Fuzzy methods and eye gaze for cooperative robot communication

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Abstract: We introduce our fuzzy signature and pattern matching with possibility calculation based approach for modelling the communication between human-control robot and a pair of assistant robots for completing cooperative tasks in a simulated environment. We show that a sophisticated extension using computerised recognition of eye gaze with fuzzy modelling based interpretation of possible intentions effectively eliminates the need of any physical control from the human's side. The experiment results show a good improvement of time saved by the use of our eye gaze intention in the context.

Keywords: cooperative robots; fuzzy signature; possibility calculation; eye-gaze inference; human-robot communication.

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1 Introduction

Intelligent robots and artificial agents, with their multi-model representations have been developed over the past decade with the expectation that they would be able to assist human to work more easily and cooperatively without active direction under a variety of circumstances. Compared with single robot or agent systems, it is obvious that multiple robots systems are much more effective and will be able to perform tasks that a single robot can not do. Furthermore, they can be expected to work cooperatively with other robots or even with human-beings. Therefore, the way to investigate the communication in a group of robots, either between 'human-controlled' robots and assistant robots, or autonomous robots themselves, has become highly significant with the clear motivation that it enables the team of robots to maximise their utility.

The main types of communications between cooperative robots can be classified into *explicit* and *implicit*. *Explicit communication* is mostly defined as direct communication for sharing specific information to achieve a common goal for a team of robots. The early research done by Yanco and Stein (1993) describes mobile robots engaged in a cooperative task that requires 'Adaptive Communication', which refers to robots communicating with a fixed uninterpreted symbolic vocabulary. The language created for the robots may not provide support for an optimal solution to a particular task, being less able to handle complicated circumstances in a dynamic environment. Other relevant examples about 'explicit communication' can also been found in Rus et al. (1995) and Chaimuwicz et al. (2001). On the other hand, 'Implicit Communication' occurs as a side-effect of robots' actions, or through the way they affect the environment (Pereira et al., 2002), which offers several immediate advantages such as simplicity, robustness to errors, lower cost and efficiency of task performance, etc. over explicit communication.

A number of inference approaches for human-robot teamwork systems and applications already exist based on different types of communications, for instance, non-verbal communication based inference (Breazeal et al., 2005), observable behaviour-based intention inference (Inagaki et al., 1995). In this paper, we describe our fuzzy signatures based inference approach, then extend the intentional inference by applying human eye gaze information for modelling the communication in a group of cooperative robots to better predict human intentions.

1.1 Eye gaze for communication

Eye gaze is tightly coupled with human cognitive processes, which has served as an informative mode of communication and interaction throughout history. In fact, human beings communicate in abbreviated ways dependent on prior interactions and shared knowledge. In addition, humans share information about intentions and future actions also using eye gaze. Among primates, humans are unique in the whiteness of the sclera and amount of sclera shown, essential for communication via interpretation of eye gaze.

According to the common capability and advantage of using eye gaze as well as the increasing availability of relatively inexpensive and reliable eye tracking systems, much interest has been sparked in their potential applications in a large number of fields, particularly for human-computer, human-robot/agent interaction, user interface design (Jacob, 1991), computer game technologies (Gedeon et al., 2008), as a disambiguation channel in conversational communication (Tanaka, 1998), and as a facilitator in computer supported human-human communication and collaboration (Vertegaal, 1999). This is also the major motivation for us to integrate richer and more complex human eye gaze information regarding a person's interest and intentions into the current cooperative robots model to further improve the inference approach.

1.2 Research scenario

We consider a research scenario of co-operating intelligent robots proposed by Terano (1993), which we style as context-dependent reconstructive communication (Zhu and Gedeon, 2008): there are set of identical oblong shaped tables in a room. Various configurations can be built from them, such as a large U shape, a large T shape, a very large oblong, rows of tables, etc. (see Figure 1).

A group of autonomous intelligent robots is supposed to build the actual configuration according to the exact instructions given to the Robot Foreman (R0). The other robots have no direct communication links with R0, but they are able to observe the behaviour of R0 and all others, and they all posses the same codebook containing all possible table configurations.

The individual tables can be shifted or rotated, but two robots are always needed to actually move a table, as they are heavy. If two robots are pushing the table in parallel, the table will be shifted according to the joint forces of the robots. If the two robots are pushing in the opposite directions positioned at the diagonally opposite ends, the table will turn around the centre of gravity. If two robots are pushing in parallel, and one is pushing in the opposite direction, the table will not move (see Figure 2).

Figure 1 Task configurations (see online version for colours)

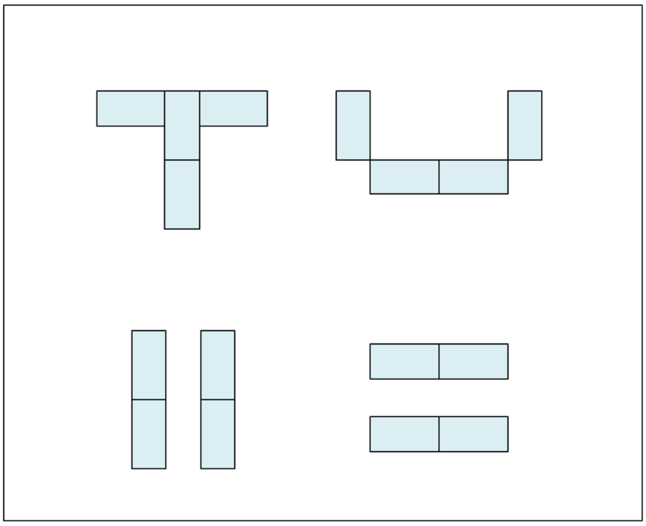
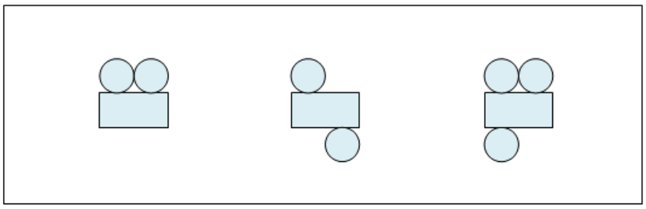


Figure 2 Push, rotate and stop configurations (see online version for colours)



Under these conditions the task can be solved, if all robots are provided with suitable algorithms that enable 'intention guessing' from the actual movements and positions, even though they might be ambiguous.

2 Fuzzy signature

Fuzzy signatures have been regarded as an effective approach to solve the problem of rule explosion in traditional fuzzy inference systems: constructing characteristic fuzzy structures, modelling the complex structure of the data points (bottom up) in a hierarchical manner (Kóczy et al., 1999; Gedeon et al., 2001; Vámos et al., 2001). Fuzzy signatures start with a generalised representation of fuzzy sets called Vectorial Fuzzy Sets (or vector valued fuzzy sets) (VFS). A VFS, $\underline{A}$, on $X = \{X_1, \ldots, X_n\}$ can be written as:

$$\underline{A} = (X, \mu_{\underline{A}}). \tag{1}$$

The membership function $\mu_{\underline{A}}$ can be defined as:

$$\mu_{\underline{A}} : X \to [0, 1]^n. \tag{2}$$

Now, a fuzzy signature is a recursive VFS such that each vector is another VFS (called a branch) or an atomic value (called a leaf):

$$A : X \to [a_i]_{i=1}^{k} \tag{3}$$

$$\text{where} \quad a_i = \begin{cases} [a_{ij}]_{j=1}^{k_i} & ;\text{ if branch} \\ [0,1] & ;\text{ if leaf} \end{cases}.$$

In general, fuzzy signatures result in a much reduced order of complexity, at the cost of slightly more complex aggregation techniques. Unlike conventional rule based hierarchical fuzzy systems, each branch in a fuzzy signature uses a different aggregation function to find the importance of that branch to its parent. Aggregation of a fuzzy signature finds the final atomic result called 'degree of match'. Also, fuzzy signatures are different to conventional decision trees as they use a bottom up inference mechanism, and when there is missing or noisy input data it still can finds a degree of match. We consider a fuzzy signature as a hierarchical fuzzy descriptor of the object it represent. Figure 3 illustrates an example of a fuzzy signature structure which was constructed for a SARS pre-clinical diagnosis system by Wong et al. (2004).

Figure 3 A fuzzy signature example

$$A_S = \begin{bmatrix} Fever \begin{bmatrix} 8a.m. \\ 12a.m. \\ 4p.m. \\ 8p.m. \end{bmatrix} \\ BloodPressure \begin{bmatrix} Systolic \\ Diastolic \end{bmatrix} \\ Nausea \\ AbdominalPain \end{bmatrix}$$

The example fuzzy signature in Figure 3 is only a descriptor for one patients data for a single day (called one data point). Mendis (2008) has shown that it is possible to use one fuzzy signature as a descriptor of several data points of the same object. This type of fuzzy signature is called a polymorphic fuzzy signature and has been used in this paper. Further, Mendis and Gedeon (2008a, 2008b) have shown that this type of fuzzy signature can outperform the results of OWA and outperform both the results and computational complexity of Choquet Integral systems in complex structured real world problems.

3 Fuzzy signatures construction for cooperative robot intention inference

The process of constructing fuzzy signature has also been discussed in Wong et al. (2004):

Let S_{S_0} denote the set of all fuzzy signatures whose structure graphs are sub-trees of the structural ('stretching') tree of a given signature S_0. Then the signature sets introduced on S_{S_0} are defined by:

$$A_{S_0} : X \to S_{S_0}. \tag{4}$$

In this case, the prototype structure S_0 describes the 'maximal' signature type that can be assumed by any element of X in the sense that any structural graph obtained by a set of repeated omissions of leaves from the original tree of S_0 might be the tree stretching the signature of some A_{S_0}.

In practice, there are two approaches to construct the sub-structures of the fuzzy signature, S_0 (Wong et al., 2003; Chong et al., 2002):

- predetermined by a human expert in the field
- determined by finding the separability from the data.

In our cooperative robots case, as we are handling complex circumstances and we actually do not have enough data, so we will only use the first approach to construct the fuzzy signatures. Based on the context of the robots scenario, we propose the use of an alternative form of fuzzy signature, which uses a better hierarchical structure where the internal nodes are simple, while the leaves are populated with small rule bases, generally of one variable. The instructions and assumptions about the CRC framework are as follows:

1 *Instructions:*

   a A group of intelligent robots of size 1×1: $R_i : R_0, R_1, \ldots, R_n$, R_0 is the 'foreman'.

   b A set of random shape tables of size 1×2: $T_1, T_2, \ldots, T_n$.

   c A set of possible configurations made up of tables: $S_1, S_2, \ldots, S_n$, where one of them is the final task.

2 *Assumptions:*

   a 'Foreman' (R_0) represents a human-being (controlled by a human).

   b Only the 'Foreman' (R_0) knows the final task.

   c Other robots (R_i) do not know the final task, but they know all the possible table shapes ($S_1, S_2, \ldots, S_n$);

   d Other robots (R_i) know who the foreman (R_0) is.

Figure 4 is a snapshot of an initial configuration of all the objects, including tables, robots and final task shape in our simulator.

According to the above descriptions, to construct the fuzzy signatures for inferring the foreman's following action, we need to figure out which 'attributes' will be essentially related to the foreman's intentional action based on the current situation. Since the current situation is that there are a set of tables, if the foreman is intended to do something, he should go and touch a particular table first or get closer at least. So the first 'essential attribute' is the 'Distance' between the foreman and each table in the environment. Figure 5 illustrates the membership function of 'Distance'.

However, there exists a possible situation that can not be handled by 'Distance' only: if the foreman moves towards to a table then touches it, but after that he moves away or switches to another table immediately, the other robots still can not infer what the foreman is going to do. In order to solve this problem, we need to add another 'attribute' called 'Waiting Time' (the membership is similar in shape to Figure 5 and is not shown) which is used to measure how long a robot (R_i) stops at a particular spot. The reason why we need to measure the stopping time is that it is too difficult for a robot to perceive the meaning of the scene using instantaneous information (a snapshot) only (Inagaki et al., 1993).

Figure 4 A random initial configuration of objects (dark squares), and robots (circles, the darker circle is the 'foreman'), and target configuration (asterisks) (see online version for colours)

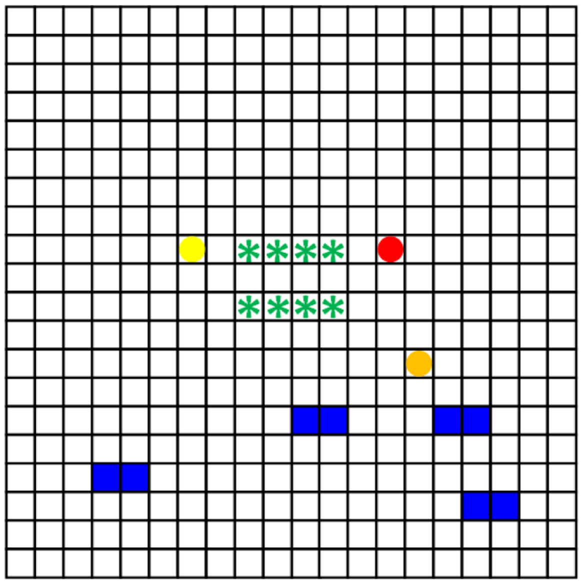
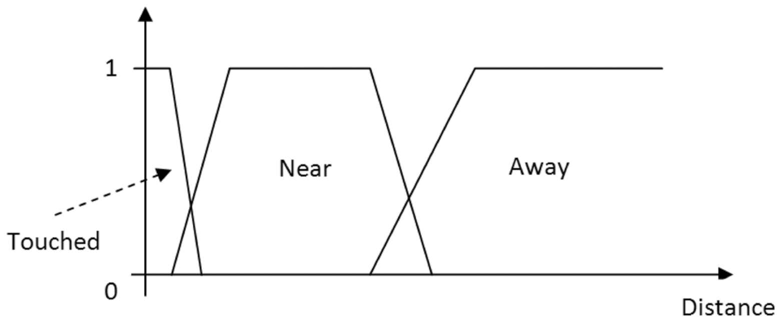


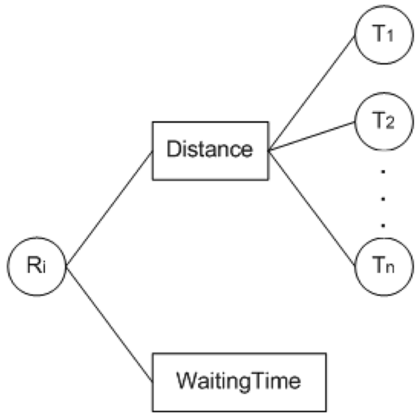
Figure 5 Fuzzy membership function of distance



By combining the 'Waiting Time' with the previous item 'Distance', the final fuzzy signatures for intention inference will be formed to the structure in Figure 6.

Under this circumstance, other robots will be able to infer the foreman's next action according to his current behaviour. For instance, if the 'Distance' between the foreman (R_0) and a table (T_i) is *Touched*, meanwhile the foreman's 'Waiting Time' at that spot is *Long*, then it implies that the foreman is 'Waiting for Help' which means another robot (R_i) should go to T_i and help the foreman. Otherwise if neither of the conditions are satisfied, this means other robots will not assume the foreman is going to carry out any intentional action because they can not figure it out by observation of the foreman's current behaviour.

Figure 6 Fuzzy signatures for CRC



$$R_i = \begin{bmatrix} Distance & \begin{bmatrix} T_1 \\ T_2 \\ . \\ . \\ . \\ T_n \end{bmatrix} \\ WaitingTime & \end{bmatrix}$$

4 Pattern matching with possibility calculation for task inference

So far we have discussed the problem of inferring the foreman's intentional action by constructing the fuzzy signatures based on the foreman's current behaviour. In some sense, it means other robots still have to count on the foreman completely and it actually does not show that these robots are intelligent enough that they can help the foreman to finish the final task effectively and efficiently as well as to truly reduce the cost of the communication between them.

In order to improve the modelling technique, it is important for us to consider the current situation after each movement of a table, which means other robots should be able to guess which table shape is likely to be the most possible one according to foreman's previous actions and the current configuration of tables. The solution here is to measure how close the current table configuration/shape matches each of the possible shapes after the foreman's intentional actions. Therefore, apart from the previous fuzzy signatures, another modelling structure has been constructed for robot's further decision making.

Figure 7 shows another tree structure with all the leaves representing each possible table shape as well as its possibility value respectively. The following strategies show how this structure works:

We have a set of tables: $T_1, T_2, \ldots, T_n$; the total number of tables is n:

1 IF foreman and a robot push a table to a place which matches one of the possible table shapes: S_i
THEN increase the possibility value of S_i: $PV_{S_i} + 1/n$

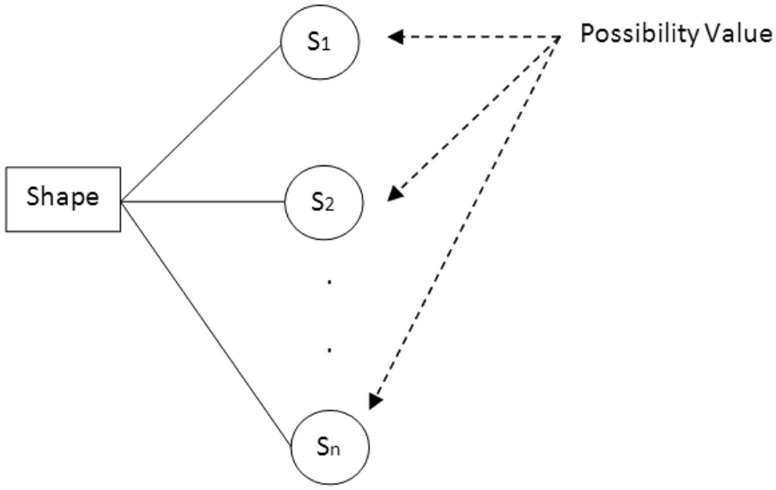
2 IF foreman and a robot push a table to a place which does not match any of the possible table shapes
THEN none of the possibility values will change

3 IF foreman and a robot push a table which matched S_i to a place where does not match any of the possible shapes
THEN decrease the possibility value of S_i: $PV_{S_i} - 1/n$

4 IF foreman and a robot push a table which matched S_i to a place where matches another possible shape: S_j
THEN decrease the possibility value of S_i: $PV_{S_i} - 1/n$
AND increase the possibility value of S_j: $PV_{S_j} + 1/n$

5 IF two robots (neither is foreman) push a table to a place where matches one of the possible table shapes: S_i
THEN the possibility value of S_i, i.e., PV_{S_i} will not change.

Figure 7 Structure of pattern matching with possibility calculation



From the above strategies we can find that the possibility value of a possible shape S_i will only change when the foreman is one of the working robots who carry out the action, otherwise the possibility value will not change. The reason why we model the situation like this is due to the initial assumption mentioned earlier, that the foreman is the only robot who knows the final task so that we assume all the actions carried out by the foreman are directly related to the final task. Since other robots do not know the final task, their actions are not considered to be definitely correct and directly related to the final task so none of the possibility values will change according to these actions.

5 Eye gaze based fuzzy inference approach

The above detailed description has shown the successful modelling of cooperative robot communication by applying our fuzzy solution. In the following section, we discuss in detail how to use fixation information from a user's eye gaze to perform the intentional inference in the same intelligent robots scenario.

Figure 8 illustrates the recorded original gaze points from a user's intentional decision-making process for identifying a particular object they intend to move as well as the corresponding destination for those two assistant robots to carry out the movement in the simulator. The raw eye-gaze path is a bit complex and difficult to interpret, consequently, we further filter the gaze points into fixations (see Figure 9), which provide a much easier and more interpretable form of information from which the user's interest and intention.

Figure 8 A user's original gaze points for identifying an object and destination (see online version for colours)

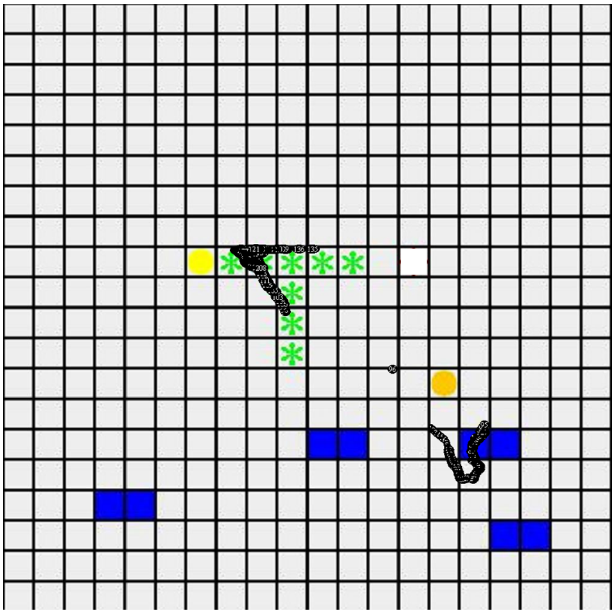


Figure 10 demonstrates an example of part of the window for a 'Horizontal Rows' task overlaid with a user's eye gaze path. The size of the black circle in the image represents the duration of the relevant fixations. Please note that the initial configuration of robots and tables is the same for all the possible tasks, and in order to make the scene be visible, the size of fixation circles on the scene representing fixation duration has been reduced to the same value, which are actually not representing the probable area of user's interest, but the exact value of fixation duration is shown below the fixation number in each of the black circles.

The following description shows the major steps of the fuzzy inference for eye-gaze fixation (Gedeon et al., 2008):

1. *Projection*: Project each of the fixation onto a corresponding trapezoidal shaped fuzzy membership function which represents the degree of possibility (between 0 and 1) of the user's eye gaze indicating his interest or intention in the particular region through rows and columns respectively.
2. *Union*: Sum the projected fuzzy membership functions by using a union operator via rows and columns respectively.
3. *Intersection*: Combine the horizontal and vertical fuzzy inference results using an intersection operator.

Figure 9 Reduced fixations for identifying an object and destination (see online version for colours)

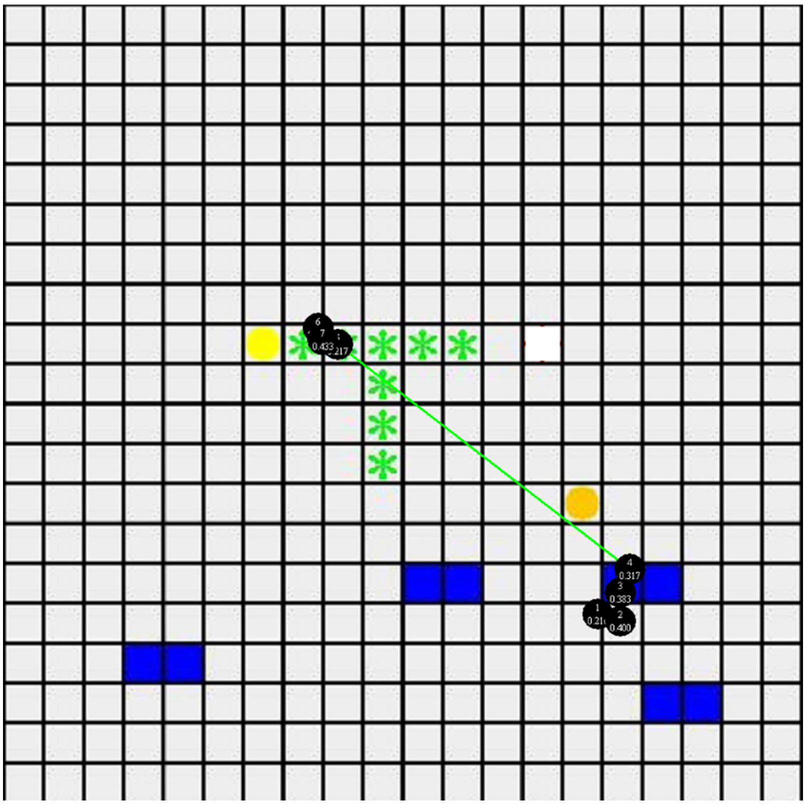
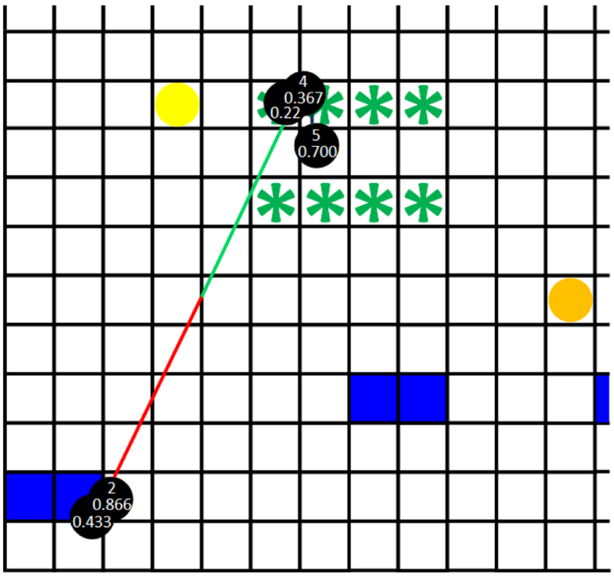


Figure 10 Fixations overlaid on part of the scene for 'HR' task (see online version for colours)



6 Evaluation

The first three experiments performed using our cooperative robot simulator mainly assess how well our assistant robots are able to cooperate with the human-controlled foreman by applying the fuzzy signature and possibility calculation based inference. The latter two experiments focus on differences between using our fuzzy inference based human eye-gaze information interpretation, eye-gaze information without the fuzzy inference, as well as performance comparison with the previous experiments. Table 1 lists the basic instructions for all the experiments.

Table 1 Basic instructions for experiments

Item	*Description*
Number of tables	4
Test cases ('Table shapes')	1 Horizontal Rows (HR) 2 Vertical Rows (VR) 3 T Shape (T) 4 U Shape (U)
Test times (Repetitions)	5
Robot's speed	About three movements per second
Measurements	1 Number of robot steps 2 Number of table movements (Shifting or Rotating) 3 Time to finish a task

6.1 Experiment description

Experiment 1: Two humans operate their own robots, they are allowed to have verbal communication.

Experiment 2: One assistant robot cooperates with a human-controlled foreman.

Experiment 3: A human-controlled foreman and one assistant robot start the task which is then accomplished by the two assistant robots.

Experiment 4: Two assistant robots complete the task by human's direct eye gaze indications (without fuzzy eye-gaze inference) of objects and targets with the confirmations of pressing a button.

Experiment 5: Two assistant robots complete the task by human's eye gaze indications of objects and targets with fuzzy eye-gaze inference and no confirmation button pressing.

6.2 Results and discussions

Although we allowed players to have verbal communications in Experiment 1 (see Table 2), the human-controlled robots still took the most steps on average to finish each of the test tasks. The reason for this phenomenon is that players might make different decisions in dynamic situations. Therefore, it is possible for them to decide to move different objects at the same time rather than aiming at the same target or placing the same object with different route plans, which will cost them extra steps to reach the common target or correct previous incorrect actions. That is, even with the explicit communication (talking) possible, it may be that it is only after incompatible moves that humans notice that they are following different plans.

Table 2 Average robot steps, table movements and time: two humans

Experiment 1	*HR*	*VR*	*T*	*U*
Robot A (controlled by human)	163.0	136.8	149.2	127.4
Robot B (controlled by human)	141.6	159.0	151.2	143.4
Total robot steps	*304.6*	*295.8*	*300.4*	*270.8*
Shifting movements	40.0	43.0	42.8	38.6
Rotating movements	7.2	6.8	7.2	5.6
Total movements	*47.2*	*49.8*	*50.0*	*44.2*
Time (s)	*74.6'*	*75.0'*	*77.6'*	*62.2'*

The result in Experiment 2 is quite good compared with Experiments 1 and 3 (see Table 3). Since the assistant robot could infer the human-controlled foreman robot's action by observation and cooperate with it, it is not necessary for the player to communicate with the other robot directly, which is different from the situation in Experiment 1. So the players can make their own decision without any other disturbance, which may be what leads to an improvement in all the costs, including robots steps, object movements, and time.

Table 3 Average robot steps, table movements and time: 1 human + 1 robot

Experiment 2	*HR*	*VR*	*T*	*U*
Foreman (controlled by human)	112.4	110.6	113.6	108.4
Robot A	153.6	141.4	156.4	143.2
Total robot steps	*266.0*	*252.0*	*270.0*	*251.6*
Shifting movements	39.2	40.6	41.0	36.8
Rotating movements	6.8	4.8	4.8	4.8
Total movements	*46.0*	*45.4*	*45.8*	*41.6*
Time (s)	*66.0'*	*56.0'*	*61.8'*	*55.8'*

Apart from the second test case (vertical rows), the robots in Experiment 3 made the most object movements in the rest of the test cases (see Table 4). The main reason here would be suboptimal strategies of route planning and obstacle avoidance.

In most of the test cases, the total steps made in Experiment 3 are more than Experiment 2 but still better than robots totally-controlled by humans. This is of course the key benefit of our work, to be able to complete the task, and to do it faster than two humans is an excellent result.

Table 4 Average robot steps, table movements and time: 1 human + 2 robots

Experiment 3	*HR*	*VR*	*T*	*U*
Foreman (controlled by human)	28.6	26.8	29.0	24.4
Robot A	115.6	103.8	118.2	106.8
Robot B	143.4	142.8	150.0	132.0
Total robot steps	*287.6*	*273.4*	*297.2*	*263.2*
Shifting movements	42.0	40.2	43.6	41.8
Rotating movements	7.4	4.8	7.2	6.0
Total movements	*49.4*	*45.0*	*50.8*	*47.8*
Time (s)	*69.0'*	*65.0'*	*71.4'*	*64.0'*

Table 5 shows the results of using user's eye-gaze indication directly. Compared with previous three experiments, we can easily find there is a big improvement in the cost of time for the two assistant robots to accomplish every test task. The statistical data in Table 7 clearly tells us that, on average, by using eye-gaze indication as the communication between the user and the other two assistant robots, it could be 21.5% faster than the case of two human-operated robots, 16% faster than 1 human-controlled robot plus two assistant robots, and even around 5% faster than the previous best case. This significant reduction is due to two major reasons:

1 The time saved during the table rotation: since the assistant robot can only infer the human-operated robot's actions, once a sequence of table shifts is completed and then a rotation is needed, the foreman will stop pushing the table and start waiting for the assistant robot to figure out they need to rotate the table. It normally takes some time for the assistant robot to finish the inference of switching shifting to rotating and also a little while to move to the other side of the object to carry out the table rotation.

2 The eye-gaze indications for the next object and corresponding destination can be performed simultaneously when the two assistant robots are still moving the last object, which keeps the process of completing the entire task progressing continuously.

Table 5 Confirmation button without applying fuzzy gaze inference method

Experiment 4	*HR*	*VR*	*T*	*U*
Robot A	130.2	123.8	127.0	119.6
Robot B	139.2	130.4	135.2	125.4
Total robot steps	*269.4*	*254.2*	*262.2*	*245.0*
Shifting movements	41.8	41.0	44.8	39.6
Rotating movements	6.4	4.0	4.0	4.8
Total movements	*48.2*	*45.0*	*48.8*	*44.4*
Time (s)	*59.9'*	*54.7'*	*58.2'*	*53.4'*

After applying our fuzzy eye-gaze inference approach, the results in Tables 6 and 8 demonstrate another significant time-saving which gives about 7% improvement compared to the experiment using eye-gaze indication directly. This is because in the 4th experiment, the other two assistant robots only inferred the user's eye-gaze indication when it was exactly located on the object with the confirmation of pressing a button, which turned out to be a bit difficult and time-consuming for the user to so precisely control his eye gaze position, since people's eye gaze might be only close to the object rather than directly on it but still show his interest and potential intention. So in Experiment 5, our new inference approach effectively provided a more efficient and natural communication between the user and the other two assistant robots through the interpretation of eye-gaze indication.

Table 6 Fuzzy inference method without confirmation button

Experiment 5	*HR*	*VR*	*T*	*U*
Robot A	121.0	118.0	125.2	121.8
Robot B	137.8	126.2	130.2	123.6
Total robot steps	*258.8*	*244.2*	*255.4*	*245.4*
Shifting movements	41.0	40.8	44.2	40.0
Rotating movements	6.8	4.0	4.2	5.2
Total movements	*47.8*	*44.8*	*48.4*	*45.2*
Time (s)	*54.8'*	*51.6'*	*53.5'*	*50.9'*

Table 7 Time improvements in Experiment 4 compared to Experiments 1–3

Experiment	*HR* (%)	*VR* (%)	*T* (%)	*U* (%)	*Average* (%)
1	19.7	27.1	25.0	14.1	*21.5*
2	9.2	2.3	5.8	4.3	*5.4*
3	13.2	15.8	18.5	16.6	*16.0*

Table 8 Time improvements in Experiment 5 compared to Experiments 1–4

Experiment	*HR* (%)	*VR* (%)	*T* (%)	*U* (%)	*Average* (%)
1	26.5	31.2	31.1	18.2	*26.8*
2	17.0	7.9	13.4	8.8	*11.8*
3	20.6	20.6	25.1	20.5	*21.7*
4	8.5	5.7	8.1	4.7	*6.8*

7 Conclusions

Through the evaluation for our discussed fuzzy methods based inference approaches, the experiments have demonstrated that it is possible for us to model the communication between robots/agents and human in a cooperative working environment, for them to correctly infer a human's intention with a suitable artificial intelligence techniques (e.g., fuzzy signatures).

A further extended notion of replacing human-action based inference by using human eye-gaze interpretation has also been discussed and evaluated based on the same cooperative robots scenario. According to the relevant results, a significant improvement has been illustrated by applying direct human eye-gaze indication, which quantitatively points out that using eye gaze can be more efficient than other human-action based inference approaches.

Furthermore, after more time-saving demonstrated in the experiment by applying our fuzzy eye-gaze inference approach, we safely arrive at the conclusion that this approach can offer us a more sophisticated way for the assistant robots to infer a human's intention, which also effectively eliminates any physical control from the human's side, providing more flexibilities for handling multiple tasks at the same time. For example, answering a phone call without stopping the current communication through eye gaze.

Such work is the first step for us to start exploring how useful a human-being's eye gaze information will be in a variety of application areas and we conclude that in the future, eye-gaze technology will be more beneficial as well as further enhance communication or interaction between human and robots.

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