Human Intention Reading by Fuzzy Cognitive Map: A Human-Robot Cooperative Object Carrying Task

Ji-Hyeong Han and Jong-Hwan Kim

Abstract Considering the symbiosis between humans and robots in coming years, robots should be able to infer the implicit human intention for the efficient human-robot interaction. This paper focuses on the human-robot cooperation problem among the various fields of human-robot interaction. The human intention reading method using fuzzy cognitive map for the efficient human-robot cooperation is proposed along with the algorithm which decides the appropriate behavior of a robot with the recognized human intention. The effectiveness of the proposed method is demonstrated through computer simulation on human-robot cooperative object carrying task.

Key words: Human-robot interaction, human intention reading method, fuzzy cognitive map.

1 Introduction

The symbiosis era of humans and robots is approaching in no distant future because of the rapid development of the robot technology and artificial intelligence (AI). For this coming era, the natural and rational human-robot interaction (HRI) is needed. In this manner, HRI researches have grown up and there have been many researches on various HRI fields. Among these researches, the efficient cooperation between humans and robots is one of crucial issues. Through the efficient human-robot cooperation, each can get particular benefits from the other.

To achieve the efficient human-robot cooperation, robots need to read the human intention without the explicit human commands. A robot can infer the human intention by recognizing the explicit human commands, such as verbal dialog. However,

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in this case, a human has a cognitive burden, since he/she has to make an explicit command all the time. Therefore, a robot should have a capability to recognize the human intention based on the implicit human information, such as human behavior, gesture, and position. There were several researches on intention reading algorithm and social robotics [1]-[6].

The one of typical applications for human-robot cooperation is human-robot cooperative object carrying task. There were several researches on human-robot cooperative object carrying [7]-[12]. Most of the researches have focused on the control issue after a robot and a human grab the object. Some researches considered the human intention by force or torque sensing, but it was still after grabbing the object. However, in the real world environment, there can be several objects and a robot should decide which object and which side of an object a human wants to carry. Also, there can be several goal points to carry an object. There is a lack of research which considers the human intention before grabbing an object as well as with the case of several possible objects and goal points. Therefore, this paper proposes the human intention reading method which recognizes the human intended object, side, and goal point using fuzzy cognitive map (FCM) for the efficient human-robot cooperative object carrying task. FCM, which was proposed by Kosko, is a symbolic representation for modeling the complex system [13]. FCM has been applied to the various research fields [14].

In this paper, human intention reading method using FCM is proposed for the efficient human-robot cooperative object carrying task. To demonstrate the effectiveness of the proposed method, computer simulation on human-robot cooperative object carrying task is carried out.

This paper is organized as follows. Section 2 briefly explains FCM. Section 3 describes the formulation of the target problem and proposes the human intention reading method using FCM. In Section 4, the simulation results for the human-robot cooperative object carrying task are discussed. Finally, concluding remarks follow in Section 5.

2 Fuzzy Cognitive Map

Fuzzy Cognitive Map (FCM) is a graphical representation which consists of concept nodes and weighted arrows [13]. The weighted arrows are connecting the concept nodes and represent the causality between the connected concept nodes. This graphical representation is able to show clearly which concept influences other concepts and how much influence. This section briefly explains FCM representation and update formulation.

2.1 Fuzzy Cognitive Map Representation

Figure 1 is a simple FCM example which consists of four concept nodes and six weighted arrows. As shown in figure 1, FCM is able to model the causal relationship between concept nodes. Each concept node has a concept variable, such as C_1, C_2, C_3, and C_4 in figure 1. Each concept variable has a number α_i which represents its value in the interval $[0,1]$. The causality from C_i to C_j is represented by the arrow which starts from C_i, which is called a causal variable, and ends to C_j, which is called an effect variable. The degree of causality between concepts is represented by weight, W_{ij} in interval $[-1,1]$. There are three kinds of causalities between concepts as follows:

1) $W_{ij} > 0$: the positive causality.
2) $W_{ij} = 0$: no relationship.
3) $W_{ij} < 0$: the negative causality.

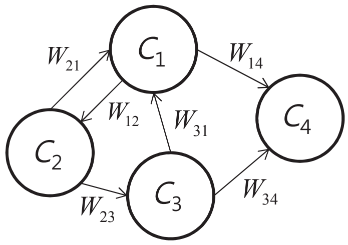


Fig. 1: A simple fuzzy cognitive map example.

At each time step, the value of concept variable C_i, α_i, is calculated as follows:

$$\alpha_i^t = f\Big(\sum_{\substack{j=1\\ j\neq i}}^{n} \alpha_j^{t-1} W_{ji} + \alpha_i^{t-1}\Big) \tag{1}$$

where α_i^t and α_i^{t-1} are the values of concept C_i at time step t and $t-1$, respectively, α_j^{t-1} is the value of concept C_j at time step $t-1$, W_{ji} is the interconnection weight from concept C_j to concept C_i, and W_{ii} is zero. The function f is a threshold function for normalizing concept value in interval $[0,1]$. Usually, the following unipolar sigmoid function is used as the threshold function in FCM.

$$f(x) = \frac{1}{1+e^{-\lambda x}},\ \lambda > 0 \tag{2}$$

where λ determines the steepness of the function f.

3 Problem Formulation and the Proposed Human Intention Reading Method

The problem trying to solve in this paper is human-robot cooperative object carrying task. For efficient cooperation between a human and a robot, the robot should recognize the human intention, such as the human intended object and the human intended goal point. To solve this issue, the human intention reading method using FCM is proposed in this paper. This section explains the problem formulation and then detailed descriptions of the proposed method follow.

3.1 Problem Formulation

Figure 2 shows the simulation environment of human-robot cooperative object carrying task. There are two blocks (B1 and B2), two goal points (G1 and G2), three robot agents (R1, R2, and R3), and a human agent (H). The goal of the task is carrying each block to any goal points. A goal point is able to have only one block and the indices of the blocks and the goal points are irrelevant. Two agents are needed to carry a block and they have to be at opposite sides of the block. After all blocks are grabbed by agents, they are carried to goal points.

The initial positions of all agents and blocks are random. The human agent moves manually by a user using keyboard and mouse inputs. The robot agents move autonomously and the details of the robot agent behavior decision process will be explained in the following Subsection 3.2. The blocks move randomly up, down, left, right, or stay with probability of 0.2 until they are grabbed by an agent. The locations of goal points are fixed.

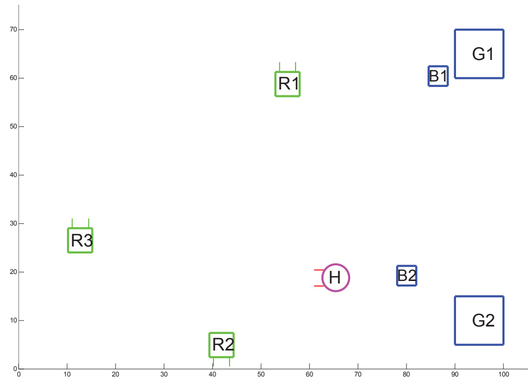


Fig. 2: The simulation environment of human-robot cooperative object carrying task.

3.2 Human Intention Reading Method using FCM

The problem trying to solve has two blocks, three robot agents, and a human agent and two agents are needed to carry a block. Therefore, there are two teams which consist of two robot agents and a human and a robot agents. To a human and a robot agents team carry a block successfully to a goal point, a human and robot cooperation is essential. To achieve the efficient human-robot cooperation, a robot should read the human intention by observing the human movement. Three kinds of human intentions are defined in this problem as follows.

1) Which block does a human want to carry?
2) Which side of the block does a human want to grab?
3) Which goal point does a human want to go?

FCM is applied to recognize the human intentions 1) and 3). Figure 3 shows the defined FCM. There are four input concept nodes, i.e., D_1, D_2, A_1, and A_2. The input concept node D_n represents the distance between the human position and Bn and Gn positions for the human intention 1) and 3), respectively. The input concept node A_n represents the angle between the human direction and Bn and Gn for the human intention 1) and 3), respectively. There are two output concept nodes for each block and goal point, i.e., B_1, B_2 and G_1, G_2, for the human intention 1) and 3), respectively. The subscript of each node is the index of the block or the goal point.

The values of the input concept nodes D_n and A_n, α_{D_n} and α_{A_n}, are defined as follows:

$$\begin{aligned} \alpha_{D_n} &= 1/(1+d_n) \\ \alpha_{A_n} &= 1/(1+a_n) \end{aligned} \tag{3}$$

where d_n is the distance between the human and Bn or Gn and a_n is the angle between the human direction and Bn or Gn. Since the block or goal point with small d_n and a_n shall be the human intended one, α_{D_n} and α_{A_n} are defined one over d_n and a_n. Plus one in the denominator of Equation 3 is to prevent dividing by zero. The values of the output concept nodes B_n and G_n for the human intentions 1) and 3), respectively, are initially zero and updated by Equation 1. When FCM reaches the equilibrium point, the output concept node which has the biggest value is selected as the human intended block or goal point.

Two different weights of FCM are defined to recognize the human intentions 1) and 3), respectively. Each of them is defined as follows:

$$W_{block} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.5 & -1 \\ 0 & 0 & 0 & 0 & -1 & 0.5 \\ 0 & 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & -1 & 0 \end{bmatrix}, \; W_{goal\,point} = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0.5 & -1 \\ 0 & 0 & 0 & 0 & -1 & 0.5 \\ 0 & 0 & 0 & 0 & 0 & -1 \\ 0 & 0 & 0 & 0 & -1 & 0 \end{bmatrix} \tag{4}$$

where W_{block} is for recognizing the human intention 1) and $W_{goal\,point}$ is for recognizing the human intention 3). The order of columns and rows is D_1, D_2, A_1, A_2,

B_1/G_1, and B_2/G_2 from left to right and from up to down, respectively. W_{block} is defined to consider that the angle is more important than the distance. On the other hand, $W_{goal point}$ is defined to consider that the distance is more important than the angle.

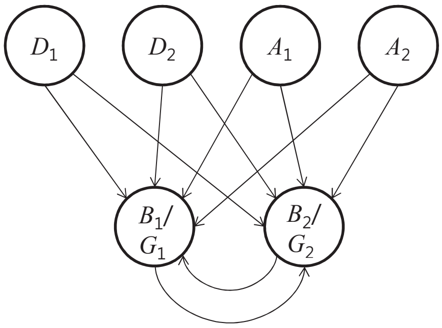


Fig. 3: The defined FCM to recognize the human intentions 1) and 3).

To recognize the human intention 2), the simple relative position between a human and a block is used as shown in figure 4. H and B in figure 4 represent a human and a block, respectively. There are four possible human intentions, i.e., up, down, left, or right sides of the block.

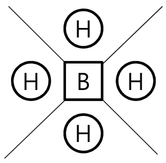


Fig. 4: The relative position between a human and a block to recognize the human intention 2).

Algorithm 1 shows the overall procedure for a human-robot cooperative carrying task using the proposed human intention reading method with FCM.

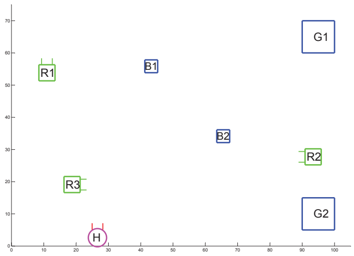
4 Simulation Results

To show the effectiveness of the proposed method, a human-robot cooperative object carrying task was simulated in MATLAB environment. Figure 5 shows the snapshots of simulation result in time order and figure 6 shows the values of FCM output concept nodes during simulation. Initially all of the agents and blocks were

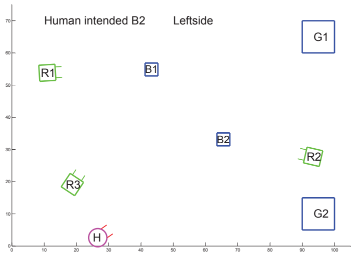
Algorithm 1 The overall algorithm for a human-robot cooperative object carrying task.

Initially, all of the agents and blocks are randomly located.
while All blocks are grabbed by agents. **do**
  i) Recognize the human intended block using FCM with W_{block}.
  ii) Recognize the human intended side of the intended block from i) using the relative position between a human and the intended block.
  iii) The closest robot to the human intended block makes a team with a human. The robot goes to the opposite side of the human intended side of the human intended block.
  iv) The other robots make a team and go to the other block. The closet robot to the other block chooses the desired side first and another robot goes to the opposite side.
end while
After all blocks are grabbed by the agents, the agents carry the block to the goal point.
while All blocks are carried to the goal point. **do**
  i) Recognize the human intended goal point using FCM with $W_{goal\,point}$.
  ii) The robot in a human-robot team goes to the human intended goal point with a human.
  iii) The other team goes to the other goal point.
end while

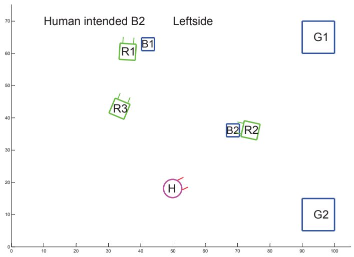
located randomly (figure 5(a)). Firstly, the human wanted to grab B2. The human intention was recognized as B2-leftside (figure 5(b)), since the value of FCM output concept node B_2 was bigger than one of B_1 as shown in figure 6(a). So R2, which was the closet robot to B2, made a team with the human and went to the B2-rightside and other robots, R1 and R3, went to B1 (figure 5(c)). Since the recognized human intention was changed to B2-downside as the human approached B2, R2 moved from B2-rightside to B2-upside (figure 5(d)). Suddenly, the human changed his/her mind to grab B1. The human intention was recognized as B1-downside (figure 5(e)), since the value of FCM output concept node B_1 was bigger than one of B_2 as shown in figure 6(a). So R1, which was the closet robot to B1, made a team with the human and grabbed B1-upside and R3 changed its direction to B2 (figure 5(f)). When a block was grabbed, the color was changed to red. Finally, all the blocks were grabbed and simulation was in next stage, i.e., carrying the object to a goal point (figure 5(g)). Firstly, the human wanted to carry B1 to G1. The human intention was recognized as G1, since the value of FCM output concept node G_1 was bigger than one of G_2 as shown in figure 6(b). So the human-robot team went to G1 and the robot-robot team went to G2 (figure 5(h)). And then suddenly the human changed his/her mind to carry B1 to G2. The human intention was recognized as G2, since the value of FCM output concept node G_2 was bigger than one of G_1 as shown in figure 6(b). Therefore, the human-robot team went to G2 and the robot-robot team changed their directions to G1 (figure 5(i)). Finally, all the blocks were carried to different goal points successfully and the simulation was over (figure 5(j).



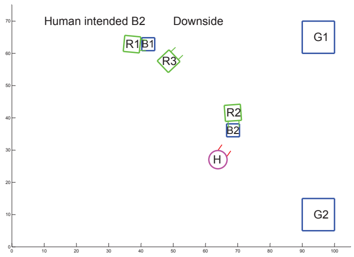
(a) Time step 1.



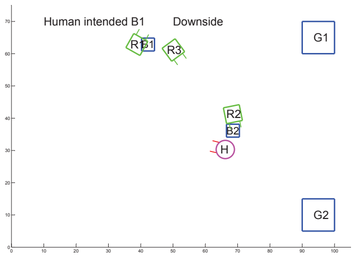
(b) Time step 2.



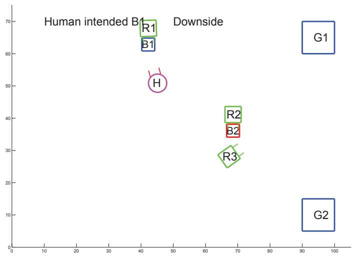
(c) Time step 31.



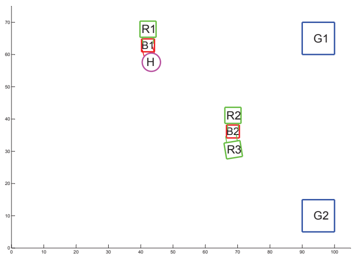
(d) Time step 50.



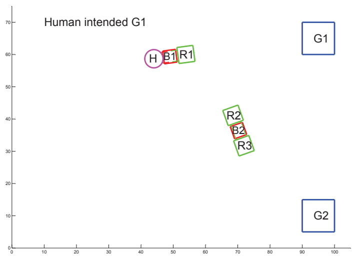
(e) Time step 55.



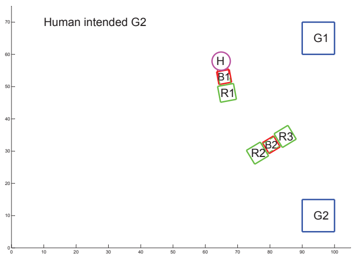
(f) Time step 90.



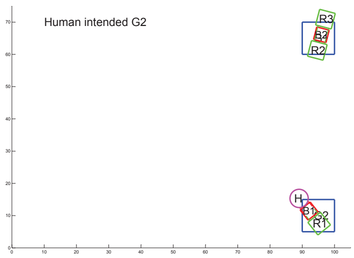
(g) Time step 97.



(h) Time step 100.

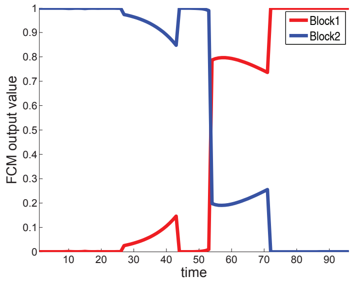


(i) Time step 125.

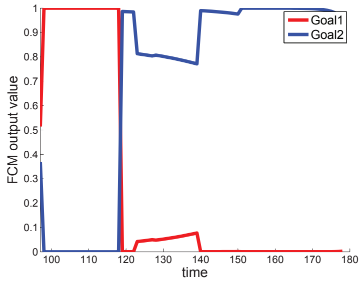


(j) Time step 178.

Fig. 5: Simulation results in time order.



(a)



(b)

Fig. 6: The values of FCM output concept nodes during simulation. (a) The values of B_1 and B_2. (b) The values of G_1 and G_2.

5 Conclusion and Future Works

This paper proposed the human intention reading method for the efficient human-robot cooperative object carrying task. FCM was applied to the human intention reading method. The three kinds of human intentions, i.e., which block, which side of a block, and which goal point, were defined and they were recognized by the proposed method with the defined FCM. The effectiveness of the proposed method was demonstrated through computer simulation on the human-robot cooperative object carrying task with two blocks and two goal points. The proposed method recognized the human intention in real time and even if the human intention was suddenly changed, the proposed method inferred it instantly. Also, the robot behavior decision process with the recognized human intention was defined for the efficient cooperation between a human and a robot.

FCM was the useful method to understand the human intention as shown in this paper. It could represent the various abstracted concepts as nodes and their relationships as weighted edges intuitively and the human intention usually consisted of the abstracted conceptions. Therefore, FCM would be the competitive method to solve the problem which could defined by the various concepts such as the human intention issue. For future work, the weights of FCM could be adjusted by using Hebbian learning or other learning methods.

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