Behavior Hierarchy-Based Affordance Map for Recognition of Human Intention and Its Application to Human–Robot Interaction

Ji-Hyeong Han, Seung-Jae Lee, and Jong-Hwan Kim, Fellow, IEEE

Abstract—To prepare for the anticipated age of human–robot symbiosis, robots should be able to interact and cooperate with humans effectively by understanding the meaning and intention of human behavior. In this paper, we define human intention as “desired behavior of the human using objects.” To infer the defined human intention, a robot should learn the object affordance along with a behavior hierarchy structure. Thus, in this paper, we propose a behavior hierarchy-based affordance network (BHAN) and a behavior hierarchy-based affordance map (BHAM) to represent the object affordance, behavior hierarchy structure, and object hierarchy structure, simultaneously. Autonomous and interactive BHAN/BHAM learning algorithms are also proposed to make a robot develop the BHAN and BHAM by itself, as well as by interacting with a human. Based on the newly developed BHANs and BHAM, a robot could infer the human intention from information observed in context and from human behavior. The effectiveness of the proposed method was demonstrated through experiments on human–robot interaction with building blocks using a simulated differential wheel robot and a real human-sized humanoid robot.

Index Terms—Behavior hierarchy, human intention reading, human–robot interaction (HRI), object affordance.

I. INTRODUCTION

In the not too distant future, it appears that robots will become a part of everyday human life, including home and work space by virtue of the rapid development of robotic and artificial intelligence technologies [1]. To get ready for this future, problems related to efficient and natural human–robot interaction (HRI) must be solved; thus, research dealing with HRI problems has already started in various HRI fields (i.e., hardware control [2], multirobot control [3], biosignal-based interaction [4], emotion-based interaction [5], learning [6], and social robotics [7]). Besides robotics, there have been various studies about interaction between human and machine [8]–[10].

For efficient HRI, especially from a human–robot cooperation point of view, a robot should be able to read human intentions to better aid humans by providing efficient and cooperative behavior. In human–human cooperation, humans do not always interact with others using explicit expressions. Humans often predict the intentions of other based on implicit information such as body language, facial expressions, and contextual information. Therefore, there would be great benefit in having robots be able to infer human intentions using implicit information during interaction.

There have been several studies focused on making a robot infer human intentions or goals. These studies can be classified according to their approaches: artificial neural approaches, imitation approaches, probabilistic inference approaches, and intention theory of agent approaches. The control architecture devised by Bicho et al. used the artificial neural approach based on dynamic neural fields to model a close perception–action linkage [11], and the model was used for the coordination of actions and goals in cooperative tasks among partners [12].

The imitation approach is one of the most popular ways for inferring human intentions or goals. Gray et al. made a robot consider itself a simulator and presented action parsing and goal inference algorithms [13], while Breazeal et al. developed robot-embodied cognition by integrating these algorithms [14]. Jansen and Belpaeme developed a computation model to infer the demonstrator’s intention by making an artificial agent imitate the demonstrator [15]. Demiris and Khadhouri devised a computational architecture that could work in dual ways, i.e., the selection and execution of robot actions, and perception and understanding of the meaning of demonstrator’s actions [16].

The probabilistic inference approaches, including Bayesian reasoning, are also promising. Schrempt et al. developed a user intention estimation model using hybrid dynamic Bayesian networks [17] and made a robot select a task based on the estimated user intention [18]. Verma and Rao presented an action planning algorithm based on probabilistic inference to infer a goal state, as well as to be used for learning goal dependent policies [19]. Kelley et al. developed an intention recognition framework based on Bayesian reasoning, using the context information of an object [20].

One of the most popular intention theories of agents is the belief-desire-intention (BDI) architecture. Compared with other philosophical theories, the distinction of BDI architecture is that it assumes the primary importance of intention to be the design of rational agents [21]. In contrast, other philosophical theories treat intention as being reducible to beliefs and
desires. Rao and Georgeff proposed the BDI formalism to realize Bratman’s theory of intention, by formalizing intentions based on a branching-time possible world model [22]. There have been efforts to apply BDI architecture for social HRI, and as one of them, Johal et al. proposed cognitive and affective interaction-oriented architecture, which is parallel to BDI architecture [23].

Most HRI or cooperation tasks include several objects like tools, equipment, or toys; thus, a robot needs to read the human intention for an object. To deal with this issue, in this paper, the target problem is defined as making a robot infer the human intention for an object from human behavioral and contextual information when they work or play together using objects. Thus, human intention in this paper is defined as “desired behavior of the human using objects.” In the studies mentioned above, various approaches were devised to create sociable robots with the ability to read human intention. However, there is a particular lack of previous research for when a robot needs to read the human intention for objects, because they have not considered the object affordance. Affordance was originally defined by Gibson as behavioral possibilities for an object, and the affordance network was defined as the relation among objects, behaviors, and effects [24], [25]. Because different objects have different object affordances, a robot needs to learn the specific affordances for the objects being used in an interaction with a human.

In addition, the previous research have not considered the hierarchical relations among human behaviors. Human behaviors are composed of hierarchical relations between each behavior to achieve a certain goal, rather than being just sequential relations [26]. Such hierarchical structures of human behavior are different when a human behaves with different objects; therefore, a robot needs to learn the behavior hierarchy structures for different objects.

To solve these issues, in this paper, we propose a behavior hierarchy-based affordance network (BHAN) and a behavior hierarchy-based affordance map (BHAM). BHAN and BHAM represent the object affordance, hierarchical relations among behaviors, and hierarchical relations among objects simultaneously. Autonomous and interactive BHAN/BHAM learning algorithms are also proposed. The robot learns BHANs and BHAM by itself using the autonomous learning algorithms and also learns BHANs and BHAM interactively during interactions with a human, using the interactive learning algorithms. The robot infers the human intentions for objects by applying the interactive learning algorithms. The proposed BHAN/BHAM learning algorithms use contextual information and human behavior as inputs. The contexts considered in this paper are information on objects from a human perspective; thus, a human visual perspective inference procedure incorporating a fuzzy integral is also proposed. Moreover, the human behaviors considered in this paper are object-related arm behaviors, because the behaviors associated with an object are mostly done by arms when humans and robots work or play together using objects at home or in workspace. The experiments on HRI of building blocks were carried out using a Webots simulated robot and a human-sized humanoid robot to demonstrate the effectiveness of the proposed method.

This paper is organized as follows. Section II is a description of the overall data flow and brief explanations of each module’s functionality. Section III is a presentation of the newly developed human visual perspective inference method, incorporating the fuzzy integral. Section IV provides our proposal for a human intention reading method using BHAN and BHAM, along with the new autonomous and interactive learning algorithms. In Section V, the experimental environment and results of HRI with the Webots simulated robot and the human-sized humanoid robot are discussed for human–robot cooperative building blocks. Finally, the concluding remarks follow in Section VI.

II. OVERALL PROCEDURE

Fig. 1 shows the overall data flows of the proposed method. The situation information and human behavior information are sensed by the sensing module and forwarded to the perception module. The perceptions are then passed to the human visual perspective inference and human behavior recognition modules, respectively. In the human visual perspective inference module, a robot simulates the situation information from the human perspective and decides, which, among several objects in the environment, is the object of human intention. The details of the human visual perspective inference procedure are explained in Section III. The identified object of human intention is transferred to the autonomous/interactive BHAM learning module.

The human arm behavior recognition module simulates the received human arm behavior information based on the robot’s arm behavior set using a dynamic time warping (DTW) algorithm [27]. In the robot arm behavior set module, robot behaviors that can be done by arms are provided. Note that there are no predefined hierarchical relations among these behaviors. The robot behavior that has the minimum final DTW distance is recognized as the human behavior [28]. The recognition result is transferred to the autonomous/interactive BHAM learning module.

The robot develops BHANs for each perceived object along with hierarchical relations between behaviors and develops BHAM that consists of BHANs along with hierarchical relations between objects by use of the newly proposed learning algorithms, i.e., autonomous and interactive BHAN/BHAM learning algorithms. The newly developed BHANs and BHAM are stored in the BHAM module, and the robot infers the human intention while interactively learning BHANs and BHAM during interaction with a human participant. The details of the BHAN/BHAM and autonomous/interactive learning algorithms are explained in Section IV. Based on the inferred human

Fig. 1. Overall procedure of the proposed method.
intention, the behavior selection module selects the corresponding robot behavior and it is executed through the actuator module.

III. THREE-DIMENSIONAL HUMAN VISUAL PERSPECTIVE INFERENCE

A robot needs to consider the current situation from the human perspective to identify the intended-object, because there is a situational difference between a human and a robot due to obstacles in the environment, as well as differences between human and robot postures. There could also be several objects in the environment. To consider the heights of objects and obstacles, the human visual perspective inference is developed in 3-D using an RGB-D camera. To determine which is the object of human intention, three criteria are considered: the confidence value from human visual perspective inference ($c_1$), the distance between a human and an object ($c_2$), and the distance between a robot and an object ($c_3$). Fuzzy measure and fuzzy integral are employed to aggregate these three criteria by considering interactions between each criterion. The object with the highest global evaluation value from the fuzzy integral is identified as the object of human intention.

A. Human Visual Perspective Inference

First, a robot needs to configure the visible points from its posture; thus, a 3-D visibility check method using an RGB-D camera was developed. Fig. 2 shows coordinates of a depth image obtained from an RGB-D camera and the relationship between a depth image and the real world. The pixels in a depth image mean they are visible from the robot’s perspective; thus, a robot can determine whether each point in real world is visible or not from its posture, by using the relationship between the depth image and the real world. The relationship between a pixel of a depth image $p(u', v')$ and a corresponding point in the real world based on the camera posture $q_c(x'_c, y'_c, z'_c)$ can be represented as follows:

$$
x'_c = \frac{2d(u' - c_u)}{I_u} \tan(\alpha_x/2), \quad y'_c = \frac{2d(v' - c_v)}{I_v} \tan(\alpha_y/2), \quad z'_c = d
$$

where $I_u$ and $I_v$ are width and height of the image, $u$ and $v$ are pixel coordinates of the image, and $C(c_u, c_v)$ is a center of the image. ($C$ is a horizontal field of view angle of the camera, $d$ is a depth value obtained from a depth image, and $x'_c$ is the point of the real world in camera’s $x$-coordinate.

![Diagram](image-url)

**Table I**

<p>| Conditional Degree of Confidence, $c(V|H)$, of the Visibility Result V When Given H Is That the Grid Has the Human-Intended Object |
|---------------------------------------------------------------|</p>
<table>
<thead>
<tr>
<th>Visible grid (R)</th>
<th>Invisible grid (R)</th>
</tr>
</thead>
<tbody>
<tr>
<td>With an object</td>
<td>Without an object</td>
</tr>
<tr>
<td>$a$</td>
<td>$c$</td>
</tr>
<tr>
<td>$c$</td>
<td>$c$</td>
</tr>
</tbody>
</table>

where $I_u$ and $I_v$ are width and height of the image, $c_u = I_u/2$, $c_v = I_v/2$, $\alpha_x$ is a horizontal field of view angle of the camera, $\alpha_y = \alpha_x (I_v/I_u)$ is a vertical field of view angle of the camera, and $d$ is a depth value of $p$ obtained from a depth image.

The next step is transforming $q_c(x'_c, y'_c, z'_c)$ to $q_h(x'_g, y'_g, z'_g)$ that is based on a global $(x, y, z)$-coordinate as follows:

$$q_h = g\mathbb{T}_e \mathbb{T}_c q_c \tag{2}$$

where $\mathbb{T}$ is a transformation matrix from a camera coordinate to a robot coordinate, and $g\mathbb{T}$ is a transformation matrix from a robot coordinate to a global coordinate. Every point that is calculated by this method is a visible point from the robot’s posture.

Each point that is identified as a visible point from the robot’s posture has three potential conditions. The first is that the point has a depth value exceeding the maximum depth range of an RGB-D camera. In this case, the point is considered empty, like a view of the sky, and is ignored. The second potential condition is that $y$-value of the point is close to zero, i.e., $y < \sigma$, where $\sigma$ is a small value like 1 cm. The last potential condition is that the point is a part of an object, when satisfying $||C_{obj} - P||_2 < Object\ Size/2$, where $C_{obj}$ is the center point of an object, and $P$ is a considered point.

To consider the situation from the human visual perspective, the robot simulates the situation that it considers the same as the human posture and applies the developed 3-D visibility check method in the same manner as its own visibility check. Thus, the robot can identify the condition of each visible point from the human perspective. By considering the identified conditions from both robot and human perspectives, the robot updates each grid on the degree of confidence that the human-intended object might be located in the corresponding grid, in the same manner as Bayesian rule as follows:

$$C(i, j)_t = \frac{c(V|H)C(i, j)_{t-1}}{c(V)} \tag{3}$$

where $C(i, j)_t$ and $C(i, j)_{t-1}$ are the degrees of confidence of grid $(i, j)$ at time steps $t$ and $t - 1$, respectively; $V$ denotes human and robot visibility results; $H$ denotes whether or not the grid is with the object of human intention; $c(V)$ is a normalization factor; and $c(V|H)$ is the conditional degree of confidence of $V$ given $H$. $c(V|H)$ is preassigned considering the identified cases of points, as shown in Table I, where $a > b \gg c$ and the sum of all $c(V|H)$ values are $a + b + 4c = 1$. $a$ has to be the largest value, because the grid that is visible from both human and robot postures and has an object would be the location of
the object of human intention with the highest confidence. \( b \) has to be some meaningful value, i.e., not close to zero, because the robot needs to search for a grid with a medium degree of confidence. The robot is aware that a human can see the grid from the result of the visual perspective inference procedure although it cannot see the grid at the current time step. Since a grid that a human cannot see or has no object would not be the human-intended location, \( c \) has to be close to zero. After the update, all the degrees of confidence are normalized to 1.

**B. Identifying the Object of Human Intention**

To identify the object of human intention among several objects, three criteria are defined: the confidence value from human visual perspective inference \((c_1)\), the distance between a human and an object \((c_2)\), and the distance between a robot and an object \((c_3)\). In the process of identifying the object of human intention, a global evaluation of each object considering both the partial evaluation over criteria and the degree of consideration of criteria is needed. The object with the highest value of global evaluation is recognized as the object of human intention. To aggregate criteria by considering interactions between criteria, a fuzzy measure is employed to represent the degree of consideration and the global evaluation is calculated using the fuzzy integral. The fuzzy measure and fuzzy integral are briefly described below.

As a general representation of fuzzy measure, \( \lambda \)-fuzzy measure, \( g : P(X) \rightarrow [0, 1] \), is defined, which satisfies the following axiom [29]:

\[
\forall A_{i,j} \in P(X), i, j = 1, \ldots, n, A_i \cap A_j = \emptyset \text{ and } -1 < \lambda, \\
g(A_i \cup A_j) = g(A_i) + g(A_j) + \lambda g(A_i) g(A_j) \quad (4)
\]

where \( \lambda \) represents a degree of interaction between \( A_i \) and \( A_j \). If \( \lambda > 0, \lambda < 0 \), and \( \lambda = 0 \), \( \lambda \)-fuzzy measure is considered the belief measure, plausibility measure, and probability measure, respectively.

Note that each kind of fuzzy measures indicates a different interaction between criteria [30]. Belief measure indicates a positive interaction (negative correlation), because \( g(A_i \cup A_j) > g(A_i) + g(A_j) \). On the other hand, plausibility measure indicates a negative interaction (positive correlation), since \( g(A_i \cup A_j) < g(A_i) + g(A_j) \). Probability measure does not represent any interaction among criteria, and it means that criteria are independent of each other.

For global evaluation of each object over criteria with respect to a degree of consideration for each criterion, the Choquet fuzzy integral can be used, which is defined in the following.

**Definition 1:** Let \( h : X \rightarrow [0, 1] \), where \( X \) can be any set. The Choquet fuzzy integral of evaluated value, \( h \) over a subset of \( X \in P(X) \) with respect to a fuzzy measure \( g \) is defined as

\[
\int_X h \circ g = \sum_{i=1}^{n} (h(x_i) - h(x_{i-1})) g(E_i) \quad (5)
\]

where \( h(x_1) \leq h(x_2) \leq \cdots \leq h(x_n) \), \( E_i = \{x_i, x_{i+1}, \ldots, x_n\} \) and \( h(x_0) = 0 \), for \( x_i \in X \) and \( i = 1, \ldots, n \).

Note that \( x_i, i = 1, \ldots, n \), denotes the \( i \)th criterion, and \( h(x_i) \) is the partial evaluation value over \( x_i \). The fuzzy measure \( g \) represents the degree of consideration for each criterion. Thus, the fuzzy integral can be used for global evaluation of each object.

Before applying the fuzzy integral to calculate the global evaluation value for each object, fuzzy measures for the criteria set should be calculated first. In this paper, \( \phi_1 \) transformation and Grabisch’s graphical interpretation are employed to calculate fuzzy measures [31, 32]. \( \phi_1 \) transformation is defined as

\[
\phi_1(\xi, u) = \begin{cases} 
1, & \text{if } \xi = 1 \text{ and } u > 0 \\
0, & \text{if } \xi = 0 \text{ and } u = 0 \\
1, & \text{if } \xi = 1 \text{ and } u = 1 \\
su - 1, & \text{if } \xi = 0 \text{ and } u < 1 \\
\text{other cases}
\end{cases}
\]

(6)

where \( s = \frac{(1-\xi)^2}{\xi} \). \( u = \sum_{i \in A} \omega_i \), \( \omega_i \) is the weight of criterion \( x_i \), and \( \xi \) is an interaction degree with \( \lambda = \frac{(1-\xi)^2}{\xi} - 1 \).

To calculate fuzzy measure using Grabisch’s graphical interpretation, the degree of interaction and the relative degree of consideration between criteria should be defined. Fig. 3 shows the defined diamond pairwise comparison diagram for identifying the object of human intention. The vertical and horizontal axes represent the degree of interaction and the relative degree of consideration between criteria, respectively. The Murofushi and Soneda’s interaction index \( I_{ij} \) for the vertical axis is defined as follows [33]:

\[
I_{ij} = g(\{c_i, c_j\}) - g(\{c_i\}) - g(\{c_j\}).
\]

(7)

The Shapley value of \( g \), \( sv_i \) and \( sv_j \), for the horizontal axis is defined as

\[
sv_i = \frac{g(\{c_i\}) + g(\{c_i, c_j\}) - g(\{c_j\})}{2}
\]

(8)

\[
sv_j = \frac{g(\{c_j\}) + g(\{c_i, c_j\}) - g(\{c_i\})}{2}
\]

(9)

where \( sv_i + sv_j = 1 \). \( sv_j \) represents the relative importance of the \( j \)th criterion with respect to the \( i \)th criterion.

The degree of interaction between \( c_1 \) and \( c_2 \) is set as a strong negative interaction (positive correlation), because an object that is closer to a human should have a higher degree of confidence from the human visual perspective inference than an object that is further from the human. The degree of interaction between
c_1 and c_3 is set as a weak negative interaction (positive correlation), because an object that is closer to a robot might have a higher degree of confidence from the human visual perspective inference than an object that is further from the robot, but it is not a strong correlation compared with c_1 and c_2. The degree of interaction between c_2 and c_3 is set as no interaction, because there is no relation between the distance from an object to the human and the distance from an object to the robot. The relative degree of consideration among criteria is set as c_1 > c_2 > c_3. Table II shows the calculated relative degree of consideration and degree of interaction between criteria, where c_{ijk} = sv_j / sv_i and \( \xi_i \) can be calculated from inverse \( \phi_i \) transformation. Table III shows the calculated fuzzy measures for all the power sets of the criteria.

The partial evaluation with respect to each criterion is defined as follows. For \( c_1 \), since the degree of confidence from the human visual perspective inference is already normalized from 0 to 1, \( h(c_1) \) is the original degree of confidence. For \( c_2 \) and \( c_3 \), since the partial evaluation should be normalized from 0 to 1 and a closer object should have a higher partial evaluation value than a further object, the partial evaluation is defined as follows:

\[
h(c_2) = 1 - \frac{d_{HO}}{\sqrt{W^2 + H^2}}, \quad h(c_3) = 1 - \frac{d_{RO}}{\sqrt{W^2 + H^2}} \tag{10}
\]

where \( d_{HO} \) and \( d_{RO} \) are distances from an object to a human and to a robot, respectively, and \( W \) and \( H \) are width and height of the environment, respectively.

By using the calculated fuzzy measure in Table III and the defined partial evaluation with respect to criteria, the global evaluation of each object in the environment is calculated using the fuzzy integral. The object with the highest global evaluation value is recognized as the object of human intention.

IV. Behavior Hierarchy-Based Affordance Map and Learning Algorithms

To make a robot infer the human behavioral intention for an object, the robot should learn the object’s morphological characteristics, which induce or limit specific behaviors for using the objects. This is defined as object affordance. If the robot could learn the affordances of objects, it could infer the intended human behavior for a certain object or could determine the object of human intention by observing human behavior. In this paper, we describe how a robot learns the object affordance by observing the object effects, such as the object’s spatial and rotational differences when a behavior is done to the object, and how a robot could figure out which behaviors are possible with the object.

The other key element is the hierarchical relation between behaviors and also the hierarchical relation between objects. The robot should learn the behavior hierarchies to understand the hierarchical structure of the observed human behaviors and to infer the human intention from human behaviors. Furthermore, when the task includes multiple objects, there exist hierarchical relations between the objects. Therefore, the robot should also learn the hierarchical relations between objects to achieve the goal of the task with a human. To deal with such issues, we herein propose a BHAN and a BHAM, along with autonomous and interactive BHAN/BHAM learning algorithms that allow the robot to develop its knowledge of object affordance, behavior hierarchy, and object hierarchy, simultaneously.

A. Behavior Hierarchy-Based Affordance Network and Behavior Hierarchy-Based Affordance Map

The BHAN is proposed to represent the affordances of objects along with hierarchical relations between behaviors. A robot can infer the human intention for an object using BHAN, defined in the following way.

Definition 2: BHAN represents the relations among an object node \((o_j)\), behavior nodes \((b_j)\), and effect nodes \((e_j)\) along with the hierarchical relations between the behavior nodes.

1) \( n(\text{perceived objects}) = n(\text{BHAN}) \).
2) \( \epsilon_j \): position and orientation changes of \( o_i \) in \((x, y, z)\), \((\alpha, \beta, \gamma)\)-coordinates from the time the behavior of \( b_j \) starts being performed upon \( o_i \) to the time the behavior ends.
3) The directional edge between behavior nodes represents the hierarchical relation between behaviors.
4) The directional edge from \( b_j \) to \( b_k \) has a transition frequency \( \text{BHAN}_{o_i}\{\text{TF}(b_{j,k})\} \) and a transition probability, \( \text{BHAN}_{o_i}\{\text{TP}(b_{j,k})\} \).

The BHAM consists of several BHANs along with hierarchical relations between objects. A robot can infer the object of human intention and human intention for the object using BHAM, defined in the following way.

Definition 3: BHAM consists of BHANs to represent the hierarchical relations between objects.

1) \( \text{BHAM} = \{\text{BHAN}_{o_1}, \ldots, \text{BHAN}_{o_n}\} \).
2) The directional edge between BHANs represents the hierarchical relation between objects.
3) The directional edge from \( o_i \) to \( o_j \) has a transition frequency, \( \text{BHAN}\{\text{TF}(o_{i,j})\} \), a transition probability, \( \text{BHAM}\{\text{TP}(o_{i,j})\} \), and a transition behavior set \( \text{BHAM}\{\text{TP}(o_{i,j})\} \).
Fig. 4 shows the structures of BHAN and BHAM. In BHAN, \(b_i\) node at the start of a directional edge is lower in hierarchy than \(b_j\) node at the end of the directional edge. On the other hand, the \(b\) nodes connected by a bidirectional edge have the same hierarchical level. If there is no directional edge between \(b\) nodes, it means they do not have any hierarchical relations, i.e., they are independent. In BHAM, \(o_i\) node at the start of a directional edge is lower in hierarchy than \(o_j\) node at the end of the directional edge. This means that the object of \(o_i\) should be placed first and then the object of \(o_j\) can be placed. If there is no directional edge between \(o\) nodes, it means they do not have any hierarchical relations, i.e., they are independent.

The directional edges in BHAN and BHAM are considered as a transition model, and each edge has a transition probability calculated from transition frequencies. The transition frequencies, BHAN(\(TF(b_{i,j})\)) and BHAM(\(TF(o_{k,l})\)) are the number of transitions from \(b_i\) to \(b_j\) and from \(o_k\) to \(o_l\), respectively. The initial transition frequency value is 1 if an edge exists between nodes and 0 otherwise. Using the transition frequencies, the transition probabilities, BHAN(\(TP(b_{i,j})\)) and BHAM(\(TP(o_{k,l})\)) are calculated as follows:

\[
\text{BHAN}(TP(b_{i,j})) = \frac{\text{BHAN}(TF(b_{i,j}))}{\sum \text{BHAN}(TF(b_{i,y}))} \quad (11)
\]

\[
\text{BHAM}(TP(o_{k,l})) = \frac{\text{BHAM}(TF(o_{k,l}))}{\sum \text{BHAM}(TF(o_{y,o}))}. \quad (12)
\]

The directional edges in BHAN additionally have a transition behavior set, BHAM(\(TP(o_{i,j})\)). This is a set of behaviors that make a positive transition from \(o_i\) to \(o_j\). The related terms of directional edges, i.e., transition frequency, transition probability, and transition behavior set, are learned using the proposed autonomous and interactive BHAN/BHAM learning algorithms. These are explained in the following sections.

### B. Autonomous Behavior Hierarchy-Based Affordance Map Learning

A robot needs to learn in advance the initial BHANs and BHAMs autonomously and developmentally, because it does not initially know any of the hierarchical relations between its behaviors and between objects. First, the robot learns the initial BHAN\(_0\) by itself using Algorithm 1, where \(i\) is the index of the object, which increases by 1 when the robot perceives another object. The robot performs the behavior of BHAN\(_0\) (\(b_i\)) one by one from its behavior set toward object \(o_i\) and observes the effect on the object. The robot learns the observed effect value to BHAN\(_0\) (\(e_j\)) which relates to \(b_j\). If there is already a learned behavior node \(b_k\) that is lower in hierarchy than \(b_j\), BHAN\(_0\) (\(e_j\)) is updated as a sum of initial learned \(e_j\) and already learned \(e_k\). Otherwise, the initial learned \(e_j\) is saved in BHAN\(_0\) (\(e_j\)). Note that if the observed effect value is smaller than predefined threshold, e.g., 0.05 m and 15.0°, then the effect value is considered 0 because the effect value has noise from observation. In Algorithm 1, the robot also learns the behavior hierarchy based on the effect values of \(e\) nodes. If the difference between effect values of \(e\) nodes is less than a small threshold, e.g., 0.05 m and 15.0°, then the robot learns that the corresponding \(b\) nodes are the same level in the hierarchy, increases the transition frequency between them, and calculates the transition probability based on the updated transition frequency. If the effect value of \(e_j\) is in the start boundary of the other behavior of \(b_j\) node, then \(b_j\) node is learned as being higher in hierarchy than the \(b_j\) node, the transition frequency from \(b_i\) to \(b_j\) increases, and the transition probability is calculated based on the updated transition frequency. Algorithm 1 is repeated until the robot performs all the behaviors in its behavior set.

After the robot learns the initial BHANs for all perceived objects by Algorithm 1, the robot learns the initial BHAM by itself using Algorithm 2, to learn the hierarchical relations between objects. The robot learns hierarchical relations of all combinations of the two objects. There are two objects in the learning environment: one is the current object \(o_i\) that is taken by the robot and the other is the target object \(o_j\) that the robot approaches. The robot takes \(o_i\) by behavior \(b_j\) that is lower in hierarchy than \(b_i\), and moves toward \(o_i\) while taking \(o_j\). After reaching \(o_i\), the robot does behavior \(b_i\) with \(o_i\) to \(o_j\) and observes the relation state between \(o_i\) and \(o_j\). If the relation state is true, then the robot learns \(o_i\) is higher in hierarchy than \(o_j\), increases the transition frequency from \(o_j\) to \(o_i\), and calculates the transition probability based on the updated transition fre-
Algorithm 2: The autonomous BHAM learning algorithm.

while BHAN\textsubscript{0} (b\textsubscript{i}) continues do
  if \(|\{b_j|\text{BHAN}_{\text{0}}(\text{TP}(b_j)) \neq 0\}| = 1\) then
    Do behavior of BHAN\textsubscript{0} (b\textsubscript{j}) to o\textsubscript{c} and move toward o\textsubscript{c}.
    Do behavior of BHAN\textsubscript{0} (b\textsubscript{i})
    \(R \leftarrow \text{relation state between } o\textsubscript{c} \text{ and } o\textsubscript{i}.
  \)
  if \(R = \text{true}\) then
    Hierarchy: \(o\textsubscript{c} > o\textsubscript{i}, \text{ BHAM(TF(o\textsubscript{c},o\textsubscript{i}))++}
    Update BHAM(\text{TP}(o\textsubscript{c},o\textsubscript{i})) and save b\textsubscript{i} in BHAM(\text{TP}(o\textsubscript{c},o\textsubscript{i})).B.
  end if
  end if
  \(i \leftarrow i + 1\)
end while

Algorithm 3: The interactive BHAM learning algorithm.

while Human interaction continues do
  Save \(b_i\) in BHAN\textsubscript{0} \( AB\) and learn BHAN\textsubscript{0} using Algorithm 4.
  if BHAN\textsubscript{0} \( (e_i) = \{0\} \) then
    Increase \(UL\).
  else if \((b_i \text{ with } o\textsubscript{H}) \& (\{|o_j|\text{BHAM(TP(o\textsubscript{H},o\textsubscript{J}))} \neq 0\}| \geq 1\) then
    \(O_{\text{HIC}} \leftarrow \forall o\textsubscript{j}\)
  else if \((b_i \text{ w/o } o\textsubscript{H}) \& (\{|o_j|\text{BHAM(TP(o\textsubscript{H},o\textsubscript{J}))} \neq 0\}| \geq 1\) then
    \(O_{\text{HIC}} \leftarrow \forall o\textsubscript{j}\)
  end if
  Increase \(UL\).
end if
if \((UL > U_0) \& (\text{duration time} > T)\) then
  \(O_{\text{HIC}} \leftarrow \forall O_{\text{HIC}} \setminus O_{\text{H1}}\).
end if
while Human Feed = \text{Negative} \& \(O_{\text{HIC}} \neq \text{NULL}\) do
  Calculate global evaluation for \(O_{\text{HIC}}\) by fuzzy integral.
  \(O_{\text{H1}} \leftarrow \text{arg max}_j \text{FuzzyIntegral}(O_{\text{Hj}})\)
  Get human feedback for \(O_{\text{H1}}\).
  \(O_{\text{HIC}} \leftarrow \forall O_{\text{HIC}} \setminus O_{\text{H1}}\).
end while
if \(\forall \text{Human Feed}(O_{\text{HIC}}) = \text{Negative}\) then
  Increase \(UL\).
else
  Do behavior of \(b_i\) with \(O_{\text{H1}}\) to \(O_{\text{H}}\).
  if \(b_i \text{ with } O_{\text{H}}\) then
    Hierarchy: \(O_{\text{H}} > O_{\text{H1}}\,
    BHAM(TF(O_{\text{H1}},O_{\text{H}}))++
    Update BHAM(\text{TP}(O_{\text{H1}},O_{\text{H}}))
    Save \(b_i\) in BHAM(\text{TP}(O_{\text{H1}},O_{\text{H}})).B.
  else if \(b_i \text{ w/o } O_{\text{H}}\) then
    Hierarchy: \(O_{\text{H1}} > O_{\text{H}}\,
    BHAM(TF(O_{\text{H1}},O_{\text{H1}}))++
    Update BHAM(\text{TP}(O_{\text{H1}},O_{\text{H1}}))
    Save \(b_i\) in BHAM(\text{TP}(O_{\text{H1}},O_{\text{H1}})).B.
  end if
end if
end while

quency. The relation state is defined according to the task. For example, if the task is building blocks, then the relation state would be defined as whether two blocks can be built or not. In addition, the behavior \(b_i\) is saved in the transition behavior set from \(o_i\) to \(o_c\). Algorithm 2 is repeated until the robot performs all the behaviors in its behavior set.

C. Interactive Behavior Hierarchy-Based Affordance Map Learning

Based on the initial learned BHANs and BHAM from Algorithms 1 and 2, the robot learns more BHANs and BHAM during interaction with a human, using Algorithms 3 and 4. While applying Algorithm 3, the robot can infer the human intention.

In the environment, there are several objects and one object among them, \(O_{\text{H}}\) is in front of the human. The robot loads the initially learned BHAN\textsubscript{0} and gets the human behavior \(b_i\). The robot saves \(b_i\) in the activated behavior nodes set of BHAN\textsubscript{0} and BHAN\textsubscript{0} \( AB\) and learns BHAN\textsubscript{0} more using the interactive BHAN learning algorithm (see Algorithm 4), which will be explained after the explanation of Algorithm 3.

The first step of the algorithm is identifying the candidate object set of human intention, \(O_{\text{HIC}}\). There are three possible conditions based on the type of \(b_i\). The first is that the effect value of \(b_i\), BHAN\textsubscript{0} \( (e_i)\), is zero, and in this case, \(UL\) is increasing because the robot needs more information to infer the human intention. The second condition is that \(b_i\) is done with \(O_{\text{H}}\). In this case, if there are objects \(o_j\) that are lower in hierarchy than \(O_{\text{H}}\), then the objects that satisfy the conditions are saved in \(O_{\text{HIC}}\). Otherwise, \(UL\) is increasing. The last potential condition is that \(b_i\) is done without \(O_{\text{H}}\). In this case, if there are objects \(o_j\) that are higher in hierarchy than \(O_{\text{H}}\) and \(b_i\) is in the transition behavior set from \(O_{\text{H}}\) to \(o_j\), then the objects that satisfy the conditions are saved in \(O_{\text{HIC}}\). Otherwise, \(UL\) is increasing. If \(UL\) exceeds the predefined threshold \(U_0\) and maintains the exceeded value during the predefined duration threshold \(T\), then all the objects except \(O_{\text{H}}\) are saved in \(O_{\text{HIC}}\).

The next step after identifying \(O_{\text{HIC}}\) is finding out which is the object of human intention \(O_{\text{H1}}\) along with the human intention and learning BHAM. The robot calculates the global evaluation for \(O_{\text{HIC}}\) by the process explained in Section III. The object with the highest global evaluation value is recognized as \(O_{\text{H1}}\) and the robot moves toward \(O_{\text{H1}}\). By doing the questioning behavior, the robot gets human feedback for \(O_{\text{H1}}\). If the human feedback is negative, the object with the second highest global evaluation value is recognized as \(O_{\text{H1}}\) and the above process is repeated until the human feedback is positive. If the human feedback for all objects in \(O_{\text{HIC}}\) is negative, \(UL\) is increasing. Otherwise, the first object with the positive human feedback is confirmed as \(O_{\text{H1}}\), and the robot does \(b_i\) with \(O_{\text{H1}}\) to \(O_{\text{H}}\) and learns the
Algorithm 4: The interactive BHAN learning algorithm.

\[
\text{for } k = 1 \rightarrow n (k \neq j) \text{ do}
\]

\[
\text{if } \text{BHAN}_o \left( \text{TP} \left( b_{k,j} \right) \right) \neq 0 \text{ then}
\]

\[
N_{\text{Lower}} \leftarrow N_{\text{Lower}} + 1
\]

\[
\text{Save } b_k \text{ to BHAN}_o \cdot AB.
\]

\[
\text{else if } \text{BHAN}_o \left( \text{TP} \left( b_{j,k} \right) \right) \neq 0 \text{ then}
\]

\[
N_{\text{Higher}} \leftarrow N_{\text{Higher}} + 1
\]

\[
\text{Save } b_k \text{ to BHAN}_o \cdot AB.
\]

\[
\text{else if } \left( \text{BHAN}_o \left( \text{TP} \left( b_{j,k} \right) \right) \neq 0 \right) \&
\]

\[
\left( \text{BHAN}_o \left( \text{TP} \left( b_{i,j} \right) \right) \neq 0 \right) \text{ then}
\]

\[
N_{\text{Same}} \leftarrow N_{\text{Same}} + 1
\]

\[
\text{end if}
\]

end for

if BHAN$_o$($b_j$) has no hierarchical relation with the nodes in BHAN$_o$ · AB then

\[
\text{Hierarchy: BHAN}_o \left( b_j \right) > \text{BHAN}_o \cdot AB
\]

\[
\text{BHAN}_o \left( \text{TF} \left( \text{BHAN}_o \cdot AB, b_j \right) \right) ++
\]

\[
\text{Update BHAN}_o \left( \text{TP} \left( \text{BHAN}_o \cdot AB, b_j \right) \right)
\]

end if

hierarchy between $O_H$ and $O_{H1}$. If $b_i$ is done with $O_H$, $O_H$ is learned as being higher in hierarchy than $O_{H1}$, the transition frequency from $O_{H1}$ to $O_H$ increases, and the transition probability is calculated based on the updated transition frequency. In addition, $b_i$ is saved in the transition behavior set from $O_{H1}$ to $O_H$. If $b_i$ is done without $O_H$, $O_{H1}$ is learned as being higher in hierarchy than $O_H$, the transition frequency from $O_H$ to $O_{H1}$ increases, and the transition probability is calculated based on the updated transition frequency. Moreover, $b_i$ is saved in the transition behavior set from $O_H$ to $O_{H1}$.

During the application of Algorithm 3 to find out the human intention along with the object of human intention and to learn BHAM, Algorithm 4 is called to learn the individual BHAN. The algorithm starts by loading the initially learned BHAN$_o$·AB. After getting the human behavior, $b_j$, the robot counts the behaviors that are at lower, higher, or the same level in the hierarchy than $b_j$, or with $b_j$, and saves all behaviors that satisfy the hierarchical condition in the activated behaviors, BHAN$_o$ · AB. Since BHAN$_o$ · AB is the cumulative set during the interaction with a human, the newly received human behavior would not have hierarchical relations with the behaviors in BHAN$_o$ · AB. In this case, the robot learns the current received human behavior is higher in the hierarchy than all the other behaviors in BHAN$_o$ · AB, increases transition frequencies from all the behaviors in BHAN$_o$ · AB to the current human behavior, and calculates the transition probability based on the updated transition frequency.

Note that if a human changes the intention very rapidly, BHAN and BHAM cannot reflect the changed human intention instantly because the proposed method is a statistics-based one and the change of probability takes some time. However, the target HRI context in this paper is a human and a robot working together using objects or tools; thus, a human should decide the final intent even though his or her intent has changed before the final decision, and BHAN and BHAM would converge to the final true human intention.

V. EXPERIMENTS

To demonstrate the effectiveness of the proposed method, experiments on HRI of building blocks were carried out. A vision system using an RGB-D camera and a Webots simulated robot were implemented for the experiments. Furthermore, a human-sized humanoid robot, Mybot-KSR, developed in the Robot Intelligence Technology Laboratory at the Korea Advanced Institute of Science and Technology (South Korea) was used for the last experiment.

A. Experimental Environment

In the experiments, a vision system was employed for perceiving the human arm behaviors and feedback using an RGB-D camera, openNI, and openCV. A differential wheel robot with two arms was simulated using the Webots simulator. The start and end of human arm behaviors and human feedback were defined by color patches to simplify the experimental setup. The parameters were assigned as $a = 0.68$, $b = 0.28$, $c = 0.01$, $\Gamma = (0.05 \text{ m}, 15.0^\circ)$, $T = 10.0 \text{ s}$, and $U_0 = 0.7$.

B. Autonomous Behavior Hierarchy-Based Affordance Map Learning Results

Before interacting with a human, the robot developed BHANs and BHAM for four different kinds of blocks, i.e., a big box, a small box, a cylinder with a conical hat, and a capsule, by itself using autonomous BHAN/BHAM learning algorithms. To develop BHAN for each block, the robot performed all its arm behaviors one-by-one to the block. It then observed effects, and learned the behavior hierarchies using Algorithm 1. The robot arm behavior set was $\{\text{waving both hands (WB)}, \text{waving one hand (WO)}, \text{pointing (Po)}, \text{touching (Tch)}, \text{pushing forward (PF)}, \text{pushing left (PL)}, \text{pushing right (PR)}, \text{grasping (Gr)}, \text{put (Pt)}, \text{moving left (ML)}, \text{moving right (MR)}\}$. Note that before the initial learning, the robot did not know any of the hierarchical relations between behaviors. Tables IV–VII show the obtained effect values of each block for corresponding behaviors. When the absolute values of the $x$, $y$, or $z$ values were smaller than 0.05 m and the absolute values of $\alpha$, $\beta$, or $\gamma$ values were smaller than $15.0^\circ$ (0.2617 rad), they were considered 0; thus, the bold values in Tables IV–VII are meaningful values and behaviors that have zero values for all effect values, e.g., WB, WO, Po, and Tch, are not shown in the tables. Fig. 5 shows the autonomous learned BHANs and transition probabilities between behaviors. As shown in Fig. 5, each block had different behavior hierarchies and object affordances.

After learning BHAN for each block, the robot developed BHAM based on the autonomously learned BHANs using Algorithm 2. The robot performed those of its behaviors that satisfied the conditions in Algorithm 2 to the current object, moved toward the target object, and observed the relation state between the current object and the target object. The task was building blocks; thus, the relation state was defined as whether
two blocks could be built or not. The autonomous BHAM learning experiments were done 12 times, because there were a total of 12 sets of current object and target object for the four kinds of blocks. Fig. 6 shows the autonomously learned BHAM. The robot learned that the big box is lower in hierarchy than the small box and the cylinder with a conical hat, and the transition behaviors were put, moving left, and moving right. In addition, the robot learned that the small box is lower in hierarchy than the cylinder with a conical hat, and the transition behaviors were putting, moving left, and moving right. Note that the robot already learned BHANs based on the effect values, therefore the robot knew the effect values of the moving left and moving right behaviors. Thus, when the robot did moving left or moving right behaviors for autonomous BHAM learning, the robot could adjust the goal position by a little bit right or left to the target object. It means that the robot can deduce the results of

<table>
<thead>
<tr>
<th>TABLE IV</th>
<th>EFFECT VALUES THAT THE ROBOT GOT IN AUTONOMOUS LEARNING FOR BHAN OF A BIG BOX</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Effect Value (x, y, z, α, β, γ) [m, rad]</td>
</tr>
<tr>
<td>PF</td>
<td>0.20176, 0.00657, −0.00028, 0.00049, 0.00070, −0.04412</td>
</tr>
<tr>
<td>PL</td>
<td>−0.00129, 0.10423, 0.00156, 0.00092, 0.00034, −0.00804</td>
</tr>
<tr>
<td>PR</td>
<td>−0.00170, −0.10221, 0.00138, 0.00001, 0.00046, 0.00735</td>
</tr>
<tr>
<td>GR</td>
<td>0.21491, 0.00668, 0.26542, −0.12393, 0.67727, −0.0062</td>
</tr>
<tr>
<td>PT</td>
<td>0.06134, −0.00190, 0.01208, −0.01161, 0.20278, 0.01460</td>
</tr>
<tr>
<td>ML</td>
<td>−0.00893, 0.06932, −0.03147, 0.08826, −0.013754, −0.12560</td>
</tr>
<tr>
<td>MR</td>
<td>0.01719, −0.11274, −0.03159, 0.01390, −0.01074, 0.18970</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE V</th>
<th>EFFECT VALUES THAT THE ROBOT GOT IN AUTONOMOUS LEARNING FOR BHAN OF A SMALL BOX</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Effect Value (x, y, z, α, β, γ) [m, rad]</td>
</tr>
<tr>
<td>PF</td>
<td>0.13836, 0.00828, −0.00036, 0.01198, 0.00088, −0.22546</td>
</tr>
<tr>
<td>PL</td>
<td>0.00019, 0.05377, −0.00161, 0.00013, −0.00282, −0.03126</td>
</tr>
<tr>
<td>PR</td>
<td>−0.00045, −0.05615, −0.00010, 0.00076, 0.00052, 0.04821</td>
</tr>
<tr>
<td>GR</td>
<td>0.22082, 0.00440, 0.25367, −0.11842, 0.66330, 0.00682</td>
</tr>
<tr>
<td>PT</td>
<td>0.06522, 0.00063, 0.00658, −0.01087, 0.14594, 0.00381</td>
</tr>
<tr>
<td>ML</td>
<td>−0.02666, 0.10848, −0.03507, 0.00925, −0.02449, −0.06810</td>
</tr>
<tr>
<td>MR</td>
<td>0.04342, −0.08885, −0.03734, 0.00654, −0.01583, 0.06806</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE VI</th>
<th>EFFECT VALUES THAT THE ROBOT GOT IN AUTONOMOUS LEARNING FOR BHAN OF A CYLINDER WITH A CONICAL HAT</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Effect Value (x, y, z, α, β, γ) [m, rad]</td>
</tr>
<tr>
<td>PF</td>
<td>0.14117, 0.03880, −0.02250, 0.03416, 0.06370, −0.37044</td>
</tr>
<tr>
<td>PL</td>
<td>−0.02638, 0.05252, −0.02780, 0.05268, −0.01066, −0.45182</td>
</tr>
<tr>
<td>PR</td>
<td>0.02561, −0.07995, −0.03085, −0.00038, 0.05165, −0.01369</td>
</tr>
<tr>
<td>GR</td>
<td>0.21569, −0.00685, 0.21467, −0.12560, 0.68260, −0.01398</td>
</tr>
<tr>
<td>PT</td>
<td>0.06004, −0.00890, −0.00633, −0.01727, 0.20125, −0.08006</td>
</tr>
<tr>
<td>ML</td>
<td>0.04357, 0.10863, −0.03490, 0.04412, −0.13583, −0.40178</td>
</tr>
<tr>
<td>MR</td>
<td>0.04349, −0.14424, −0.03512, 0.25214, 0.03112, 0.93381</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>TABLE VII</th>
<th>EFFECT VALUES THAT THE ROBOT GOT IN AUTONOMOUS LEARNING FOR BHAN OF A CAPSULE</th>
</tr>
</thead>
<tbody>
<tr>
<td>B</td>
<td>Effect Value (x, y, z, α, β, γ) [m, rad]</td>
</tr>
<tr>
<td>TCH</td>
<td>0.04972, −0.24612, −0.02041, −3.92699, 1.05791, −0.44683</td>
</tr>
<tr>
<td>PF</td>
<td>0.18042, 0.02633, −0.02098, −0.78540, −1.54711, 0.17189</td>
</tr>
<tr>
<td>PL</td>
<td>0.02143, 0.20581, −0.02076, −3.92699, 0.51359, 0.08255</td>
</tr>
<tr>
<td>PR</td>
<td>0.00346, −0.09733, −0.02104, −0.78541, −1.39667, −0.35875</td>
</tr>
<tr>
<td>GR</td>
<td>0.21879, 0.00782, 0.19543, −0.07092, 0.52098, 0.00259</td>
</tr>
<tr>
<td>PT</td>
<td>0.07009, 0.00581, −0.01652, −0.06936, 0.07324, −0.00051</td>
</tr>
<tr>
<td>ML</td>
<td>0.48386, −0.08080, −0.04277, −0.78651, 1.01851, 0.47217</td>
</tr>
<tr>
<td>MR</td>
<td>0.66798, −0.25468, −0.04159, −0.78762, −0.27663, 0.58959</td>
</tr>
</tbody>
</table>

Fig. 5. Autonomous learned BHANs for four different blocks and graphs of their transition probabilities. This figure shows the emphasizing behavior hierarchies from the whole structure of learned BHANs by eliminating effect nodes.
behaviors based on the effect values, and it is one of the main advantages of learning the object affordance.

C. Human Intention Reading Results Using a Webots Simulated Robot

In these experiments, the robot cooperated with a human to build blocks in three different scenarios. The robot added to its knowledge from the autonomous learned BHANs and BHAM based on human behaviors and feedback using Algorithms 3 and 4. In these experiments, the actual human participant performed in front of an RGB-D camera and the virtual human was modeled in the Webots environment, as shown in Figs. 7, 9, and 11. In the snapshots of Webots in Figs. 7, 9, and 11, the two left pictures are views from the robot and the human, respectively, and the three top pictures show the human visual perspective inference results, i.e., the robot visible region and visible objects, the calculated degree of confidence for each grid, and the human visible region and visible objects, respectively. In the snapshots of human behavior in Figs. 7, 9, and 11, the graph shows the FDTW values of each robot behavior, in which the bars are in order of WB, WO, Po, Tch, PF, PL, PR, Gr, Pt, ML, MR, and the behavior with the lowest FDTW was recognized as the human behavior.

1) Experiment 1: Fig. 7 shows the key snapshots from Experiment 1. (See the attached movie clip “experiment1_webots.wmv” for the whole experiment.) In this experiment, there was a big box in front of the human and the robot tried to infer the block of human intention and the behavior that the human wanted. First, the human did “waving one hand” and “waving both hands” behaviors to show the intention of “bring the small box and build it.” However, in the autonomous learned BHAM, “waving one hand” and “waving both hands” were not in the transition behavior set for the big box; thus, \( UL \) was increasing and the robot asked for more information from the human by doing a questioning behavior [see Fig. 7(a)]. The human did “moving right” behavior and the robot recognized it [see Fig. 7(b)]. The robot inferred the object candidates of human intention as the small box and the cylinder, because “moving right” was in the transition behavior set from the big box to the small box and to the cylinder of BHAM. Since the cylinder was closer to the human than the small box, the cylinder had the higher global evaluation value than the small box. Therefore, the robot approached the cylinder first and asked for human feedback [see Fig. 7(c)]. However, the human gave negative feedback, after which the robot approached the small box, which had the second highest global evaluation value, and asked for human feedback again [see Fig. 7(d)]. This time the human gave positive feedback.
Since “moving right” in BHAN$_{\text{SmallBox}}$ had a lower hierarchy behavior, “grasping,” the robot grasped the small box [see Fig. 7(e)]. The robot moved toward the human and did “moving right” behavior to build the small box on the big box [see Fig. 7(f)]. At this point, the object in front of the human was
changed from the big box to the small box, because the robot built the small box on the big box. The human did “pointing” behavior and the robot recognized it [see Fig. 7(g)]. In the autonomous learned BHAM, “pointing” was not in the transition behavior set from the small box; thus, $UL$ was increasing and the robot asked for more information from the human by doing a questioning behavior [see Fig. 7(h)]. The human did “put” behavior and the robot recognized it [see Fig. 7(i)]. The robot inferred the object candidate of human intention as the cylinder, because “put” was in the transition behavior set from the small box to the cylinder of BHAM. Therefore, the robot approached the cylinder and asked for human feedback [see Fig. 7(j)]. The human gave positive feedback for the cylinder. Since “put” in BHAN$_{\text{Cylinder}}$ has a lower hierarchy behavior, “grasping,” the robot grasped the cylinder [see Fig. 7(k)]. The robot moved toward the human and did “put” behavior to build the cylinder on the small box [see Fig. 7(l)].

While the robot inferred the blocks and behaviors of human intention, the robot learned BHANs and BHAM using the interactive learning algorithms. Fig. 8 shows the interactively learned BHANs and BHAM in Experiment 1.

2) Experiment 2: Fig. 9 shows the key snapshots from Experiment 2. (See the attached movie clip “experiment2_webots.wmv” for the whole experiment.) In this experiment, there was a small box in front of the human and the robot tried to infer the block of human intention and the behavior that the human wanted. First, the human did “waving both hands” and “pointing” behaviors to show the intention of “bring the big box and build it.” However, in the autonomous learned BHAM, they were not in the transition behavior set for the small box; thus, $UL$ was increasing and the robot asked for more information from the human by doing a questioning behavior [see Fig. 9(a)]. The human did “moving left” behavior with the small box and the robot recognized it [see Fig. 9(b)]. Since the small box was grasped by the human, and in the autonomous learned BHAM, the big box was lower in hierarchy than the small box with the transition behavior “moving left,” the robot inferred the object candidate of human intention as the big box. Thus, the robot approached the big box and asked for human feedback [see Fig. 9(c)] and the human gave positive feedback. Since “moving left” in BHAN$_{\text{BigBox}}$ has a lower hierarchy behavior, “grasping,” the robot grasped the big box [see Fig. 9(d)]. The robot moved toward the human and did “moving left” behavior with the big box to place the big box under the small box.

After doing “moving left” behavior, the robot recognized that there was still some distance from the small box to the big box. The robot inferred that “pushing forward” behavior should be performed to reduce the distance between the two boxes, because the robot learned the effect of the behavior in BHAN$_{\text{BigBox}}$. Thus, the robot did “pushing forward” behavior until the big box was close enough to be placed under the small box [see Fig. 9(e)] and the human did “moving left” behavior to build the small box on the big box [see Fig. 9(f)]. At this point, the object in front of the human was still the small box because the small box was on the big box. The human did “put” behavior and the robot recognized it [see Fig. 9(g)]. The robot inferred the object candidate of human intention as the cylinder, because “put” was in the transition behavior set from the small box to the cylinder of BHAM. Therefore, the robot approached the cylinder and asked for human feedback [see Fig. 9(h)]. The human gave positive feedback for the cylinder. Since “put” in BHAN$_{\text{Cylinder}}$ has a lower hierarchy behavior, “grasping,” the robot grasped the cylinder first [see Fig. 9(i)]. Then, it moved toward the human and did “put” behavior to build the cylinder on the small box [see Fig. 9(j)].

While the robot inferred the blocks and behaviors of human intention, the robot learned BHANs and BHAM using the interactive learning algorithms. Fig. 10 shows the interactively learned BHANs and BHAM in Experiment 2. As shown in Fig. 10, the new hierarchical relations from “waving both hands” and “pointing” to “grasping” were learned in BHAN$_{\text{SmallBox}}$.

3) Experiment 3: Fig. 11 shows the key snapshots from Experiment 3. (See the attached movie clip “experiment3_webots.wmv” for the whole experiment.) In this experiment, there was a big box in front of the human and the robot tried to infer the block of human intention and the behavior that the human wanted. First, the human did “waving both hands” and “waving one hand” behaviors to show the intention of “bring the small box and build it.” However, in the autonomous learned BHAM, they were not in the transition behavior set for the big box; thus, $UL$ was increasing and the robot asked for more information from the human by doing a questioning behavior [see Fig. 11(a)]. The human did “grasping” behavior with the big box and the robot recognized it [see Fig. 11(b)]. Since the big box was grasped by the human, and in the autonomous learned BHAM, there were not blocks that were lower in hierarchy than the big box, $UL$ was increasing and the robot asked for more information from the human by doing a questioning behavior [see Fig. 11(c)]. However, the human did not give the new behavior and the $UL$ duration time exceeded the predefined threshold; thus, the robot inferred the object candidates of human intention as the cylinder and the small box that were all the blocks with the highest degree of confidence except the big box. Since the cylinder was closer to the human than the small box, the cylinder had a higher global evaluation value than the small box. Therefore, the robot approached the cylinder first and asked for human feedback [see Fig. 11(d)]. However, the human gave negative feedback for the cylinder; thus, it approached the small box which had the second highest global evaluation value and asked for the human feedback again [see Fig. 11(e)]. The human gave positive feedback this time and the robot grasped the small box [see Fig. 11(f)]. It moved toward the human and did “put” behavior with the small box to build the small box under the big box [see Fig. 11(g)]. After doing “put” behavior, the robot recognized that there was still some distance from the big box to the small box. The robot inferred that “pushing forward” behavior should be performed to reduce the distance between the two boxes, because the robot learned the effect of the behavior in BHAN$_{\text{SmallBox}}$. Thus, it did “pushing forward” behavior until the small box was close enough to be placed under the big box [see Fig. 11(h)] and the human did “put” behavior to build the big box on the small box [see Fig. 11(i)]. At this point, the object in front of the human was still the big box because the big box was on the small box. The human did “put” behavior...
and the robot recognized it [see Fig. 11(j)]. It inferred the object candidate of human intention as the cylinder, because “put” was in the transition behavior set from the big box to the cylinder of BHAM. Therefore, the robot approached the cylinder and asked for human feedback [see Fig. 11(k)]. The human gave positive feedback for the cylinder. Since “put” in BHAN_{Cylinder} has a lower hierarchy behavior, “grasping,” the robot grasped the cylinder, moved toward the human and did “put” behavior to build the cylinder on the big box [see Fig. 11(l)].

While the robot inferred the blocks and behaviors of human intention, the robot learned BHANs and BHAM using the interactive learning algorithms. Fig. 12 shows the interactively learned BHANs and BHAM in Experiment 3. As shown in Fig. 12, the new hierarchical relations from “waving both hands” and “waving one hand” to “grasping” were learned in BHAN_{BigBox}. The new hierarchical relation from the small box to the big box along with “put” transition behavior was also learned in BHAM.

4) Experiments for Various Situations: To verify that the proposed method worked generally, experiments under various situations were conducted and statistical results were generated. The experiments were conducted by increasing the number of interaction objects and placing the objects randomly. The statistical results were obtained by doing experiments 100 times for each situation.

Table VIII shows the correct human intention inference rate and task success rate. As the number of interaction objects increased, a human participant changed the intended object more frequently during experiments; thus, the correct human intention inference rate decreased. The task success rate means whether a robot accomplished the task as the human participant intended, i.e., a robot successfully built blocks as a human participant intended. Even though a robot correctly inferred the blocks and the behaviors of human intention, the task success rate decreased as the number of interaction objects increased because the number of irrational intentions by the human participant, e.g., build a block on an uneven one, increased.

### Table VIII

<table>
<thead>
<tr>
<th># of objects</th>
<th>Correct human intent inference rate (%)</th>
<th>Task success rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>4</td>
<td>100</td>
<td>90</td>
</tr>
<tr>
<td>5</td>
<td>96</td>
<td>87</td>
</tr>
<tr>
<td>6</td>
<td>92</td>
<td>76</td>
</tr>
</tbody>
</table>

D. Human Intention Reading Result Using Mybot-KSR

This experiment was conducted to show that the proposed human intention reading method works well in the real environment by using a human-sized humanoid robot (Mybot-KSR). The experimental scenario was the same as in the previous experiments using the Webots simulated robot, i.e., a human and Mybot-KSR built different kinds of blocks together. The upper body of Mybot-KSR has 15 degrees of freedom (DOFs) and each arm has seven DOFs [34]. Mybot-KSR has a robotic head with 19 DOFs and a Xtion camera [35].

Fig. 13 shows the key snapshots from the experiment using Mybot-KSR. (See the attached movie clip “experiment_mybot.wmv” for the whole experiment.) In this experiment, there were a big box, a small box, and a cylinder with a conical hat [see Fig. 13(a)]. First, the human grasped the small box and the robot recognized the human behavior [see Fig. 13(b)]. Since the small box was grasped by the human, and in the autonomous learned BHAM, the big box was lower in hierarchy than the small box, the robot inferred the object of human intention as the big box. The robot placed the big box in front of the human by pushing it to the right, because the robot learned the effect of “pushing right” behavior in BHAN_{BigBox} [see Fig. 13(c)]. Then, the human put the small box on the big box [see Fig. 13(d)]. The human did “put” behavior and the robot recognized it [see Fig. 13(e)]. Since “put” was in the transition behavior set from the small box to the cylinder of BHAM, the robot inferred the object of human intention as the
Inferred the objects and the behaviors of human intention using the BHANs and BHAM.

REFERENCES


Ji-Hyeong Han received the B.S. and Ph.D. degrees in electrical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, Korea, in 2008 and 2015, respectively. Since 2015, she has been with the Electronics and Telecommunications Research Institute, Daejeon, where she is currently a Researcher. Her research interests include human intent recognition, human–robot interaction, intelligent robotics, and smart factory.

Seung-Jae Lee received the B.S. and M.S. degrees in electrical engineering from the Korea Advanced Institute of Science and Technology, Daejeon, Korea, in 2012 and 2013, respectively, where he is currently working toward the Ph.D. degree.

His current research interests include the area of humanoid robotics, in particular, in arm trajectory generation and task planning.

Jong-Hwan Kim (F’09) received the Ph.D. degree in electronics engineering from Seoul National University, Seoul, Korea, in 1987. Since 1988, he has been with the School of Electrical Engineering, KAIST, Daejeon, Korea, where he is currently a Professor and Director for the Robot Intelligence Technology Laboratory. His research interests include intelligence technology, intelligence super agent, ubiquitous and genetic robots, and humanoid robots. He has authored five books and five edited books, two journal special issues, and more than 300 refereed papers in technical journals and conference proceedings. He has delivered more than 200 invited talks on computational intelligence and robotics including more than 40 keynote speeches at the international conferences.

Dr. Kim was an Associate Editor of the IEEE TRANSACTIONS ON EVOLUTIONARY COMPUTATION and the IEEE COMPUTATIONAL INTELLIGENCE MAGAZINE.