complex tasks using the degree of consideration-based mechanism of thought (DoC-MoT). The four input (context) symbols and seven target (atom behavior) symbols are defined to perform five complex tasks. The degree of consideration (DoC) for each input symbol is represented by the λ-fuzzy measure and the knowledge link strengths between input and target symbols are represented by the partial evaluation values. Each target symbol is globally evaluated by the fuzzy integral of the partial evaluation values with respect to the fuzzy measure values. Then, one target symbol with the highest evaluation value is selected and activated. To make corrections to the robot's wrong behaviors, a learning process from a human's behaviors is employed to update the DoCs and the knowledge link strengths. To show the effectiveness of the proposed method, simulations are performed in a text-based simulator developed in Visual Studio 2012. The results show that the proposed method can generate human-like behaviors.

Keywords: Behavior selection algorithm, learning algorithm, complex tasks, humanoid robots, human-like mechanism of thought.

1 Introduction

A complex task of a humanoid robot can be executed by a series of atom behaviors. For example, "toasting bread" task can be executed by approaching, grasping and moving bread behaviors. To do so effectively, the atom behaviors should be described as descriptive symbols not low-level motor actions [1]. Also, a humanoid robot should select a behavior considering the context information and learn which behavior is more appropriate for a certain situation based on the user's feedback [2], [3].

In this regards, this paper proposes a behavior selection method using the degree of consideration-based mechanism of thought (DoC-MoT) [4]. The DoC for each input symbol is represented by the λ-fuzzy measure and the knowledge link strengths between input and target symbols are represented by the partial evaluation values. Each target symbol is globally evaluated by the fuzzy integral

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of the partial evaluation values with respect to the fuzzy measure values, and after that, one target symbol with the highest evaluation value is selected and activated. To make corrections to the robot's wrong behaviors, a learning process from human behaviors is employed to update the DoCs and the knowledge link strengths. The effectiveness of the proposed method is demonstrated by simulations carried out with a text-based simulator developed in Visual Studio 2012.

This paper is organized as follows. Section II presents the DoC-MoT, which is a well-modeled mechanism of human thought. Section III proposes the behavior selection method to perform complex tasks using the DoC-MoT. Section IV presents the simulation results to demonstrate the effectiveness of the proposed method. The concluding remarks and future works follow in Section V.

2 Degree of Consideration-Based Mechanism of Thought

The DoC-MoT was proposed to explain how humans make a conclusion from several perceived information [4]. A human brain is formed of a number of well-connected neurons and each set of adjacent neurons represents an input symbol, i.e. perceived information, or a target symbol, i.e. conclusion. The link between input and target symbols represent the knowledge about perceived entities, and therefore, it is called a knowledge link. Since the human thought process is largely affected by personal biases [5], the degree of consideration (DoC) or importance for each input symbol was represented by the λ-fuzzy measure [6]. The knowledge link strength between input and target symbols represents a partial evaluation value of the target symbol over the input symbol. Then, each target symbol is globally evaluated using the Choquet fuzzy integral aggregating the DoCs and partial evaluation values and one target symbol with the highest evaluation value is selected as a conclusion [7].

The λ-fuzzy measure of a subset of input symbols is calculated as follows:

$$g(A \cup B) = g(A) + g(B) + \lambda g(A)g(B), \tag{1}$$

where $g(A)$ and $g(B)$, $A, B \subset X$ represent the DoCs of the subsets A and B, respectively, and $\lambda \in [-1, +\infty]$ denotes an interacting degree index. If the two subsets A and B have negative (positive) correlation, (1) becomes a plausible (belief) measure and λ is a positive (negative) value so that $g(A \cup B) < g(A) + g(B)$ ($g(A \cup B) > g(A) + g(B)$). If the two subsets are independent, (1) becomes a probability measure and the value of λ is zero so that $g(A \cup B) = g(A) + g(B)$.

The evaluation value of each target symbols is calculated by the Choquet fuzzy integral as follows:

$$I(z) = \sum_{i=1}^{n} g(A_i)\{h(x_i) - h(x_{i-1})\}, \tag{2}$$

where the input symbol set X is sorted so that $h(x_i) \geq h(x_{i+1}), i = \{1, \ldots, n-1\}$ and $h(x_0) = 0$, $g(A_i)$ is the fuzzy measure value of A_i, $A_i = \{x_i, x_{i+1} \ldots, x_n\}$ is the subset of X, and $h(x_i)$ is the partial evaluation value of the target symbol z over the i^{th} input symbol x_i. Note that the value of $I(z)$ also represents the evaluation value of z to be a conclusion of the information-processing.

3 Behavior Selection Method

In this section, the DoC-MoT is applied to the behavior selection to perform complex tasks. Fig. 1 shows the overall architecture of the proposed method, which is composed of eight modules: sensor, perception, context, behavior selection, actuator, user command, learning and memory modules. The context module identifies the current environmental context based on the perceptions from the perception module. The memory modules stores all necessary memory contents including the DoCs for contexts and the knowledge link strengths between the contexts and atom behaviors. The behavior selection module evaluates each atom behavior using the DOC-MoT and one atom behavior with the highest evaluation value is generated through the actuator module. The learning algorithm based on a user's feedback is executed in the learning module. The key modules for behavior selection, namely context, behavior selection and learning modules, are described in the following.

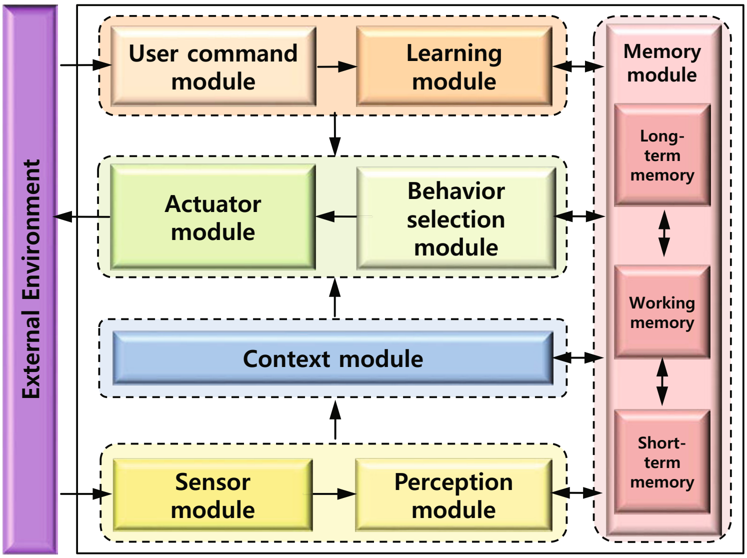

Fig. 1. Overall architecture of the proposed method

3.1 Context Module

As shown in Table 1, four contexts are defined in the context module; the distance between the robot's upper body and the target object, the distance between the robot's hand and the target object, the distance between the current and target positions of the grasping object and the difference between the current and target rotations of the grasping object. Note that the context information is used as the criteria for behavior selection in the behavior selection module.

Table 1. Four input symbols (contexts)

	Context	Unit	Range	DoC
1	The distance between the robot's upper body and the target object	m	[0,5]	4
2	The distance between the robot's hand and the target object	m	[0,1]	3
3	The distance between the current and target positions of the grasping object	m	[0,1]	2
4	The difference between the current and target rotations of the grasping object	°	[0, 360]	1

3.2 Behavior Selection Module

As shown in Table 2, five complex tasks and seven atom behaviors are defined in the behavior selection module. The global evaluation value $E(b_i)$ of i^{th} atom behavior b_i, is computed by the Choquet fuzzy integral as follows:

$$E(b_i) = \sum_{j=1}^{4} \{w_{ij} \cdot h_{ij}(t) - w_{i(j-1)} \cdot h_{i(j-1)})t(t)\}g(A), \tag{3}$$

where $h_{ij} \in [0, 1]$ is the partial evaluation value of b_i over j^{th} context c_j, w_{ij} is the weight of h_{ij} and $g(A)$ is a λ-fuzzy measure of $A \subset X$, identified by (1). After evaluating all atom behaviors, one atom behavior with the highest evaluation value is selected and activated.

Table 2. Five complex tasks and seven target symbols (atom behaviors)

	Contents
Complex tasks	Watering a plant, finding stuff in a drawer, taking contents from a bottle, putting away toys, toasting a bread
Atom behaviors	B_LOOK_AROUND (b_1), B_APPROACH (b_2), B_BEND_BODY (b_3), B_GRASP (b_4), B_MOVE (b_5), B_TILT (b_6), B_TAKE_CONTENT (b_7)

3.3 Learning Module

In the learning module, learning from the user's feedback signals is performed for humanoid robots. The learning process is executed in real time and the user's feedback signals cause the change of the DoCs for contexts and the weights of the knowledge link strengths. The DoC $d_j(t)$ for c_j at time t, is calculated as follows:

$$d_j(t+1) = d_j(t) + k_1 \cdot h_{ij}, \tag{4}$$

where $k_1 \in [0, 1]$ is the learning rate and h_{ij} is the partial evaluation value of the recommended behavior b_i^r over c_j.

The weight w_{ij} of knowledge link strength h_{ij} is changed at the same time as the DoCs for contexts are updated as follows:

$$w_{ij}(t+1) = w_{ij}(t) + k_2 \cdot h_{ij}(t), \tag{5}$$

where $k_2 \in [0, 1]$ is the learning rate.

4 Simulations

To show the effectiveness of the proposed behavior selection method, we developed a text-based simulator on Visual Studio 2012 (C++). To use as an feedback signals in the learning module and compare with the robot's behaviors, we stored

Table 3. The context information and selected behaviors for "toasting a bread" task

	Target object	Context				Selected behavior		
							Humanoid robot	
		c_1	c_2	c_3	c_4	human	Before learning	After learning
1	Table	-	-	-	-	B_LOOK_AROUND	B_LOOK_AROUND	B_LOOK_AROUND
2	Table	4.0	4.1	-	-	B_APPROACH	B_APPROACH	B_APPROACH
3	Table	2.6	2.6	-	-	B_APPROACH	B_APPROACH	B_APPROACH
4	Table	1.1	1.2	-	-	B_APPROACH	B_APPROACH	B_APPROACH
5	Bread	0.5	0.6	-	-	B_BEND_BODY	B_BEND_BODY	B_BEND_BODY
6	Bread	0.3	0.6	-	-	B_GRASP	B_GRASP	B_GRASP
7	Bread	0.3	0.1	-	-	B_GRASP	B_MOVE	B_MOVE
8	Bread	0.3	0.0	0.3	0	B_MOVE	B_MOVE	B_MOVE
9	Toaster	0.6	0.5	-	-	B_APPROACH	B_BEND_BODY	B_APPROACH
10	Bread	0.4	0.0	0.0	90	B_TILT	B_TILT	B_TILT
11	Bread	0.4	0.0	0.1	0	B_MOVE	B_TAKE_CONTENT	B_MOVE
12	Lever	0.3	0.1	-	-	B_GRASP	B_GRASP	B_GRASP
13	Lever	0.3	0.0	0.1	0	B_MOVE	B_TAKE_CONTENT	B_MOVE
14	None	-	-	-	-	B_LOOK_AROUND	B_LOOK_AROUND	B_LOOK_AROUND
15	Toast	-	-	-	-	B_LOOK_AROUND	B_LOOK_AROUND	B_LOOK_AROUND
16	Toast	0.3	0.1	-	-	B_GRASP	B_GRASP	B_GRASP
17	Toast	0.3	0.0	0.1	0	B_MOVE	B_TAKE_CONTENT	B_MOVE
18	Plate	0.6	0.6	-	-	B_APPROACH	B_BEND_BODY	B_APPROACH
19	Toast	0.4	0.0	0.0	90	B_TILT	B_TILT	B_TILT
20	Toast	0.4	0.0	0.3	0	B_MOVE	B_MOVE	B_MOVE

Table 4. The behavior similarities with a human

	Complex task					Total
	1	2	3	4	5	
P-MoT	70%	45%	55%	30%	55%	51%
DoC-MoT w/o learning	75%	95%	100%	70%	70%	82%
DoC-MoT with learning	75%	100%	100%	75%	95%	89%

100 events for five complex tasks and each event has context information and the selected behavior by a human. Table 3 shows the stored events related to "toasting a bread" task. If the selected behavior by the robot was different from the human behavior for the same event, the learning process was performed and the human behavior was used as the user's feedback signal.

After learning from the stored events, the robot selected behaviors again using the updated DoCs and knowledge link strengths. The behavior similarities with a human in three behavior selection methods were compared, as shown in Table 4. In the behavior selection using the probability-based mechanism of thought (P-MoT) [3], the behavior similarity was 51%. In the behavior selection methods using the DoC-MoT, the behavior similarities were 82% without the learning process and 89% with the learning process. The results show that the generated behaviors by the proposed method were the most similar to human behaviors.

5 Conclusions and Future Works

The behavior selection method of humanoid robots to perform complex tasks was proposed using the DoC-MoT. The four input (context) symbols and seven target (atom behavior) symbols were defined to perform five complex tasks. The degree of consideration (DoC) for each input symbol was represented by the λ-fuzzy measure and the knowledge link strengths between input and target symbols were represented by the partial evaluation values. Each target symbol was globally evaluated by the fuzzy integral of partial evaluation values with respect to the fuzzy measure values. Then, one target symbol with the highest evaluation value was selected to be activated. To make corrections to the robot's wrong behaviors, a learning process from human behaviors was performed to update the DoCs and the knowledge link strengths. To show the effectiveness of the proposed method, the behavior similarities with a human were compared in the three behavior selection methods. The results showed that the generated behaviors by the proposed method were most similar to human behaviors. The future work focuses on applying the proposed method to a real humanoid robot to perform complex tasks, e.g. finding an object in a drawer, toasting a bread, etc. The robot will select behaviors based on the past experiences, including the success/fail of the generated behaviors.

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