Indefinite Observation for Spontaneous Trend Generation

Content Areas: adaptive systems, cognitive robotics, human computer interaction

Abstract

This paper describes a trend generation method to encourage human-robot interaction. For the generation, Indefinite Observation Architecture (IOA) is proposed, which achieves a trend generation among various types of robots and group dynamics between the robots throughout the interaction. The results of the actual evaluation system of IOA indicated that a heterogeneous robot group emerged and collapsed according to the trend generation.

1 Introduction

Communication between a human and a computer has been studied for achieving information transfer where the person gives the computer commands and the computer gives the person a response action or information [Winograd, 1986]. We express the communication as human-centered communication. There is no significant difference between the computer and a robot in terms of such a man-machine interaction, except for robot's physical activities. However, robot-centered communication takes the place of the human-centered communication for communication-robots recently developed [Fujita and Kageyama, 1997] [Ishiguro *et al.*, 2001], where the robots direct communication context to actively communicate with a human. An important design issue for the communication-robots is how to increase a variety of communication contents. This paper concentrates on the generation of a communication trend which gives the robots advantage to encourage the robot-centered communication. The trend dealt with in this paper is not a goal or a task but a subjective preference between robots.

To generate the trend between the robots, they have to obtain the same evaluation function of sensor information. On the other hand, actual robots differ in the evaluation function for each task given to them: a route guide task, a receptionist task, a transportation task, and a dairy chore task. Therefore, the evaluation function for the trend should be based on flexible structure and be generated throughout interaction between the heterogeneous robots. Moreover, several different trends should exist simultaneously to activate social dynamics between persons and robots.

Several studies have investigated the difficulties in generating a shared evaluation function. The common methodology in the studies is to observe the other robot's action because any robots take physical action regardless of its internal structure. For example, heterogeneous cleaner robots named Joh and Flo are able to obtain shared expressions of physical environments [Jung and Zelinsky, 2000]. When one of the robots obtains the expression, it connects the current expression to the observed action of the other robot. Here, the current expression used by the other robot is obtained by questioning the other robot. A learning system named DRAMA has succeeded in sharing robot commands between instructor and learner robots [Billard and Hayes, 1999]. The teacher robot teaches a command in response to the observed action of the learner robot. A system named Talking Heads develops shared language in a naming game [Steels *et al.*, 2002]. Talking Heads find out the relationship between a word used by the other head and a feature observed by the other head throughout naming game interactions. In resolving a name, the action observation also plays an important role.

However, in spite of observing robot's actions, the above ordinal approaches are insufficient to achieve our goal. The following difficulties must be solved for a trend generation.

1. Stability: to posses a stable structure of a trend among every members of a robot group.
2. Openness: to find out a trend from as many types of a robot as possible.
3. Group dynamics: not to generate a stable homogeneous trend among all robots.

It is hard for the ordinal approaches to achieve Difficulty 2. In the ordinal studies except for Talking Heads, all robots share the definitions of each relationship between robot's actions and environmental information. Since the ordinal approaches are based on such a definition, they cannot generate shared expressions from different definitions. Although Talking Heads do not posses the definitions, labels which they exchange express each different environmental feature. The constraint on the labels is also the obstacle to achieve Difficulty 2. Moreover, it is much more difficult for the ordinal learning system to deal with Difficulty 3 because the behavior of the systems converge on a learning target.

This paper proposes a method which generates a trend from a relationship between an observed action and observed environemnetal information. It does not from internal structures of a robot. In particular, this paper proposes Indefinite Obsevation Architecture (IOA) for a trend genaration. Here, the indfinite observation means that the robot cannot observe the relashionship between a robot action and an internal evaluation function form an objective viewpoint.

IOA consists of four modules for the difficulties: Context module, Observation module, Generation module, and Order function module. IOA deals with Difficulty 1 by Context module which obtains stable structure of a trend. Indefinite observation module deals with Difficulty 2, which induces an observation error and obtains an unknown trend. This observation error comes from the indefiniteness of the action observation. Order function module deals with Difficulty 3, which controls whether a robot obeys a current trend or not.

The rest of this paper is organized as follows. Section 2 describes the problem in achieving a trend generation, and explains the features of the indefiniteness of an observation. In addition, we describe a communication robot named Robovie employed as a platform to develop IOA. Section 3 explains the feature of IOA in generating a trend. Section 4 shows the execution outcome when IOA generates trends throughout an action observation. Section 5 concludes the paper with a summary and future works.

2 Human-Robot Interaction with a Trend

2.1 Spontaneous trend generation

Human-robot interaction this paper deals with is robot-centered communication where a robot is in charge of a communication with a person. This paper develops a trend generation system to direct robot's behaviors (utterance words and gestures) for the robot-centered communication.

This subsection explains the trend we focus on referring to the generation of a robot's action. Although the robot can behave without sensor information, the generation of almost robot's actions can be formalized as the following from.

Action Rule 1
$Sensor\_data \rightarrow Evaluation\_function \rightarrow Action$

In the rule, $Evaluation\_function$ selects the action in response to $Sensor\_data$. $Evaluation\_function$ in ordinal systems is always based on a system's internal sate or a plan sequence. In addition, there are also simple action rules omitting $Evaluation\_function$ from **Action Rule 1**. As it is, $Evaluation\_function$ depends on a design policy.

Since $Evaluation\_function$ differs according to each robot's task, this paper generates a trend by observing directly the relationship between a robot action and external world information. The following from expresses the observation.

Observation Rule 1

$$\begin{array}{ccc} Sensor\_data & \rightarrow & Action \\ & \uparrow & \\ & Observation & \end{array}$$

For developing an actual trend generation system, this paper prepares an example task. In the task, the system generates a robot's favorite color and the trend of the action is that the robot follows the position of a person who is wearing the favorite color. The example is very simple but it is important that the robot selects a communication partner spontaneously,

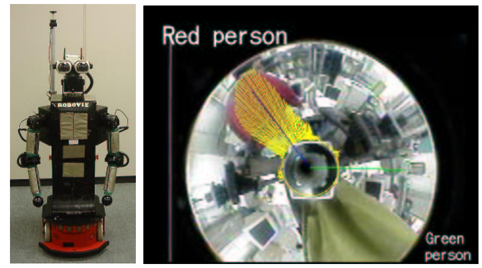

Figure 1: Communication Robot "Robovie" and Omnidirectional camera

in achieving robot-centered communication. The example can be expressed with the following observation rule.

Observation Rule 2

$$\begin{array}{ccc} Person\_location\ (color) & \rightarrow & Robot\_orientation \\ & \uparrow & \\ & Observation & \end{array}$$

The goal in this paper is to generate a robot's trend with **Observation Rule 2**.

2.2 Indefiniteness of action observation

There is indefiniteness when executing **Observation Rule 1**. The indefiniteness is that the system cannot detect which of the following two rules is used by the other robot for the action generation because $Evaluation\_function$ cannot be observed from an objective viewpoint.

Action Rule 2
$Sensor\_data \rightarrow Trend \rightarrow Action$

Action Rule 3
$Sensor\_data \rightarrow Other\_evaluation\_function \rightarrow Action$

However, the system must handle the indefiniteness to generate a trend for any types of robots. Moreover, it is impossible to define $Evaluation\_function$ for a robot controlled by multi-agents because its action is determined as a result of all agents' decision [Brooks, 1991]. In the agent's approach, the connection between the emerged action and sensor data is not always fixed. Consequently, the ability that the system handles the indefiniteness is crucial to the trend generation.

2.3 Group dynamics on trend generation

The ideal dynamics for steady robot-centered communication are that several robot groups exist and each group has a different trend. In addition, the trend varies throughout interaction between the robots and a group appears and disappears according to changes in the trend. It is a challenging problem to tackle the spontaneous dynamics generating a new trend as well as the indefiniteness of the action observation.

2.4 Communication robot Robovie

To develop a trend generation system, we employed the communication robot named Robovie (left picture in Figure 1). Robovie has two 4 DOF hands and a 3 DOF head to generate gestures. It also has a movable base and several types of

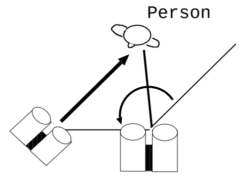

Figure 2: Recognition of other's observation target

sensors: touch sensors, ultrasonic distance sensors, and two types of vision sensors. One of the vision sensors uses an omni-directional camera that can capture panoramic scenes around Robovie. The other vision sensor uses two CCD cameras on Robovie's head for stereo vision. Robovie is also equipped with speech recognition and generation software.

The trend generation system uses the omni-directional camera to find out a person's location. Since the degree of chroma of the wall in our laboratory is low, we employ a simple recognition method using chroma information to recognize the clothes color. For instance, when a region in a captured scene has enough size and the high chroma beyond a threshold, the method interprets the color region as an object and outputs its orientation θ_p^i (i and p denote a robot's ID and a person's ID respectively). the definition of θ_p^i is that the direction of robot's front is zero degree, the right direction has plus sing and the left direction has minus sing. There is no limit on the number of persons that the method recognizes as long as they do not overlap each other in the captured scene.

In addition, when the trend generation system carries out the observation based on **Observation Rule 1**, each Robovie needs to observe both the action of other Robovies and the environment around them. In this example task, the system observes the position and the orientation of other Robovie as $Action$, and the clothes color to which other Robovie pays attention as $Sensor\_data$. Figure 2 shows the process when right Robovie finds out the target that left Robovie recognizes. At first, right Robovie directs its attention parallel to left Robovie orientation. Then, it turns its attention from the orientation to the direction of left Robovie until it finds out the target. This paper employs notation C_i to express the clothes color focused on by Robovie i. With the notation, **Observation Rule 2** is expressed as the following from.

Observation Rule 3

$$\begin{array}{c} C_i \rightarrow \theta_p^i \\ \uparrow \\ Observation \end{array}$$

3 Indefinite Observation Architecture

This paper proposes Indefinite Observation Architecture (IOA) to generate a trend between robots throughout robot's interaction. IOA has the following features.

1. The generated trend is stable in some periods of time.
2. The generation method is open to many types of robots with an indefinite observation.

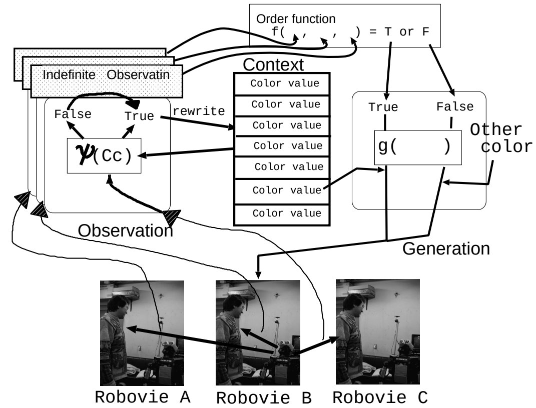

Figure 3: Overview of IOA

3. The group whose members have the same trend appears and disappears in long period of time.

The following subsections explain the details of IOA.

3.1 IOA and indefinite observation

IOA observes Robovie actions and generates a trend. Figure 3 shows the observation process and the generation process with IOA. In Fig. 3, Robovie A, B, and C exist[1]. IOA in Fig. 3 is Robovie B's. Robovie A and C also have the same IOA. The orientations of these Robovie are expressed as θ_o^A, θ_p^B, θ_q^C. The observed colors are expressed as C_A, C_B, and C_C.

IOA consists of Observation module, Context module, Generation module, and Order function module. IOA observes the actions of near two robots and the own action. The reason why own action is observed is to adapt IOA for use by any types of robots including multi-agent robots.

Context module is data storage space. The observed color data is saved in Context module for the decision of Observation module. Although the saved data are color data in the example, Context module is also able to save the other data.

Observation module decides whether the observed color is a trend or not, comparing the observed color C_A, C_B, and C_C with the sample data randomly chosen from Context module. Then it outputs truth-information. The observation ψ is expressed as the following equation.

$$\psi(C_i) = T \ or \ F \tag{1}$$

If the result of the observation is true, Observation module writes the observed data on Context module. Since the size of the storage space is finite, Observation module rewrites one of the the storage space.

The behavior of Generation module depends on the return value of Order function module. We explain Order function module in the next subsection. When the output of Order function module is $True$, Generation module outputs color data randomly chosen from the context module. If it is $False$, it outputs color data randomly selected from the

[1] Although A, B, and C is the same picture, we assume that each pair of Robovie and the person is different for the explanation.

omni-directional camera. The generation g is expressed as the following equation.

$$g(B) = C_i \quad (2)$$

Here, B denotes a $True$ or $False$ value. Robovie tries to turn to the direction where the generated color exist.

As a result of the interaction between these modules, the contents of Context module between Robovie A, B, and C become similar to each other and a stable trend is generated.

The behavior explained above occurs under an assumption that all of Robovie behave completely depending on the trend. In short, they behave according to **Action Rule 2**. However, there is indefiniteness in an action observation as we explained. From an objective viewpoint, any systems do not decide which of **Action Rule 2** or **Action Rule 3** is used by the other robot.

IOA employs an indefinite observation which introduces incomplete structure into the trend generation. Strictly speaking, Observation module decides that the observed color is $True$ at a probability, which should be decided as $False$ under a normal observation. The indefinite observation introduces the following equation into Observation module.

$$\psi(C_i) = F \rightarrow \psi(C_i) = F \; or \; T \quad (3)$$

As a result, the indefinite observation is able to insert a new color data into Context module. In spite of the dynamic feature of IOA, the generated trend does not vary until almost storage space of Context module (the context contents) is filled with the new color. When the new data become major one in Context modules, the trend shifts to new one.

3.2 Order Function

Order function module has an order function which determines the behavior of Generation module. The order function returns a truth-value in response to the observation results. For example, the form of the order function in Robovie B's IOA is $f(\psi(C_A), \psi(C_B), \psi(C_C)) = T \; or \; F$. In the form, the first and third arguments are the observation results of the other robot's action. The second one is the observation results of itself action. Since there are eight variations from FFF to TTT in a combination of three arguments, the function has several characteristics (Table 1). In the rough outline of the characteristics, there are two types of the order function. When the output value is $True$, variations in a trend converge and a group emerges because the trend color comes from the context contents. When the output value is $False$, variations in a trend diverge and a group collapses because the trend color is generated regardless of the context contents.

Each output value is determined according to the following self-observation process. The process is that the output value of each oder function is replaced with a new value which is the results of Observation module when the module observes the color generated by the same order function itself. Depending on the self-observation process, the generation of a trend, and the emergence and the collapse of a group occur spontaneously because the ratio of $True$ to $False$ varies according to the effect of the change in the context contents induced by the indefinite observation.

Table 1: Trend tendency and output from Order function

Inputs	F output	T output
FFF	a diverging trend	systematization
FFT	original action	participation in a group
FTF	searching a trend	keeping an original trend
FTT	leaving a group	keeping a group
TFF	original action	participation in a group
TFT	original action	participation in a group
TTF	leaving a group	keeping a group
TTT	destruction of a trend	a converging trend

We explain the change in the ratio in the rest of the subsection in more detail. When there was $True$ in the argument of the order function, there is a possibility that an indefinite observation $F \rightarrow T$ have occurred. In the situation, $True$ output in an order function sometimes changes into $False$ when Order function module revises the order function. The probability becomes higher even if the color is generated from the context contents in response to $True$ output. The reason of the change is that the context contents at the time of generating a color are different from the time of observing the generated color by the indefinite observation. In addition, when there are many $False$ output values in Order function module, Robovie turns to a direction where the colors in the context do not exist. However, in this time, the $False$ output in the order function changes into $True$ when Order function module revises the order function with the indefinite observation. In other words, the trend becomes unstable and the robot's group collapses when the number of $True$ increases and the trend becomes stable. On the other hand, the trend becomes stable and the robot's group emerge when the number of $False$ increases and the trend becomes unstable. As a result, The change in the ratio of $True$ to $False$ is occurred spontaneously.

3.3 Behavior of IOA

This subsection explains the behavior of IOA by showing its execution process and simulation data.

To make the explanation brief, let us focus on one of three Robovie. Also, let us consider a situation where there are two persons around Robovie. They are wearing blue or red clothes respectively. Robovie turns to one of the persons according to the change in a trend. Figure 4 shows the process of a trend generation under the situation. In the upper figure of Fig. 4, the context contents are filled with red color data. When IOA observes a red color at this moment, the result of Observation module is $\psi(Red) = T$ because the red color is compared with the color (Red) selected from the context contents. Generation module generates a red color from the context contents when the output of the order function is $True$. Then Robovie turns to the person wearing the red clothes.

Generation module generates a blue color regardless of the context contents when the output of the order function is $False$ (the lower figure of Fig. 4). Then Robovie turns to the person wearing the blue clothes. Next, Observation module observes the blue color because the color is in front of

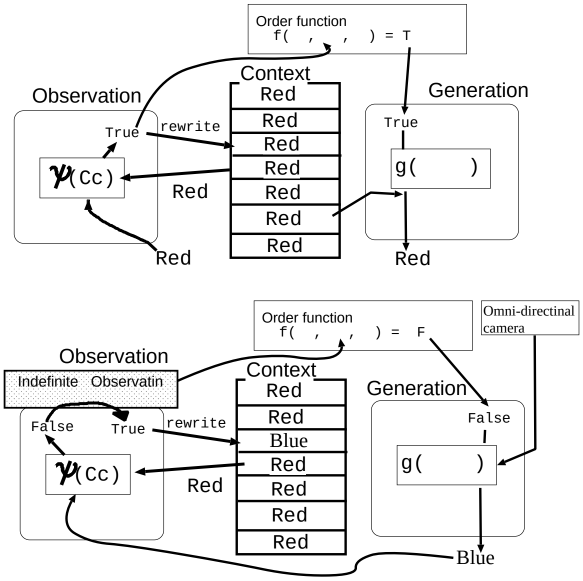

Figure 4: Process of a trend generation by IOA

Robovie. The result of Observation module is $\psi(Bule) = F$ because the blue color is also compared with the color (Red) selected from the context contents. However, the observation becomes sometimes $\psi(Bule) = T$ with the indefinite observation, and the blue color is inserted into the context contents.

Even if there is one blue color in the context contents, the trend color is still red because the major color in the context contents is red. However, if an indefinite observation occurs in a row, the number of the blue color increases and the trend shifts from red to blue.

The rest of the subsection explains the relationship between the probability of an indefinite observation, the type of an order function, and emerged groups. Figure 5 shows the average of the context contents in transition. The difference of the graphs from A to D is the ratio of $True$ in the order functions; A's ratio is 0, B's is 0.5, C's is 0.9, and D's is 1.0. To investigate a static feature of the ratio, the self-revision of the order function is not applied to the simulation. Also, the simulation does not employ color data but numerate data to obtain the average of the context contents. Strictly speaking, the data show robot's moving speed and the speed data of ten robots are shown in the graph. In graph A, all output values of the order function were $False$, and the average results diverged according to time transition. On the other hand, since all output values were $True$ in graph D, the average results converged on a value. Also, in graph C, although almost average data was stable at a speed of 3.0 by the 1600 step stage, some kind of catastrophe occurred near 1600 steps. The average data rose to the speed of 8.0 and the two groups emerged after this catastrophe. Consequently, IOA exhibited both construction and destruction of group at 0.9 ratio.

Figure 6 shows the ratio in transition by the self-revision in Order function module. The difference of the graph from A to C is the occurrence probability of an indefinite observation; A's probability is 0.5, B's is 0.25, and C's is 0.01. By com-

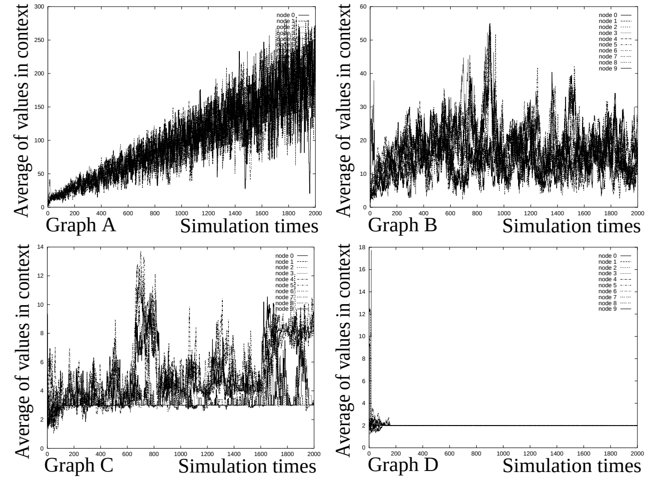

Figure 5: Diversity of context in response to the ratio of truth-value: in graph A, 0; in B, 0.5; in C, 0.9; and in D, 1.0

paring the three graphs, it is noticeable that the ratio became about 0.9 when the probability was 0.5. As a result of figure 5 and 6, to generate group dynamics by IOA, we employ 0.5 as the occurrence probability of the indefinite observation.

4 Evaluation

4.1 Evaluation environment

We have developed IOA on three actual omni-directional cameras to evaluate IOA's trend generation. The reason why we did not employ actual Robovie is to make the evaluation outcome obvious to be understood. The actions of Robovie were virtually achieved in a computer. It took a time for the virtual Robovie to turn to a direction. Only orientation information of Robovie were communicated between IOA. Figure 7 shows an experimental scene where there were three omni-directional cameras and two persons. Each person was wearing red and green clothes. The red person was in front of these cameras and the green person was behind the cameras.

4.2 Evaluation outcome

Figure 8 shows the directions of three Robovie A, B, and C in transition. The vertical axis represents the orientation of Robovie. The red person was in zero radian and the green person was in π or $-\pi$ radian. In the figure, there is a group of all Robovie at first when they turned to the red person for a while. Then the group collapsed and a new group of Robovie A and B emerged at that time when A and B turned to the green person. After that, B withdrew from the group and joined in C turning to the red person. At this time, C attempted to join in A turning to the green person. In addition, the C's behavior attracted B to the green person and B joined in A. However, C stopped on the way turning to A and turned back to the red person. After these explained interaction, many groups emerged and collapsed according to the change in a trend.

Figure 9 shows a trend generation between heterogeneous Robovie. In the graph, Robovie A had a different mechanism, which make A turned to only the red person. On the other

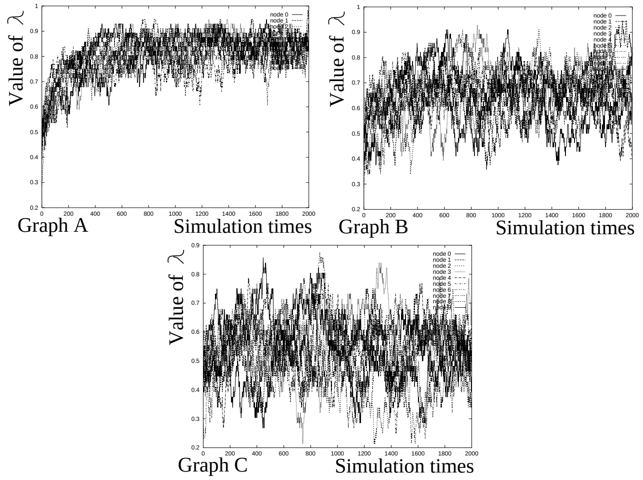

Figure 6: The change of the ratio λ in response to the probability of indefinite observation: in graph A 0.5, in B 0.25, and in C 0.01

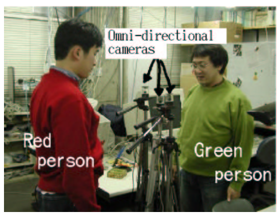

Figure 7: Experimental scene

hand, Robovie B and C were controlled by IOA. Even in the situation, group dynamics also emerged. At first, all Robovie turned to the red person. However, C started to turn to the green person. And then B also turned to the green person by being attracted by C's behavior. For a while, B turned back to the red person. As a result, the graph indicates that IOA was able to generate a trend among heterogenous robots.

5 Conclusion

This paper proposed Indefinite Observation Architecture to generate a trend between robots. IOA of each robots observes the other robot's actions in generating the trend. In the observation, IOA employs an indefinite observation to be adapted for the other types of a robot controlled by unknown rules. In addition, since a robot's group emerges and collapse repeatedly throughout the IOA's interaction, IOA achieves various types of communication between persons and robots. The group dynamics are attributed to the order function of IOA. To evaluate IOA, the evaluation system has been developed on omni-directional cameras. As a result, the IOA's ability of the trend generation and the group dynamics was confirmed.

Since the proposed IOA is a prototype, there are many remaining issues to use IOA in practice. In future work, we plan to investigate the effect of IOA's each parameter on the trend generation. Moreover, the method to deal with many types of sensors and Hybrid architecture between IOA and the other task executive must be also developed to achieve an actual application system.

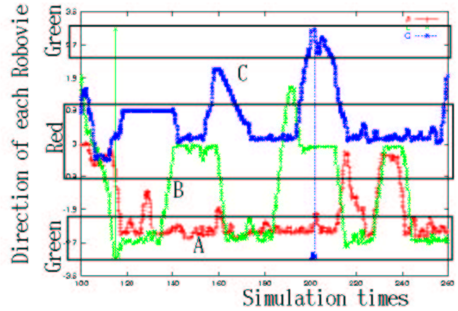

Figure 8: Generated trends between robots controlled by IOA

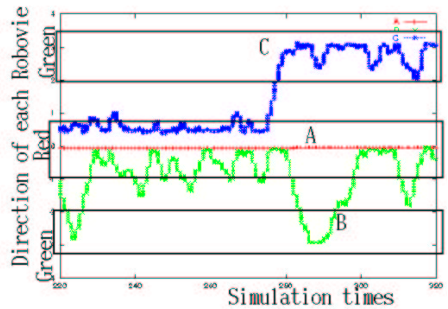

Figure 9: Generated trends between heterogeneous robots

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