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Multi-robot Cooperation Behavior Decision Based on Psychological Values

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Abstract: The method based on psychology concept has been proved to be a successful tool used for human-robot interaction. But its related research in multi-robot cooperation has remained scarce until recent studies. To solve the problem, a decision-making mechanism based on psychological values is presented to be regarded as the basis of the multi-robot cooperation. Robots give birth to psychological values based on the estimations of environment, teammates and themselves. The mapping relationship between psychological values and cooperation tendency threshold values is set up with artificial neural network. Robots can make decision on the bases of these threshold values in cooperation scenes. Experiments show that the multi-robot cooperation method presented in the paper not only can ensure the rationality of robots' decision-making, but also can ensure the speediness of robots' decision-making. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Multi-robot systems, Psychological value, Artificial neural network, Cooperation tendency, Variable threshold value.

1. Introduction

Multi-robot systems have become a main research domain within the robotics research community in recent years. With the increasing of the need for dealing with dynamically perceived tasks [1], centralizing control and programming in advance can not meet the need more and more. Robots should have more cooperation behavior self-determination abilities when they face sudden cooperation occasions. It has important signification for us to study how robots make proper decision according to dynamically changing environment and the states of their teammates and themselves when they face cooperation occasions.

In recent years, a large number of psychology and cognitive science researches [2] show that there are wide interactions between the emotion and the reasoning of human beings. Emotion has great influence on the intelligence level and information acquisitioning ability. Bechara [3], a neurology researcher, showed that the brain section which controls emotion affects man's decision-making ability. Sometimes man's judgment even firstly depends on emotional level, rather than depending only on reasoning. Damasio [4], a neurophysiology scientist, discovered that the part of human being's cerebra which controls emotion can affect people's decision-making ability.

At present, in the study of robotics domain, the most applied psychology concepts are personality and emotion. Terrence Fong [5] considered multiple mobile robots coordination and cooperation. The word of personality can be used to describe the ability and requirement differences of robots. The method based on the personality concept not only can be used for homogeneous multiple mobile robots system but also can be used for heterogeneous multiple mobile robots system. Makiko [6] studied the influence of three personality values of positive, tender and temper on multiple mobile robots system task execution efficiency. These personality values were fixedly distributed to robots by researchers. Makiko [6] considered robots can know the personalities of other robots by observing their behaviors. But he didn't put forward the concrete observing method. Aaron Gage [7] and Y. Y. Ding [8] put forward multiple mobile robots cooperation method based on personality to solve the problem of conflict resolution.

Researchers have applied the emotion method to robotics field in four ways: The first way is that emotion is applied to regulate the group behaviors of robots [9]. The second way is that emotion is applied to the behavior of single robot [10]. For example, low electric quantity of battery is interrelated with "hunger". The status of "hunger" will trigger the behavior of charging. The third way is that emotion is applied to human-robot interaction [11]. However, the forth way, the application of emotion to action selection, is usually neglected. Toda [12] considered that emotion can provide the autonomous ability for robot and can be regarded as the source of intelligence. Parker [13] put forward an anxiety conception model. If other teammates didn't perform a task, a robot will become anxiety after waiting for a long time. The emotion of anxiety will make the robot replace its teammates. The anxiety conception model effectively solves the problem of multi-robot task reallocation.

These scholars introduce single psychology concept such as personality and emotion to robot research. But they didn't consider the combined influence of multiple psychology concepts on multi-robot cooperation. Simulating the mechanism of mentation decision-making, the paper presents a multi-robot cooperation behavior decision method based on psychological values (mentation parameters). Psychological values synthetically reflect the comprehension of the robots to their surroundings and the state of their teammates and themselves. With the changing of inter and outer condition, the psychological values of robots will chang too. Robots adjust their "cooperation tendency threshold values" which measure the strength or weakness of their cooperation tendency. Then robots consider the threshold values as the basis of the proper reactivity to cooperation scenes stimulation. If the stimulation is higher than the threshold values, then the robots will execute the corresponding cooperation behavior. Otherwise, the robots will not execute the corresponding cooperation behavior. This kind of reactivity strategy not only is based on the rational judgement to environments, teammates and themselves, but also keeps the reactivity speediness which is the merit of the reactivity control.

The rest of this paper is organized as follows. We present the task description in Section 2, followed by a description of the algorithm model in Section 3. Next we describe the behavior decision method based on psychological values and the experimental validation in Section 4 and Section 5. Finally, we give the conclusion and our directions for future research in Section 6.

2. Task Description

In the paper, multi-robot foraging [14] was used as the multi-robot task to validate the algorithm. The task has wide application background: such as multi-robot cooperation pollution limination [15], multi-robot cooperation searching and rescueing in disaster scene [16], multi-robot cooperation collecting soil and mineral sample on planets in the future [17]. In the multi-robot foraging task condition, we validated the cooperation behavior decision-making method based on psychological values with experiments. Experiments results showed that the method can make multiple robots accomplish foraging task effectively.

In the paper, the foraging task can be stated as follows: A group of n robots and m objects (for example, m trunks with different sizes) are scattered in a planar area. The whole task can be described that the robots must find the objects and transport them to a goal location (named as "the base area"). Single robot can carry back lighter objects independently. But heavier objects must be carried back by more than one robots cooperatively. We measure the performance of the robots cooperation strategy used in the foraging experiments within a preconcerted time with the number of the objects which was carried back to "the base area" by robots. There are many scenes where robots should cooperate together to achieve task during robots foraging. For example, when robots found a object which can not be carried back by itself, it will judge if it should ask for the assistance of its teammates or give up the object to find other objects. When robots received the appealing signal from its teammates, it should judge if it should give help to its teammates. Robots broadcasted the position information and size information of the objects which they found but did not need. Other robots will judge whether they should accept the information to catch back the objects or ignore the information to look for other objects independently. When more than one robots come back to the base area at the same time, every robot will judge if it should give way to its teammates voluntarily to let them put the objects to the base area firstly. Because the number and position of the objects which scared in the foraging area are unknown to the robots before the foraging course, the foraging task researched in the paper is a kind of dynamically perceived tasks. In these cooperation scenes robots must execute proper cooperation behavior to improve the robots system efficiency.

3. Algorithm Mode

The cooperation behavior decision-making process based on psychological values includes two parts:

a) Cooperation tendency judgement strategy based on psychological values

This part also includes two sub-parts: The calculation of robots' psychological values (it is lined out with marker ① in Fig. 1) and the confirmation of cooperation tendency threshold values based on artificial neural network(ANN) (It is lined out with marker ② in Fig. 1).

b) Reflection strategy based on variable threshold values

This part also includes two sub-parts: The calculation of cooperation scenes stimulation values (it is lined out with marker ③ in Fig. 1) and the stimulation reaction mechanism based on Route Wasp Principle (It is lined out with marker ④ in Fig. 1).

In the paper, the calculation of robots' psychological values and the confirmation of cooperation tendency threshold values based on ANN are the research emphases.

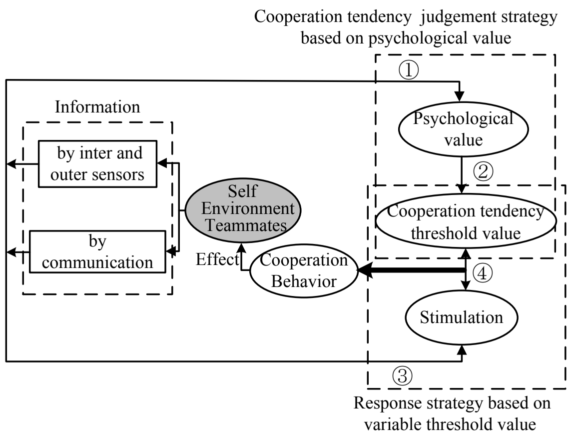


Fig. 1. Cooperation behavior decision model.

The work state of robots includes the usual state and the emergency state. The usual state is the state that robots do not fall across cooperation scenes. The emergency state is the state that robots fall across cooperation scenes. In Fig. 1, the course denoted with marker ① and marker ② is completed in the usual state. The course denoted with marker ③ and marker ④ is completed in the emergency state. The computation of psychological values is completed in usual state. This kind of proper time distribution of computation quantity is the key to ensure the robots' decision-making speediness in the course of cooperation behavior decision.

4. Behavior Decision Based on Psychological Values

4.1. The Calculation of Psychological Value

In the paper, multi-robot cooperation scenes come down to these psychological values: despair value, abashment value, anxiety value and impatience value. In the following, we will give the computation method of these psychological values. In these expressions symbols, i denotes the sequence number of a robot.

a) The calculation of despair value.

The despair value of robots will increase with the time of robots waiting for their teammates extending. The bigger the despair value is, the stronger the incline to give up waiting for its teammates' help will be. The despair value is calculated with equation (1).

$$D_i = 1 - e^{-kt}, \tag{1}$$

where parameter k is the set to 0.02. The despair value satisfies $D_i = [0,1]$.

b) The calculation of abashment value.

The abashment value of robots increases with the times of robots refusing its teammates increasing. The bigger the abashment value is, the stronger the incline to satisfy their teammates' appealing will be. The abashment value is calculated with equation (2).

$$A_i = \begin{cases} k_a n_a & , \quad A_i < 1 \\ 1 & , \quad A_i \geq 1 \end{cases}, \tag{2}$$

where k_a stands for the increasing rate and is set to 0.1. n_a stands for the times of robots refusing its teammates. After the scene finished, A_i is set to 0. The abashment value satisfies $A_i = [0,1]$.

c) The calculation of anxiety value.

The anxiety value of robots increases with the self-confidence degree to accomplish task decreasing. If there are less remaining objects in the foraging area and there are less remnant energy in the robots, the anxiety value of robots will be greater. The greater the anxiety value of robots is, the stronger the incline of robots to accept the objects which are found by teammates will be. The anxiety value is calculated with equation (3).

$$\tau_i = \frac{T \cdot W_{\min} V_l}{(W_0 - W_t)\sum N_t}, \tag{3}$$

where T stands for the time from the beginning of the foraging to time t . $W_{\min}$ stands for the least remaining energy value. If the remaining energy value is lower than $W_{\min}$, robots will have to stop its current task to charge. $W_0 - W_t$ stands for the current remaining energy value. $\sum N_t$ is the total number of the objects foraged by the multi-robot system at the time of t . V_l is the experience value of foraging speed which was set in advance when the objects are least in the foraging area. If the current anxiety value exceeds 1 because the objects are sparser than the value set in advance, actual τ_i will be set to 1. During the course of carrying back by robots, A_i is set to $\tau_i = 0$. The anxiety value satisfies $\tau_i = [0,1]$.

d) The calculation of impatience value.

The impatience value of robots increases with the impendency degree of current task increasing. The less the remaining energy is and the bigger the importance degree is, the bigger impatience value J_i will be. The impatience anxiety value is calculated with equation (4).

$$J_i = \frac{(W_0 - W_t)\gamma_i}{W_0 \gamma_{max}}, \tag{4}$$

where γ_i stands for the importance degree of robot's current task. $\gamma_{\max}$ stands for the most importance degree of robot's tasks. The meanings of W_0 and W_t are same as the ones in equation (3).

4.2. The Calculation of Cooperation Tendency Threshold Values Based on ANN

Table 1 enumerates several corresponding relationships of representative cooperation scenes, psychological values and cooperation tendency. Table 1 shows that one psychological value can influence more than one cooperation tendency and at the same time, one cooperation tendency can be influenced by more than one psychological values. ANN is fit for setting up complicated nonlinear relationship between input variables and output variables. So the mapping relationship between psychological values and cooperation tendency threshold values is set up with ANN in the paper. Fig. 2 shows a three-layer ANN model. Input variables are psychological values. The number of nerve cells in input layers is N_x .Output variables are cooperation tendency threshold values. The number of nerve cells in output layers is N_y . According to part A of section 4, the calculation results of despair value, abashment value, anxiety value and impatience value have been in [0,1] . It doesn't need normalization processing.

Table 1. Comparison of representative cooperation scenes, psychological values and cooperation tendency.

Cooperation scenes	Psychological value	Cooperation tendency
Wait for help by teammates (tasks can't be accomplished by itself)	Despair Anxiety	The tendency to give up current task
Receive the appeal signal by teammates (robot itself found objects)	Abashment Impatience	The tendency to give up current task and go to help teammates
Receive the appeal signal by teammates (robot itself didn't find object)	Anxiety Abashment	The tendency to help teammates
Receive information of objects found by teammates (robot itself didn't need)	Anxiety	The tendency to accept the objects found by teammates
Fall across other teammates in the base area	Impatience	The tendency to Prevent collision

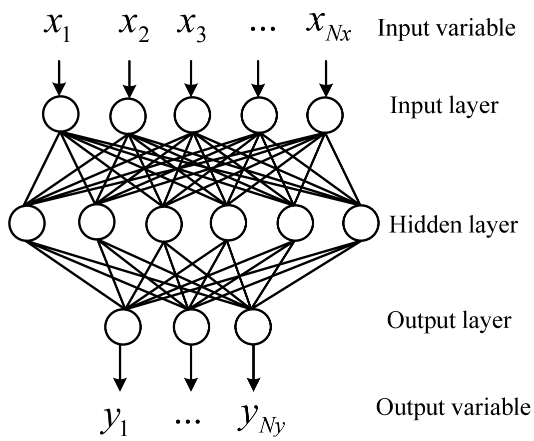


Fig. 2. The neural network structure for the confirmation of cooperation tendency threshold values.

4.3. The Calculation of Cooperation Scenes Stimulation Values

There are four different stimulation values in the cooperation scenes listed in Table 1. Here we call the stimulation value SV. They are respectively the SV caused by refused by teammates, the SV caused by teammates' appealing, the SV caused by teammates' invitation and the SV caused by collision danger.

a) The SV caused by refused by teammates.

The SV caused by refused by teammates is determined by the time waiting for teammates' help. The longer the time is, the greater the SV will be. The value is calculated with equation (5).

$$S_D = 1 - e^{-\beta t}, \tag{5}$$

where parameter β is set as 0.02. The SV satisfies $S_D = [0,1]$.

b) The SV caused by teammates' appealing.

The SV caused by teammates' appealing is determined by the appealing times received from teammates. With the appealing times increasing, the SV will be greater. The value is calculated with equation (6).

$$S_H = \begin{cases} k_{sh} n_{sh} & , \quad S_H < 1 \\ 1 & , \quad S_H \geq 1 \end{cases}, \tag{6}$$

where n_{sh} stands for the appealing times received from the same teammate. Coefficient k_{sh} is set to 0.2. The SV satisfies $S_H = [0,1]$.

c) The SV caused by teammates' invitation.

The SV caused by teammates' invitation is determined by the invitation from the robots which found the objects but didn't need them. The nearer the distance from the robot to the object is, the greater the SV will be. The value is calculated with equation (7).

$$S_I = \begin{cases} \dfrac{L_{\max} - L}{L_{\max}} & , \quad L \leq L_{\max} \\ 0 & , \quad L > L_{\max} \end{cases}, \tag{7}$$

where $L_{\max}$ stands for the farthest permission distance of the objects which can be accepted by robots from their teammates. L stands for the distance from the robot to the object. The SV satisfies $S_H = [0,1]$.

d) The SV caused by collision danger.

The SV caused by collision danger is determined by the teammates which may collide with the robots. The nearer the distance is, the greater the SV will be. The value is calculated with equation (8).

$$S_C = \begin{cases} \dfrac{l_{\max} - l}{l_{\max} - l_{\min}} & , \quad l_{\min} \leq l \leq l_{\max} \\ 0 & , \quad l > l_{\max} \\ 1 & , \quad l < l_{\min} \end{cases}, \tag{8}$$

where $l_{\max}$ stands for the farthest distance which can be detected by sensors. $l_{\min}$ stands for the nearest safety distance between robot and its teammates. l stands for the current distance between robot and its teammates. The SV satisfies $S_C = [0,1]$.

4.4. Stimulation Reaction Mechanism Based on Route Wasp Principle

Theranlaz [18] put forward the Route Wasp Principle expressed as formula (9). Bonabeau [19] put forward that one determines whether it should execute a task with the contrast of task associated stimulation S and threshold value θ. In the paper, we considered that a robot determines whether it should execute a cooperation behavior with the contrast of cooperation scene associated stimulation S and cooperation incline threshold value θ.

$$P(\theta, S) = \frac{S^n}{S^n + \theta^n}, \tag{9}$$

where S stands for the SV. And θ is the threshold value. Exponent $n \in N^+$.

To meet the need to study multi-robot cooperation, we extend the concept of the stimulation value S in equation (9). The meanings of the stimulation in the paper not only include the stimulation of environment, but also include the stimulation from the communication among the robots (Such as the stimulation caused by teammates' appealing and the stimulation caused by teammates' invitation). When θ is given different values (such as θ=0.3, θ=0.7 and θ=1), the function curves can be shown in Fig. 3. From Fig. 3, we can see that with the increasing of n, function curves gradually change into step curves. The less the cooperation incline threshold value θ is, the less the stimulation value will be. Which makes the cooperation behavior startup probability of robots $P(\theta, S)$ come to be 1. When n is an infinity positive integer, we get the equation (10). We consider the equation (10) as the calculation equation of the cooperation behavior startup probability $P(\theta, S)$ of robots.

$$P(\theta, S) = \begin{cases} 1 & , \quad S_j - |C^i \cdot e_j| \geq 0 \\ 0 & , \quad else \end{cases}, \tag{10}$$

where e_j is the basis vector, the jth element is 1. Here C^i is a diagonal matrix called cooperation tendency threshold value matrix which is expressed as (11). The diagonal values of C^i are cooperation tendency threshold values θ_{Qi}, θ_{Hi}, θ_{Ai} and θ_{Ji}.

$$C^i = \begin{bmatrix} \theta^i_{x1} & & \\ & \cdots & \\ & & \theta^i_{xk} \end{bmatrix}, \quad \theta^i_{xj} \geq 0 \quad , j = 1, \ldots k, \tag{11}$$

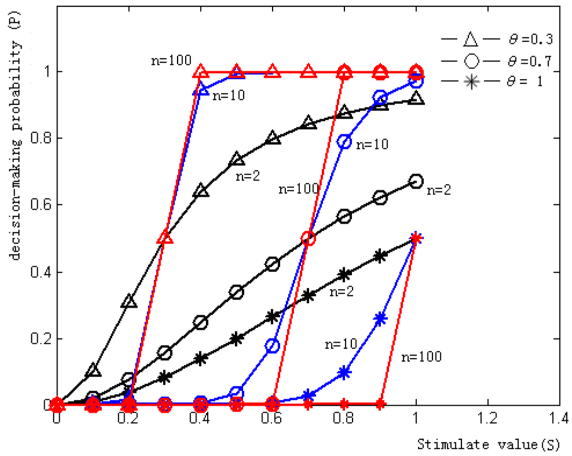


Fig. 3. Decision probability variation curves.

5. Experimental Validation

5.1. ANN Training and Forecasting Simulation Experiments

We set up a ANN structure which has four input layer nerve cells: the despair value D_i , the abashment value A_i , the anxiety value τ_i and the impatience value J_i .The ANN structure has four output layer nerve cells: the threshold value to give up current task θ_{Qi} , the threshold value to accept teammates' appealing θ_{Hi} , the threshold value to accept teammates' invitation θ_{Ai} and the threshold value to avoid teammates θ_{Ji} . Symbol i is the sequence number of a robot. Learning rate η is set to 0.05. The goal error E is set to 0.00008. Part of samples used in NN training are listed in the Table 2.

Table 2. Part of the training samples.

Sample output (Psychology)				**Sample output (Cooperation tendency threshold value)**			
D_i	A_i	τ_i	J_i	θ_{Qi}	θ_{Hi}	θ_{Ai}	θ_{Ji}
0	0.4	0.2	0	1	0.7	0.3	0
0.3	0	0.8	0.8	0.7	1	0.7	0.7
0	0.4	0.8	0	1	0.3	0	0
0	0	0	0.8	0	0.7	1	1
0	0	0.6	0.4	0.3	0.3	0.3	0
0	0	0	0.7	0	1	1	1
0	0	0	0.6	0	1	1	0.7
0	0	0.5	0	0.7	0.3	0.3	0
0	0	0.1	0	0.3	0.7	0.7	0
0	0	0.1	0	0.3	0.7	0.7	0

Fig. 4 shows the errors changing curve of the ANN training process. 100 times training process are executed. The average convergence learning periods is 14.5.

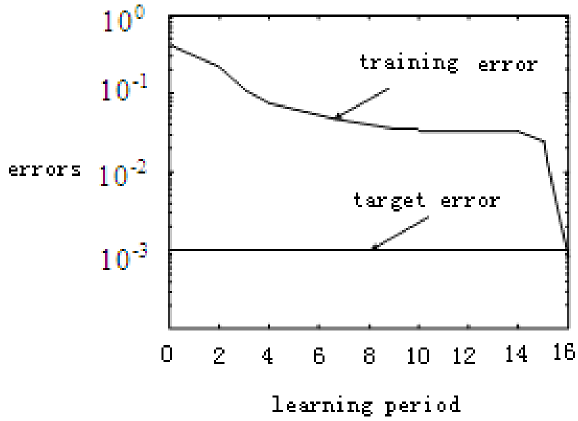


Fig. 4. NN training process curve.

To validate the ANN model, we use the three suits of data in Table 3 to validate the output data. The ANN model can forecast the correct cooperation tendency threshold values.

Table 3. Forecasting results with the ANN.

Output (Psychology)				**Expectation output Practice output**			
D_i	A_i	τ_i	J_i	θ_{Qi}	θ_{Hi}	θ_{Ai}	θ_{Ji}
0.3	0	0.8	0.8	0.7 0.784	1 0.984	0.7 0.784	0.7 0.784
0	0	0.5	0	0.7 0.784	0.3 0.384	0.3 0.384	0 0.084
0	0.4	0.2	0	1 0.984	0.7 0.784	0.3 0.384	0 0.084

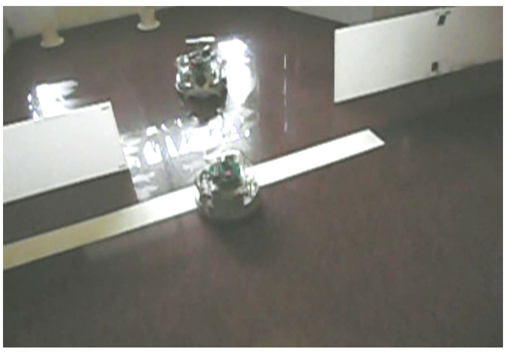
5.2. Multi-robot Foraging Experiment

The configuration of the robots used in the multi-robot foraging experiment is following: The radius of the robot is 20 cm. The movement velocity of the robot is 20 cm/s. The maximal collision detection radius is 70 cm. The radius of the object is 10cm. In the multi-robot foraging experiment, the ANN learning course, with which the relationship between psychological values and cooperation tendency threshold values is set up and executed on PC. We save the known samples into the chips of the robots with a kind of table. In cooperation scenes, a robot will check the table. If current psychological value of the robot is in the table, the robot can obtain its corresponding cooperation tendency threshold values, or the robot will transfer its psychological values to PC. PC executes ANN calculation and gets the corresponding cooperation tendency threshold values with the generalization ability of ANN. PC transfers the cooperation tendency threshold values to the robot. It is an eclectic scheme which fully considers the finite calculation capability and communications capability of the robots.

Fig. 5 shows snapshots of the experiment of the cooperative foraging task. The sub-plot Fig. 5(a), Fig. 5(b) and Fig. 5(c) respectively show the three scenes of robots foraging. Sub-plot Fig. 5(a) shows that robot A and robot C receive the appeal information at the same time. At this time, the psychology values of robot B are following: D_i =0.3, τ_i =0.8, cooperation tendency threshold value θ_{Qi} =0.7. At the time, the scene stimulation value S_D =0.2 is lower than its cooperation tendency threshold value θ_{Qi} . The cooperation behavior decision-making result is still waiting teammates' help. The psychology values of robot B are following: A_i =0.4, τ_i =0.2, cooperation tendency threshold value θ_{Hi} =0.7. At the time, the scene stimulation value S_H =0.4 is lower than its cooperation tendency threshold value θ_{Hi} . The cooperation behavior decision-making result is not to help robot B. The psychology values of robot C are following: A_i =0.4, τ_i =0.8, cooperation tendency threshold value θ_{Hi} =0.3. At the time, the scene stimulation value S_H =0.4 is higher than its cooperation tendency threshold value θ_{Hi} . The cooperation behavior decision-making result is to help robot B. Sub-plot Fig. 5(b) shows that robot A found object which it didn't need and sent the information of the object to its teammates. At this time, robot still didn't find objects and robot C was carrying back its object to the base area. The psychology values of robot B is $\tau_i = 0.6$, cooperation tendency threshold value θ_{Ai} =0.3. At this time, the appeal stimulation of robot B from robot A is S_I =0.3. The cooperation behavior decision-making result is that robot B will forage according the information got from robot A. The psychology values of robot C is τ_i =0. Cooperation tendency threshold value θ_{Ai} =1. At this time, the appeal stimulation of robot C from robot A is S_I =0.2. The appeal stimulation was lower than the cooperation tendency threshold value θ_{Ai} . The cooperation behavior decision-making result is that robot B will refuse the information got from robot A. Sub-plot Fig. 4(c) shows that robot A falls across robot C in the base area. Robot C is beginning to forage from the base area. At this time, The psychology values of robot A is τ_i =0.6, cooperation tendency threshold value θ_{Ai} =0.7. The psychology values of robot C is τ_i =0, cooperation tendency threshold value θ_{Ji} =0. The stimulation of two robots are all S_C =0.4. The stimulation is lower than the cooperation tendency threshold value of robot A and higher than the cooperation tendency threshold value of robot C. Robot A chooses to execute the current task and Robot C chooses to forwardly avoid its teammates. From the sub-plots, we can see that robots can rationally realize cooperation with the cooperation behavior decision-making method based on psychology values. The psychology values and the cooperation tendency threshold values are listed in Table 4. Symbol a(A) stands for the robot A in Table 4.

(a) Robot A and Robot C receive the appeal information

(b) Robot A found object



(c) Robot A fell across robot C

Fig. 5. Multi-robot foraging experiments scenes.

Table 4. Comparison of psychological values and cooperation trend threshold values.

Scenes (Robots)	Psychological values				Cooperation tendency threshold value			
	D_i	A_i	τ_i	J_i	θ_{Qi}	θ_{Hi}	θ_{Ai}	θ_{Ji}
a (A)	0	0.4	0.2	0	1	0.7	0.3	0
a (B)	0.3	0	0.5	0.2	0.7	1	0.7	0.3
a (C)	0	0.4	0.8	0	1	0.3	0	0
b(A)	0	0	0	0.8	0	0.7	1	1
b (B)	0	0	0.6	0.4	0.3	0.3	0.3	0
b (C)	0	0	0	0.7	0	1	1	1
c (A)	0	0	0	0.6	0	1	1	0.7
c (B)	0	0	0.5	0	0.7	0.3	0.3	0
c (C)	0	0	0.1	0	0.3	0.7	0.7	0

The cooperation strategy presented in the paper is contrasted with the active strategy and the conservative strategy. We did respectively 20 experiments with the three strategies. We expressed the mean number of the objects foraged by multi-robot system in 30 minutes in Fig. 6. The abscissa of the figure is the initial objects number before the robot system began foraging. The ordinate of the figure is the objects number foraged in determinative time.

As shown in Fig. 6. Using the conservative strategy, robots execute their tasks independently. The objects which cannot be foraged by single robot can't be carried back to the base area all along. This kind of strategy can't acquire the superiority brought by the cooperation of multi-robots. So this kind of strategy is the most inefficient one of the three strategies. Using the jacobinical cooperation strategy, robots are more easy to blindly accept the invitation of teammates and lose the chance to forage objects more quickly (Especially there are more objects in the foraging area.). Using the cooperation strategy presented in the paper, robots can decide when to use the active cooperation strategy and when to use the conservative strategy according to the characteristic of environment all the time. The strategy ensures that in different environment the robots have better foraging speed and better foraging efficiency.

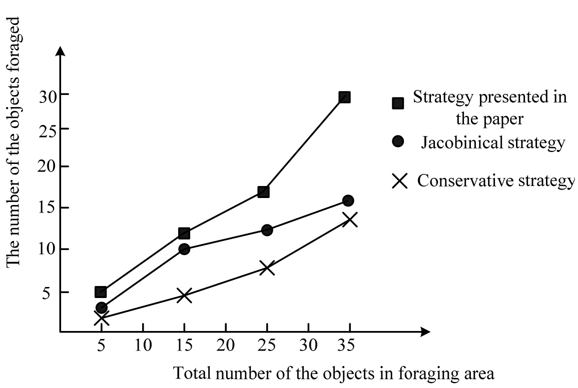


Fig. 6. Multi-robot foraging experiments scenes.

6. Conclusions

A kind of behavior decision method based on psychological value for multi-robot cooperation is presented in the paper. This method includes two parts: cooperation tendency judgment strategy and reactivity strategy based on variable threshold value. The first part of the method ensures that the robots' decision-making is based on the rational judgment to environments, teammates and themselves. The second part of the method uses the route swap principle to keep the speediness which is the merit of the reactivity control when the robots meet the cooperation scene stimulation. Experiments show that the method can make the robots execute proper cooperation behaviors.

The algorithm presented in the paper can be transplanted to the ANN chip [20] and realize the on-line learning of ANN. On the basis of the paper, we will study the method to use unsupervised methods such as reinforcement learning to set up the relationship of the psychological values and cooperation incline threshold values.

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References

[1]. D. D. Zhang, G. M. Xie, J. Z. Yu, et al., Adaptive task assignment for multiple mobile robots via swarm intelligence approach, *Robotics and Autonomous Systems*, Vol. 55, Issue 7, 2007, pp. 572-588.

[2]. R. W. Picard, Affective Computing: challenges, *International Journal of Human-Computer Studies*, Vol. 59, Issue 2, 2003, pp. 55-64.

[3]. A. Bechara, The role of emotion in decision-making: evidence from neurological patients with orbitofrontal damage, *Brain and Cognition*, Vol. 55, 2004, pp. 30-40.

[4]. R. D. Antonio, Descartes error: emotion, reason, and the human brain, *Grosset Putnam Press*, New York, 1994.

[5]. F. Terrence, A survey of socially interactive robots, *Robotics and Autonomous Systems*, Vol. 42, Issue 3, 2003, pp. 143-166.

[6]. M. Tauchi, Y. Sagawa, T. Tanaka, et al., Collaboration among a group of self-autonomous mobile robots with diversified personalities, in *Proceedings of the IEEE International Conference on Intelligent Robots and Systems (RSJ' 04)*, Sendai, Japan, 2004, pp. 388-393.

[7]. A. Gage, Multi-robot task allocation using affect, Doctoral Dissertation, *University of South Florida, USA*, 2004, pp. 38-51.

[8]. Y. Y. Ding, Y. He, J. P. Jiang, Introducing 'Personality' into the multi-robot cooperation, in

Proceedings of the American Control Conference, Oregon, Portland, 2005, pp. 5003-5008.
[9]. G. Murphy, Sensor scheduling in mobile robots using incomplete information via min-conflict with happiness, *IEEE Transactions on Systems, Man and Cybernetics*, Vol. 34, Issue 1, 2004, pp. 454-467.
[10]. C. S. Yu, L. Xu, An emotion-based approach to decision making and self learning in autonomous robot control, in *Proceedings of the 5th World Congress on Intelligent Control and Automation*, Hangzhou, China, 2004, pp. 2386-2390.
[11]. F. Terrence, N. Illah, D. Kerstin, A survey of socially interactive robots, *Robotics and Autonomous Systems*, Vol. 42, Issue 3-4, 2003, pp. 143-166.
[12]. P. Stone, M. Veloso, Multi-agent systems: a survey from a machine learning perspective, *Autonomous Robots*, Vol. 8, Issue 3, 2000, pp. 345-383.
[13]. L. E. Parker, ALLIANCE: an architecture for fault tolerant multi-robot cooperation, *IEEE Transactions on Robotics and Automation*, Vol. 14, Issue 2, 1998, pp. 220-240.
[14]. Thomas H. Labella, Marco Dorigo, Jean-Louis Deneubourg, Division of labor in a group of robots inspired by ants' foraging behavior, *ACM Transactions on Autonomous and Adaptive Systems*, Vol. 1, Issue 1, 2006, pp. 4-25.
[15]. D. Fritsch, K. Wegener, R. D. Schraft, Control of a robotic swarm for the elimination of marine oil pollutions, in *Proceedings of the IEEE Swarm Intelligence Symposium*, 2007, pp. 29-36.
[16]. R. T. Vaughan, K. Sukhatme, G. S. Stoy, et al., Whistling in the dark: Cooperative trail following in uncertain localization space, in *Proceedings of the 4th International Conferences Autonomous Agents*, 2000, pp. 187-194.
[17]. M. J. Mataric, G. S. Sukhatme, E. H. Ostergaard, Multi-robot task allocation in uncertain environments, *Autonomous Robots*, Vol. 14, Issue 2, 2003, pp. 255-263.
[18]. A. C. Vincent, F. S. Stephen, Wasp-like agents for distributed factory coordination, *Autonomous Agents and Multi-Agent Systems*, Vol. 8, Issue 3, 2004, pp. 237-266.
[19]. G. Theraulaz, E. Bonabeau, J. L. Deneubourg, Threshold reinforcement and the regulation of division of labor in insect societies, *Proceedings Royal Society of London B*, Vol. 263, 1998, pp. 327-335.
[20]. C. Lu, B. X. Shi, L. Chen, An expandable BP on-chip learning neural network chip, *Acta Electronica Sinica*, Vol. 30, Issue 9, 2002, pp. 1270-1273.