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The Task Allocation Model based on Reputation for the Heterogeneous Multi-robot Collaboration System*

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***Abstract* - Reputation plays an important role in the collaboration in people's daily life. In many cases, task allocation in the human world is based on someone's reputation, which is gained from the evaluation of the completion of historical tasks. In the collaboration system of the heterogeneous multi-robot, reputation is introduced to solve the task allocation problem. A detailed formal model based on reputation for heterogeneous multi-robot collaboration is given, including the framework, reputation matrix, reputation attenuation curve, new robot member reward characteristics and robot alliance reward characteristics. The reputation in the collaboration system is divided to three categories: direct reputation from one robot to the other, overall reputation of a robot in the collaboration system and the robot where the group's reputation. Task attempts to be assigned to the robot with relatively high reputation, which can greatly improve the success rate of implementation of its mandate, thereby reducing the time of the system task recovery and redistribution. Simulation results show that the model can be used in a multi-robot task allocation system, and has good efficiency.**

Index Terms - Heterogeneous multi-robot, Task allocation, Reputation, Robot collaboration.

I. Introduction

The field of distributed robotics has its origins in the late 1980s, when several researchers began investigating issues in multiple mobile robot systems. Prior to this time, research had concentrated on either single robot systems or distributed problem-solving systems that did not involve robotic components. The topics of particular interest in this early distributed robotics work include [1]: 1. Cellular (or reconfigurable) robot systems, 2. Multi-robot motion planning, 3. Architectures for multi-robot cooperation.

In recent years, multi-robot systems research has made great progress in many areas [2]. For example, multi-robot architecture, perception and multi-sensor data fusion, communication and consultation, learning, motion planning, task allocation, conflict resolution, impact planning and system implementation [3].

Collaboration is an important characteristic and a major evaluation indicator of multi-robot system [4]. Multi-robot systems can complete the function of a single robot can not be achieved through collaboration. It is no longer a physical sense of the role of a single robot linear summation and includes the individual-based interactive incremental beyond the linear summation, thereby increasing the system's overall performance [5].

Heterogeneous robot collaboration technologies are in particular concern in the multi-robot research [6]. From a practical point of view, the individuals of a robot team that are often different in design, structure, sensor configuration as well as intelligence, can not be the homogeneous system. Heterogeneous robots can play the advantages of a single structure robot in a given area to achieve an overall optimal allocation [7]. The current study in the heterogeneous robots includes the measurement differences of individual robot, the compatibility between individual robot and isomers, communication between heterogeneous robots, the rapid deployment of the heterogeneous robots hardware system, the individual robot positioning and so on. Heterogeneous multi-robot collaboration between the principle of collaboration with the robots and household appliances are basically the same principle.

In the real world, the reputation plays an important role in the collaboration between people. In many cases, task delegations are based on someone's reputation, which is gained from the evaluation of the completion of historical tasks. In the world of robots, the task allocation model based on reputation is presented for the heterogeneous multi-robot collaboration system to resolve the problem of the distributed task allocation.

The contribution of the paper includes the following two aspects:

1) Reputation is introduced to solve the task allocation problem. A detailed formal model is given;

2) The model is history and experience related, relaying on the past experience valued by reputation to make decision.

The rest of the paper is organized as follows:

Section 2 introduces research background and the progress of the related work. Section 3 presents the reputation task allocation model, which includes the framework and detailed definitions. An experiment of the model in practical research and conclusion is given in section 4 and section 5 respectively.

II. Research Background and Related Work

At the beginning, the task allocation is mainly based on contract net protocol (CNP) [8].Using communication, it can provide the solution for each issue by consulting to avoid

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conflict. Parker [9] has developed a behavior-based distributed multi-robot collaboration structure named L-ALLICANCE and the corresponding system with the ability of parameters learning named L2-ALLICANCE [10] in MIT, which utilize incentive-based task allocation mechanisms for behavior and enhance the generalization and error tolerance of multi-robot system. Gerkey applied the market algorithm in multi-robot system to cope with dynamic task allocation problem named MURDOCH [11].Matchell [12] proposed cooperative co-evolution method based on the nature of species co-evolution mechanism, which may acquire optimizing task allocation.

Behavior-based task allocation algorithm is generally divided into three steps [13]:

1) To find a robot with the largest utility – tasks (i, j);

2) To assign the task j to the robot i, and no longer consider them;

3) Back to No. 1) step.

The typical representatives are ALLIANCE [10] and Broadcast of Local Eligibility (BLE) [14]. Both of these two kinds of methods achieve task allocation based on behavioral inhibition. Each robot has certain degree of expectation for each task, and inhibits the activities of other robots on the behavior layer directly. In 2005, Parker also proposed a behavior-based task allocation mechanisms ASyMTRe [15].It can acquire necessary flow of information from the environment and the perception. The information collected reconstructs the connections between various models among robots automatically and achieves the behaviors that can complete the task [16].

Combinatorial optimization method, including linear programming method and the Hungarian algorithm [17] and so on, can be applied to solve simple tasks and robot combinatorial optimization problems. Although this method can obtain the optimal solution, essentially these two kinds of methods are matrix operations. When the number of robots and tasks increase in the system, the computational complexity will be exponentially. Moreover, it usually needs to gather all the information of robots and tasks, and this information handle through a centralized manager, so it is of low efficiency and poor expansion.

The market mechanism based method in task allocation is based on consultations. The robots complete the task assigned through mutual consultation and negotiation on the basis of certain agreement in Multi-robot system. This approach is suitable for solving distributed problems by consulting in small and medium-sized heterogeneous multi-robot system when the task and the status of robot are known. It is able to achieve the global optimal task allocation.

Allocation problem is generally divided into three steps [18]:

1) Each robot tenders for designated tasks according to their suitability to the tasks;

2) The auction mechanism decides the distribution of tasks to which robots;

3) The winning robot completes the task through the implementation of one or more actions.

Swarm intelligence methods derived from the social organization methods of the gregarious creature, such as ants, bees and so on. They can form an organization with stable structure, make an effective allocation of labor and complete specific tasks together through a very limited cognitive abilities and simple interactions. The typical methods are threshold value method and ant colony algorithm. As individuals in the group are distributed, such system is more robust and will not fail to solve the whole affection by one or a certain number of individuals. Moreover, individuals in this system use indirect communications in collaboration, so the cost of system communications will increase very little when a new individual is added to this system. This provides a better scalability. Therefore, swarm intelligence method is very suitable for heterogeneous multi-robot systems and an increasing number of researchers have already applied it to multi-robot task allocation system, especially in a dynamic task allocation environment. But the disadvantage of this method is that it is hard to predict accurately the behavior of robot, so the analysis of such system is very difficult and can not ensure efficiency.

In general, the robot collaboration can be divided into two categories, the advantages and disadvantages as shown in Table I.

Reputation theory is attracting strong interest from industrial and academic research communities and increasingly being integrated with online services and applications, especially in P2P system. We propose a task allocation model of heterogeneous multi-robot system based on reputation.

Reputation is the overall assessment and the summary of past actions observed from one entity to the other entities through the gradual dynamic capabilities in a continuous interactive process. The assessment can be used to guide further actions of this entity.

Thereby, the reputation of robot can be defined as:

DEFINITION 1. ROBOT REPUTATION is the overall assessment and the summary of past actions observed from one robot to the other robots through the gradual dynamic capabilities in a continuous interactive process. The assessment can be used to guide further actions of this robot. Robot reputation includes four attributes:

ATTR.1. Environmental context related Characteristics.

ATTR.2. Dynamic Characteristics. Decaying over time if no interaction.

TABLE I
COLLABORATION METHODS OF ROBOTICS

Category	Method	Advantages	Disadvantages
Intent style	Behaviour-based	Real-time, fault tolerance , robustness	Local optimal
	Combinatorial optimization	Global optimal	Low efficiency Poor expansion.
	The market mechanism	Global optimal	Communications resource-consuming
Emerging style	Swarm intelligence	Communications resource-saving better scalability	Difficult in analysis Uncertain efficiency

ATTR.3. Time lag Characteristics. Reputation is forming through the continuous history learning and experience.

ATTR.4. Alliance Characteristics. Reputation is affected by the group or alliance of the robot.

Factors should be considered include the three aspects:1. reputation decay over time, for example, if the reputation from robot R_1 to Robot R_2 was based on the experience of five years ago and they have no interaction from then on, the reputation from R_1 to R_2 must be very low. 2. Robots may form alliance, more likely to cooperate with the robot in their alliance, and not to believe the other robots. 3. The impact of factors between R_1 and R_2 collaboration is the direct reputation from R_1 to R_2 and the overall reputation of R_2.

III. The Reputation Task Allocation Model

The Robots in the collaboration team are represented: R_1, $R_2 \ldots R_n$, The special group or the alliance of several robots is represented D. The value on the line from robot R_1 to robot R_2 is the reputation value between them, the overall reputation value of the robot R_1 is the value on the robot. Fig. 1 shows the structure. The reputation of the alliance is the value beside the name of the alliance, for example the reputation of D_1 is 0.5.

Therefore, reputation of the collaboration system has three components: 1. robot's overall reputation, 2. the group's reputation where robot belongs to, 3.the reputation between the two robots intending to collaborate.

RRL（Robot Reputation Level）is the reputation level of the particular robot, the value is based on the history experience and on the group reputation of the robots. Provides reputation values are always between 0 and 1. The level is roughly divided into five kinds of class, as shown in Table II.

Eight kinds of features are used to evaluate the cooperative system of robots: Loyalty, honesty, Improvement, Random, Concealment, Foxiness, Corruption and Deception. The feature will be discussed in detail in next section.

The collaboration relationship between robot R_1 and robot R_2 is represented as $\Gamma(R_1, R_2, t, c, l)$, c denotes the Environmental context, t denotes the time of collaboration and l denotes the specific group or alliance.

The matrix is used to describe the reputation relationship among collaboration robots. For instance, DTM (Direct Reputation Matrix) represents the direct reputation relationships among robots.

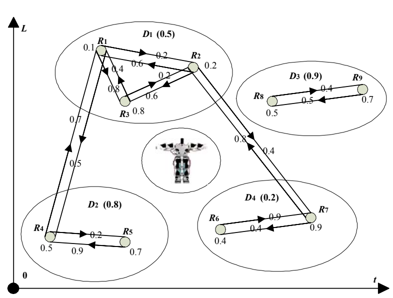

Fig.1 Reputation of the robot cooperation system

Within some range of reputation, robot may not find suitable mandate holders to allocate task. There are two solutions: 1. sending a request to require other robots to recommend suitable robot. 2. Assigning the task to other robots in a way of delegation, other robots can continue to allocate the task.

A. *Framework of the Model*

DEFINITION 2. (MODEL FRAMEWORK)

Given robot R_1 in group D_1 and robot R_2 in group D_2, c denotes the environmental context, t denotes the time of collaboration and l denotes the specific group or alliance. The collaboration relationship from R_1 to R_2 expressed as $\Gamma(R_1, R_2, t, c, l)$.

$$\begin{aligned}\Gamma(R_1, R_2, t, l, c) = {} & \alpha \times \Theta(R_1, R_2, t, l, c) \\ & + \beta \times \Omega(R_2, t, l, c) \\ & + \theta \times \Psi(D_1, D_2, t, c)\end{aligned} \quad (1)$$

$\Theta(R_1, R_2, t, l, c)$ denotes the direct reputation relationship between robot R_1 and robot R_2. α denotes the direct reputation weight coefficient, $0 \le \alpha \le 1$;

$\Omega(R_2, t, l, c)$ denotes the overall reputation value of robot R_2, β is the reputation weight coefficient. $0 \le \beta \le 1$;

$\Psi(D_1, D_2, t, c)$ denotes the reputation value from the robot group D_1 to the group D_2. θ denotes the group weight coefficient, $0 \le \theta \le 1$, $\alpha + \beta + \theta = 1$, $\alpha, \beta, \theta \ge 0$.

Different systems can dynamically set the weighting factor according to the different effects of three kinds of reputation.

DEFINITION 3. (DIRECT REPUTATION)

Given robot R_1 in group D_1 and robot R_2 in group D_2, c denotes the environmental context, t denotes the time of collaboration and l denotes the specific group or alliance. The direct reputation relationship from R_1 to R_2 expressed as:

$$\begin{aligned}\Theta(R_1, R_2, t, l, c) = {} & \mathrm{DRM}(R_1, R_2, t, c) \\ & \times \gamma(t - t_{a-b}, c) \\ & \times \tau(l_a, l_b, c)\end{aligned} \quad (2)$$

The Specific definitions of DRM (Direct Reputation Matrix) see the definition 6;

t_{a-b} denotes the last collaboration time between robot R_1 and robot R_2;

$\gamma(t - t_{a-b}, c)$ denotes the function of time calibration;

TABLE II
REPUTATION LEVEL OF ROBOT

Level	Value	Description.
E	[0, 0.2)	Very low
D	[0.2, 0.4)	Low
C	[0.4, 0.6)	Normal
B	[0.6, 0.8)	High
A	[0.8, 1.0]	Very high

$\tau(l_a, l_b, c)$ denotes the function of group or alliance calibration function;

$\gamma(t - t_{a-b}, c)$ denotes the function of time calibration.

DEFINITION 4. (ROBOT OVERALL REPUTATION)

Given robot R_1 in group D_1 and robot R_2 in group D_2, c denotes the environmental context, t denotes the time of collaboration and l denotes the specific group or alliance. The overall reputation of robot R_2 in the collaboration system:

$$\Omega(R_2, t, l, c) = \frac{1}{n}\sum_{i=1}^{n} S(\triangle\rho_i + \Gamma_i(R_i, R_2, t, l, c)) \times \gamma(t - t_{z_i-b}, c) \times \tau(l_{z_i}, l_b, c) \tag{3}$$

$S(\triangle\rho_i + \Gamma_i(R_i, R_2, t, l, c))$ denotes the function of the reputation calibration;

$\triangle\rho_i$ denotes the standard deviation of reputation value at the collaboration i;

$\lambda(t - t_{z_i-b}, c)$ denotes the function of time calibration;

$\tau(l_{z_i}, l_b, c)$ denotes the function of group or alliance calibration function;

n denotes the number of robots in the collaboration system who have cooperated with robot R_2.

DEFINITION 5. (GROUP REPUTATION)

Given robot R_1 in group D_1 and robot R_2 in group D_2, c denotes the environmental context, t denotes the time of collaboration and l denotes the specific group or alliance. Its reputation in the network is:

$$\Psi(D_1, D_2, t, c) = \Psi(D_1, D_2, t_{a-b}, c) \times \gamma(t - t_{a-b}, c) \tag{4}$$

$\Psi(D_1, D_2, t_{a-b}, c)$ denotes the group reputation value of the last collaboration between the group D_1 and the group D_2;

$\gamma(t - t_{a-b}, c)$ denotes the function of time calibration.

DEFINITION 6. (DIRECT REPUTATION MATRIX)

If the cooperative system composed of n robots, DRM will be n*n matrix. Direct reputation value $\Theta(R_1, R_2, t, l, c)$, c denotes the environmental context, t denotes the time of collaboration and l denotes the specific group or alliance. $\Theta \in [0,1]$.

For instance, if there are 26 robots in the collaboration system, named R_A to R_Z, DRM will be the following matrixes.

$$\begin{bmatrix} 1 & \Theta(R_A, R_B, t, l, c) & \dots & \Theta(R_A, R_Z, t, l, c) \\ \Theta(R_B, R_A, t, l, c) & 1 & \dots & \Theta(R_B, R_Z, t, l, c) \\ \dots & \dots & \dots & \dots \\ \Theta(R_Z, R_A, t, l, c) & \Theta(R_Z, R_B, t, l, c) & \dots & 1 \end{bmatrix} \tag{5}$$

B. Time Decay Characteristics

DEFINITION 7. (TIME CALIBRATION)

Given robot R_1 in group D_1 and robot R_2 in group D_2, c denotes the environmental context, t denotes the time of collaboration and l denotes the specific group or alliance. t_{a-b} denotes the last collaboration time between robot R_1 and robot R_2. The time calibration function expressed as:

$$\begin{aligned} \gamma(t, c) = {} & k_0\gamma(t_{a-b}, c) + k_1 e^{-k(t-t_{a-b})}\left(\frac{t - t_{a-b}}{T} r^+\right) S \\ & - k_2 e^{-k(t-t_{a-b})}\left(\frac{t - t_{a-b}}{T} r^-\right)(S-1) \\ & - k_3(1 - e^{-k(t-t_{a-b})})\gamma(t_{a-b}, c) \end{aligned} \tag{6}$$

k_0 denotes the history experience coefficient, normally k_0 =1;

k_1 denotes the reputation award coefficient;

$e^{-k(t-t_{a-b})}$ denotes the correction operator;

k_2 denotes the reputation penalty coefficient;

r^+ denotes the incentive rate in time T;

r^- denotes the penalty ratio in time T;

S denotes validation coefficient of the collaboration, if successfully achieve the assigned task, S = 1, otherwise S=0;

k_3 denotes the decay coefficient. If the robot does not take on any assigned task, its reputation will diminish as the time went on. $0 < k_0, k_1, k_2, k_3 \le 1$, $k > 0$.

INFERENCE 1. TIME DECAY CHARACTERISTICS

PROOF Suppose the time t_1 and t_2, where $t_1 < t_2$, in the absence of compensation cases, as long as proof of $\gamma(t_1) > \gamma(t_2)$, which may permit proposition.

$$\gamma(t_1, c) = k_0\gamma(t_0, c) - k_3(1 - e^{-k(t_1-t_0)})\gamma(t_0, c)$$
$$\gamma(t_2, c) = k_0\gamma(t_0, c) - k_3(1 - e^{-k(t_2-t_0)})\gamma(t_0, c)$$
$$\gamma(t_1, c) - \gamma(t_2, c) = k_3\gamma(t_0, c)(e^{-k(t_1-t_0)} - e^{-k(t_2-t_0)})$$

Because $k_3\gamma(t_0) > 0$,and $t_1 < t_2$, so the equation above is greater than 0, therefore, the proposition may permit.

From the certification process, we can see that in the absence of compensation cases, the function as time goes on, and the value of the constant attenuation.

INFERENCE 2. NATURAL ATTENUATION CURVE

Under the normal circumstances, the value of K_0 is 1. The magnitude of changes is related to K and K_3. Take $k > 0, 0 < k_3 \le 1$, a different set of curves will be obtained, called attenuation curve.

Stipulate when $k = 0.2$, $k_3 = 0.5$, called natural attenuation curve. Assumed that the initial value $k_0\gamma(t_0, c)$ = 1, K_3 = 0.5 could be the case, k is 0.1,0.2,0.3 and 0.4 respectively, the attenuation curve is as shown in Fig. 2, in which the second curves from above is the natural attenuation curve.

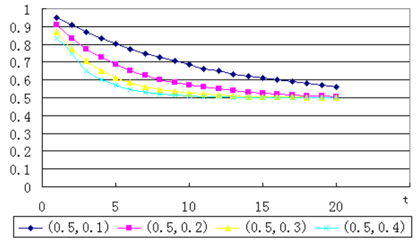

Fig.2 Attenuation curve

INFERENCE 3. HISTORY EXPERIENCE RELATED

PROOF. Assuming that algorithm does not have the historical relevance, in the absence of natural attenuation as well as under the circumstances of no penalty and award compensation , reputation will has nothing to do with the historical experience. then $k_0\gamma(t_{a-b},c)$ = 0, because $\gamma(t_{a-b},c)$ is not equal to zero, then k_0=0, which is conflicted with $k_0 \neq 0$. Therefore the assumption is wrong; it is history experience related.

DEFINITION 8. (GROUP CALIBRATION)

l_a denotes group reputation value of the robot R_1, l_b denotes the group reputation value of the robot R_2, c denotes the environment context, the group calibration function expressed as:

$$\tau(l_a,l_b,c)=\begin{cases}\dfrac{m_0}{1+m_1\sqrt{\dfrac{\Omega_{D_1}+\Omega_{D_2}}{2}}} & l_a \neq l_b \\ 1 & l_a = l_b\end{cases} \tag{7}$$

If Ω_{D_1} =NULL or Ω_{D_2} =NULL, then $\tau(l_a,l_b,c)\in$ [0.5-0.8]. $0<m_0\le 1, 0<m_1\le 1$, m_0 denotes the improvement correct coefficient, m_1 denotes the degeneration correct coefficient. Typical specifications of groups are defined as table III shows:

INFERENCE 4. NEW ROBOT REWARD

PROOF. According to the definition 8, if some robot is not in some group or has no collaboration with any of the robot in the group, the group reputation of the robot is NULL. When cooperating with the other robot, $\tau(l_a,l_b,c)$ $\in$[0.5-0.8], which stands for relatively high reputation.

If the first collaboration is successful, the value will be the history reputation value, thus the reputation of group and the robot will increase. Otherwise, reputation value will be near zero. Therefore, new robot in the group can get reword at the first collaboration.

INFERENCE 5. ALLIANCE REWARD

PROOF. The alliance is robot group. Task attempts to be allocated to the robots that are in the same group of the task issuer, if the reputation of the target robot is relatively not very low, which will greatly increase the efficiency.

TABLE III
TYPICAL GROUP SPECIFICATIONS

	Loyalty	honesty	Improvement	Random
M1	0～0.1	0.1-0.2	0.2-0.3	0.4-0.6
M0	0.9-0.99	0.8-0.9	0.7-0.8	0.5-0.7
	Concealment	Foxiness	Corruption	Deception
M1	0.6-0.7	0.7-0.8	0.8-0.9	0.9-0.99
M0	0.4-0.5	0.3-0.2	0.1-0.2	0-0.1

If robot R_1 and robot R_2 is in the same domain, $l_a = l_b$ therefore $\tau(l_a,l_b,c)=1$. Therefore, when the robots in the same group carry out collaboration, there are reputation award.

DEFINITION 9. （REPUTATION CALIBRATION）

$S(\vartriangle\rho_i+\Gamma_i(z_i,b,t,l,c))$ denotes the reputation calibration function, $\vartriangle\rho_i$ denotes the reputation standard deviation, g_0 denotes weight coefficient, $0\le g_0\le 1$.

$$S(i,\Gamma)=g_0\sqrt{\frac{\sum\Gamma_{i-1}^{\ 2}-\dfrac{(\sum\Gamma_{i-1})^2}{n}}{n-1}}+\Gamma_{i-1} \tag{8}$$

IV. Simulation and Experiments

The platform of the system is divided to three levels: 1. Configuration layer: robot DOF(Degrees Of Freedom), ARM9 basic system, servo parameters, memory type and capacity, upper and lower computer communication protocol, CAN bus protocol, basic information of sensors, voice playback module, etc. 2. Driver Layer: servo control module, data access module, communication module, CAN bus interface module, the sensor module, voice recorder module, and module driver. 3. Application Layer: biped robot reset, normal running, automatic running, action programming, voice and movement synchronized, walk balanced self-adjusting fuzzy control and other functions to achieve. The appearance of robots collaboration system is shown in Figure 3.

The basic shape parameters of each robot are: vertical height 33.3cm, shoulder width 9.9cm, arm length 15.9cm, its arms stretched flat horizontal length 41.7cm, upper body height 13.9cm, waist height 19.4cm, weight 1kg. Multi-robot inter-communication uses the serial RF module to send and receive data through radio frequency, and then the data is changed into a standard serial data and communicates with the robot. The effective transmission distance is 300m.

Fig.3 Experiment platform of the biped robot

On the multi-robot platform developed by our team, sixteen sensor network nodes are fixed in the experimental area. Each robot is equipped with communication modules, so the robots, the network nodes and between the robots and the network nodes can communicate with each other. The basic principles are shown in Figure 4.

If robot group G_{11} (R_1, R_2, R_3) wants to complete the task set T (T_1, T_2, T_3), but robot R_1 and R_3 are far in the distance and can not communicate directly. The direct reputation of the robot in group G_{11}, The matrix of direct reputation is as follows:

$$\text{DRM}\ (R_1, R_2, R_3) = \begin{bmatrix} 1 & 0.8 & 0 \\ 0.7 & 1 & 0.6 \\ 0 & 0.9 & 1 \end{bmatrix}$$

In this case of not taking the overall reputation into account, robot R_1 accepts the task set T (T_1, T_2, T_3) and robot R_1 accepts T_2, then robot R_1 will assign the remaining tasks to the robot R_2 according to the direct reputation value. At the same time, R_2 accepts the task T_1 and assigns the remaining tasks to the robot R_3 according to the direct reputation. If a robot can not complete the task, and there is no robot can complete the task within the scope of sense, the task will be returned to the original task issuer.

After experimental platform authentication, the reputation-based approach in the actual task allocation system is feasible, especially for the small assignments of the collaboration system.

V. Conclusion

Task allocation is a critical issue in multi-robot collaboration system research. The major indicators of the task allocation system focuses on real-time, robustness, reliability, optimization, communication requirements, computing ability, and so on.

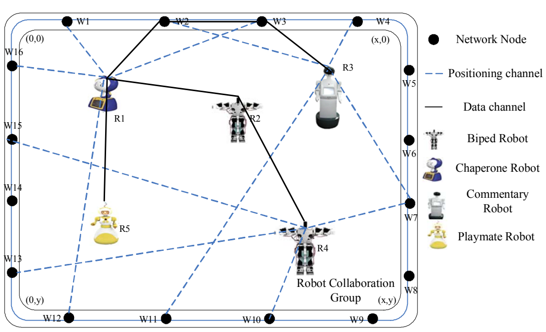

Fig.4 Collaboration group system of the robots

The paper presents a reputation based task allocation model, which can effectively improve robustness, reliability, and can optimize the overall system performance. The task is assigned to the robot with relatively high reputation, which can greatly improve the success rate of implementation of its mandate, thereby reducing the time of the recovery and redistribution of the task. Simulation results show that this model can be used in a multi-robot task allocation system, and has good efficiency.

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