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Collaborative task assignment of interconnected, affective robots towards autonomous healthcare assistant

Baofu Fang [a], Xiaoping Guo [a], Zaijun Wang [b], Yong Li [a], Mohamed Elhoseny [e], Xiaohui Yuan [c,d,*]

[a] School of Computer Science and Information Engineering, Hefei University of Technology, Hefei, 230009, China
[b] CAAC Academy of Flight Technology and Safety, Civil Aviation Flight, University of China, Guanghan, 618307, China
[c] China University of Geosciences, Wuhan, 430076, China
[d] University of North Texas, Denton, TX, 76203, USA
[e] Mansoura University, Mansoura, 35516, Egypt

HIGHLIGHTS

- A method for scheduling collaborative robots to maximize outcomes and efficiency.
- The interconnected robots leverage emotion and personality for better synergy.
- Improved performance and promising results for healthcare applications.

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ABSTRACT

Emotion renders the behavior and decision-making more autonomous, intelligent and diversified. How to deal with the cooperation of affective robots is a new research field and is explored in the applications for healthcare and education This paper studies the interaction of affective robots in a cooperative system. We build a model of personality and emotion, and map the personality to behavior and devise emotional interactions. For personalized multi-robot systems, we propose an algorithm of pursuit task allocation based on emotional contagion (PTA-EC). Our experimental results based on simulations demonstrate that the greatest contribution among all types of robots to a group is the frank type, while the sympathetic and the indifferent robots have little effect to the group progress. In addition, it is shown that the emotional contagion positively impacts task allocation and the efficiency of the proposed algorithm is competitive with the state-of-the-art methods.

1. Introduction

Interconnected robots have been developed to collaboratively complete complex tasks such as search and rescue post disasters. The promising technologies inspired exploring multi-robot collaboration in healthcare via Internet-of-things [1], especially for elderly care. However, a challenge exists in the field of emotional artificial intelligence, i.e., how human emotions are recognized, processed, and handled in human–robot and robot–robot interactions.

Emotion is an important symbol of human intelligence. The research and applications of emotion have gradually become a focus of realizing artificial intelligence. Emotion renders intelligent behaviors and influences decision-making towards autonomous, intelligent and diversified. Researchers abstract human emotion according to psychological knowledge and construct computable mathematical models, which have been applied to robots. Emotional models have now become commonplace in the domain of human–robot interaction, which is applied in fields such as healthcare and education [2–4]. However, the emotional model is mostly formulated for a single entity in a temporal space without considering interactions among multiple entities including human beings and robots.

In multi-robot systems (MRS), task allocation has attracted great attention and been studied towards the applications of healthcare, space exploration, rescue simulation, military, etc. [5–9]. Multi-robot task allocation (MRTA) assigns tasks to robots for efficiency and reward. In healthcare, for instance, robots with different functionalities are used to serve senior citizens with various needs. How to allocate robots to assist elderly that maximizes the utilities of the robots and provide quick responses as needed is a pressing issue in autonomous human–computer interactions systems for healthcare. Das [10] proposed a distributed algorithm

* Corresponding author at: University of North Texas, Denton, TX, 76203, USA.
  E-mail address: xiaohui.yuan@unt.edu (X. Yuan).

for task allocation in a system of multiple heterogeneous autonomous robots deployed in a healthcare facility, based on auction and consensus principles. But those studies of conventional multi-robot task allocation mainly aimed at the optimal allocation strategy to maximize benefit and minimize cost, there may be irreconcilable interest conflict among rational robots because of their self-interests. Emotion is, hence, considered to balance the conflicts.

There are a few types of research on affective robots task allocation. Banik [11] proposed an emotion-based MRTA algorithm and considered four emotions (namely, joy, anger, fear, and sadness) and described emotional changes using a Markov model. Fang et al. [12,13] introduced emotions of joy, fear, and anger, described emotional decay, and stimulation and proposed the cooperation intention for the cooperative affective robot in task allocation. But those above methods did not take the emotional interaction among robots into the account.

In a group, each individual with its unique personality and emotional state will subconsciously imitate other individual's emotional expression in communication, which will affect the emotional experience of itself ultimately, in the field of psychology this process is referred to as emotional contagion [14]. Ta [15] presented an emotional contagion model but focuses on fear-related emotions and their positive impact on the survival capabilities of human beings in case of crisis situations. Most contagion models [16,17] in social networks draw on the experience of the epidemic model [18]. However, the epidemic model requires no knowledge of the personality of individuals and hence it excludes the consideration of personality in the process of emotional interaction. The personality [19–22] is an important factor in human interactions, e.g. an apathetic individual is less willing to express emotion than a frank individual and is less easily affected by the emotion of others than a sympathetic individual.

In respect of the aforementioned issues, this paper proposes a multi-robot task allocation algorithm based on emotional contagion with consideration of personality. Based on the definitions of personality, emotion, and the mapping of personality to behavior, we present an emotional contagion model to realize emotional interaction among cooperative robots. Our method takes into account the effect of personality on the emotion change. It was in the cooperative system that we construct affective model for the robot, and the emotional contagion is a model for robot–robot interaction. Then we propose a task allocation algorithm combined with affective factors. The effectiveness of our model is evaluated using simulation in the context of emotional multi-robot pursuit for elder care.

The main contributions of this paper are (1) proposed a novel method for scheduling collaborative robots to maximize outcomes and efficiency; (2) leveraged emotion and personality of interconnected robots for better communicate and synergy; (3) improved performance in comparison to the state-of-the-art methods and demonstrated promising results for healthcare applications.

The rest of this article is organized as follows. Section 2 presents our emotional model of collaborative robots. Section 3 gives details of our proposed method for task allocation. Section 4 discusses our experimental results. Section 5 concludes this work with a summary and future work.

2. Emotion model of cooperative robot

2.1. Emotion and personality

An emotional space can be described as a collection of four basic emotions as follows:

$$E = \{calm, happy, sad, angry\}. \tag{1}$$

Table 1
The personality components in the OCEAN model.

Personality component	Description
Openness	Open, imaginative
Conscientiousness	Responsibility, cautious
Extroversion	Outgoing, social
Agreeableness	Amiable, gentle
Neuroticism	Anxious, anger, impulse

Positive emotions, i.e., happy and calm, enhance the motivation and initiative of an individual; and negative emotions, i.e., sad and angry, reduce the willingness of an individual to get involved in a task. Hence, positive emotions should be cultivated [23]; yet, in the communication with human beings, mood needs to be in sync to better convey messages and provide assistance. We can use PAD space [24] as a transition space to get the emotional state as defined in the following.

The emotion of a robot can be in two distinct states: positive and negative states. Let f_s denote the state factor and the emotional state is expressed as follows

$$f_s = \begin{cases} 1, & Emo \geq \xi \\ 0, & Emo < \xi \end{cases} \tag{2}$$

where ξ is the boundary value between the two states, Emo is the value of the emotional state of robots. If the emotional state is greater than ξ, a robot r_i is in a positive emotional state and it is qualified to be allocated a task; whereas if emotional state is less than ξ, a robot r_i is in a negative emotional state and it is excluded from participating task allocation.

In contrast to emotion, personality is the relatively stable social tendencies of an individual. There are many personality models describe character traits and the most common one is the OCEAN model [20]. The OCEAN model describes personality through five dimensions as listed in Table 1. Based on the OCEAN model, we derive personality, expressiveness, and susceptibility.

The personality of a robot gives the probabilistic state of all five possible personalities in the OCEAN model:

$$Pers = \langle P_O, P_C, P_E, P_A, P_N \rangle \tag{3}$$

where each component follows the Gaussian distribution, i.e., $P_i = N\left(\mu_i, \sigma_i^2\right), \mu \in [0, 1], \sigma \in [-0.1, 0.1]$. Given the personality, the expressiveness is the ability of an individual expressing its emotions to others, which is mainly determined by the extroversion of personality,

$$Exp = w_{EE} \bullet P_E \tag{4}$$

where Exp denotes the expressiveness, P_E is the extroversion component of personality, w_{EE} is the weight.

Susceptibility is the ability of an individual capturing the emotions of others, which depends on the openness component of personality,

$$Sus = w_{OS} \cdot P_O \tag{5}$$

where Sus denotes susceptibility, P_O is the openness of personality, w_{OS} is the weight.

The expressiveness and susceptibility are the key factors of influencing on emotional contagion. Robots can be classified into four types: incentive, sympathetic, frank, indifferent. The incentive robot is of both stronger expressiveness and susceptibility; the sympathetic robot is of both weaker expressiveness and stronger susceptibility; the frank robot is of both stronger expressiveness and weaker susceptibility; the indifferent robot is of both weaker expressiveness and susceptibility.

Table 2
Behaviors and influencing personality factors.

Behavior	Description	Influence Factor
Emotional expression	Sociable, Active	P_E
Emotional acceptance	Perceptual, Introverted	P_O
Emotional contagion	Interact	P_E, P_O
Emotional attenuation	Decrease, Spontaneous	K_{type}, T
Leadership	Dominating, Confident, Independent	Emo, P_E, P_O

2.2. Mapping personality to behavior

The behavior of an affective robot is determined by its personality. For an affective robot, its behaviors are functions of personality:

$$BH = \{bh_1, bh_2, \ldots, bh_n\} \tag{6}$$

where each behavior bh_i is a function of personality:

$$bh_i = f_i (Pers), i = 1, \ldots, n \tag{7}$$

Table 2 lists the behaviors in task allocation and the most influencing factors of personality component. In this table, K_{type} is the coefficient of personality and f_s is emotional a state factor.

2.3. Emotion contagion

Robots form groups to meet the requirements of a task. We assume that the robot is permitted to perform the task only under the positive emotional state. Robots in the group are bound to be influenced by emotional contagion from others but vary in degree because of their different traits, e.g. expressiveness and susceptibility. In the same situation, robots' emotional experience type is the same but vary in the degree of recognition and evaluation. The formalized definition of emotional contagion is given as follow.

In a group $G = \{r_1, r_2, \ldots, r_n\}$, for the robot r_i, Emo_i denotes its value of the emotional state, Exp_i is its expressiveness, Sus_i is its susceptibility. The connection strength between the robot r_i and r_j is represented with con_{ij}, $con_{ij} \in [0, 1]$.

The behavior of robots' emotional expression through interaction depends on the robot's expressiveness which is further determined mainly by the extroversion of personality:

$$\begin{aligned} bh_{\exp} &\propto Exp, \\ bh_{\exp} &\propto P_E \end{aligned} \tag{8}$$

The behavior of robots accepting emotions of other robots depends on its susceptibility, which is further determined mainly by the openness of personality:

$$\begin{aligned} bh_{sus} &\propto Sus, \\ bh_{sus} &\propto P_o \end{aligned} \tag{9}$$

Emotional contagion represents the emotional interaction between robots in the group. After Δt time emotional contagion, the emotional state of the robot r_j has been changed to:

$$Emo_j^{t+\Delta t} = Sus_j Emo_{group_k} \Delta t + Emo_j^t \tag{10}$$

where $Group_k$ is the group where the robot r_j belongs to. Emo_{group_k} is the group emotion which is the weighted summation of the emotions of all members of the group:

$$Emo_{group_k} = \sum_{i \neq j, r_i \in group_k} Exp_i con_{ij} \omega_{ij} \Delta Emo_{ij} \tag{11}$$

where

$$\omega_{ij} = \frac{Exp_i con_{ij}}{\sum_{r_i \in group_k} Exp_i con_{ij}}, \quad \Delta Emo_{ij} = \begin{cases} Emo_i - Emo_j & , i \neq j \\ 0 & , others. \end{cases}$$

where ω_{ij} is the weight of the robot r_j in the group which represents its influence.

Without the stimulus, our emotion tends to decay to calm. Similarly, the emotion intensity of a robot decays over time and the attenuation rate is determined by personalities:

$$bh_{Att} = e^{-\frac{K_{type} \bullet T}{size}} \tag{12}$$

where K_{type} is the coefficient of personality, T is the detection period of attenuation.

The emotional state is influenced by the external emotional contagion and the internal emotional attenuation:

$$Emo^{t+1} = Emo^t + Emo_{Att}^t + Emo_{EC}^t \tag{13}$$

In a task environment, robots play different roles in a team, and there is a leader that takes on the responsibility of building a team. A leader is usually more confident, of excellent communication ability and able to better motivate other members.

A leader is selected based on the leadership property, which depends on the individual's emotional state, expressiveness, and susceptibility:

$$\begin{aligned} bh_{leadership} &= Emo \bullet Exp^{-Sus}, \\ bh_{leadership} &\propto Emo, \\ bh_{leadership} &\propto Exp, \\ bh_{leadership} &\propto^{-1} Sus \end{aligned} \tag{14}$$

In task allocation, the robot with strong cooperative intention has stronger team consciousness and is more willing to team up to perform a task together.

3. Task allocation based on emotional contagion

3.1. Pursuit task

In a multi-robot collaborative system, there are two roles: affective robot (pursuer)[1] and target (patient). A pursuer is an entity that has four properties, i.e., $R_i = \langle Pos_i^t, Emo_i^t, Pers_i, Cap_i \rangle$ where

Pos_i^t is the position of pursuer i at the time t, $Pos_i^t = (x_i^t, y_i^t)$;
Emo_i^t is the emotional state of pursuer i;
$Pers_i$ is the personality of pursuer i;
Cap_i is the capability of the pursuer i.

The pursuers form teams and are assigned to complete a task. Without loss of generality, we use the pursuit of a target in the rest of this article to explain our idea. A target is described as an entity with three properties, i.e., $T_j = \langle Pos_j^t, Cap_j, Reward_j \rangle$, where

Pos_j^t is the position of the target j at the time t, $Pos_j^t = (x_j^t, y_j^t)$;
Cap_j is the required capability of the target j;
$Reward_j$ is the reward of the target j.

The cost of each pursuer performing each task is represented with a matrix $Cost_{n*m}$, where an element $c_{ij} \in Cost_{n*m}$ is a distance between the pursuer i and target j, where

$$c_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \tag{15}$$

The gain of a team that fulfills a task T_j is computed by the difference between the rewards and costs:

$$Gain_j = Reward_j - Cost_j \tag{16}$$

where $Reward_j$ means the rewards brought by completing the task T_j and $Cost_j = \sum_{R_i \in team_j} c_{ij}$ is the total cost of the team j that is assigned to complete the task T_j.

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[1] Affective robot and pursuer refer to the same meaning in the following.

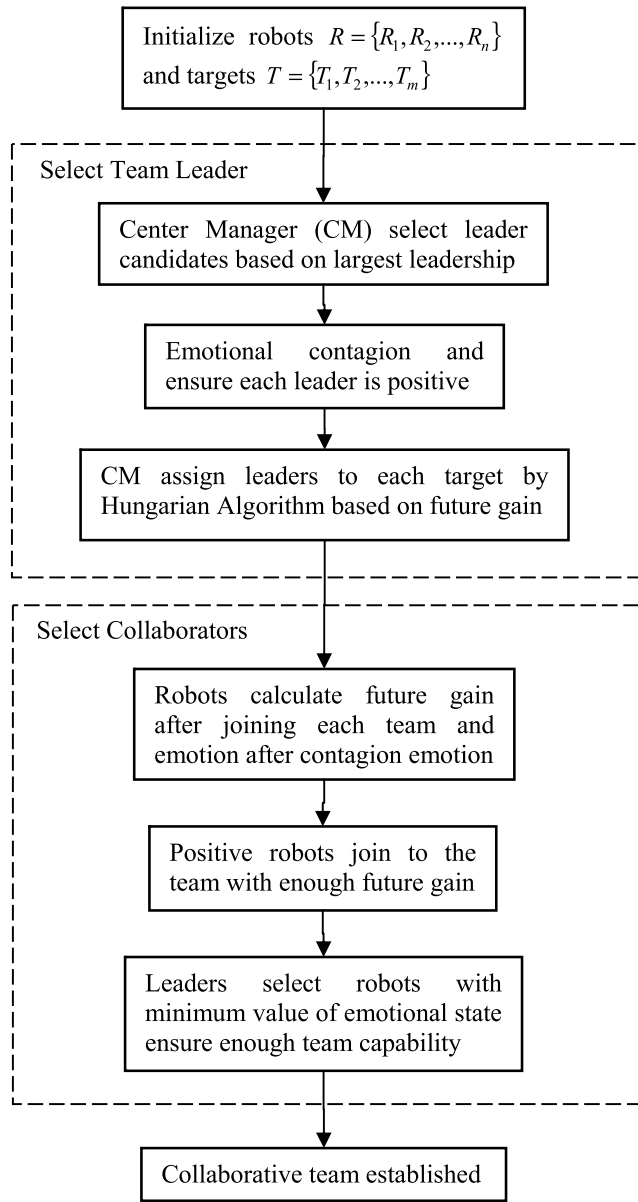**Fig. 1.** The flow chart of affective multi-robot task allocation algorithm.

The task allocation is presented with an allocation matrix $\boldsymbol{Q}_{N*M}$, each element of this matrix is a binary value that indicates if a target is assigned to a robot:

$$Q_{ij} = \begin{cases} 1, & \text{target } j \text{ is allocated to pursuer } i \\ 0, & \text{others} \end{cases} \tag{17}$$

3.2. Task allocation

Since robots may be not meet task requirements, their emotional state need be improved through emotional contagion. Thus emotional contagion throughout the process of task allocation. Task allocation algorithm includes two stages: selecting team leaders and selecting team collaborators. Leaders are selected based on their leadership and assigned task by Hungarian algorithm [25]. Collaborators join the team and are selected by leader based on their emotional state (see Fig. 1).

(1) **Selection of the team leader** See Fig. 2.

(2) **Selection of collaborators**

Table 3
The type of affective robot.

	Incentive	Frank	Empathetic	Indifferent
P_o	0.8	0.2	0.8	0.2
P_E	0.9	0.7	0.3	0.2

See Fig. 3.

3.3. Pursuit strategy

After the formation of the teams, teams adopt an appropriate strategy to pursue the targets. To simplify our discussion, we assume that the pursuers and targets' motion is in a virtual force field. Pursuers generate repulsive forces for targets, but the targets generate attractive forces for pursuers. Definition of repulsive and attractive force as follows:

$$F_{att} = \gamma \frac{1}{E_{dis_i}} \tag{18}$$

$$F_{rep} = \gamma \sum_{i \in group} \frac{1}{P_{dis_i}} \tag{19}$$

where γ is the scale factor, E_{dis_i} is the Euclidean distance between target and pursuer, P_{dis_i} is the Euclidean distance between the target and pursuer of corresponding pursuit team. Around the target position as the center draw a unit circle and divide the circle into h parts equally. The target calculates the repulsive force on each division point and chooses the point with minimum repulsive force as the next position. The pursuer adopts the similar strategy that is taking the maximum attractive force direction as pursuit direction.

Task complete determining factor $f_{capture}$ is defined as follow:

$$f_{capture} = \begin{cases} 1, & \exists E_{dis_i} \leq \varepsilon \\ 0, & \forall E_{dis_i} > \varepsilon \end{cases} \tag{20}$$

where $f_{capture} = 1$ denotes task success, $f_{capture} = 0$ denotes task failure, E_{dis_i} is the distance between pursuer and target, ε is the radius of success captured.

4. Experimental results

4.1. Emotional change of robots within a group

Various personalities of robots effect differently on the emotion of itself and others. The research of personality and emotion is useful to find a more efficient and agreeable combination of healthcare affective robots.

The affective robot is classified into four types based on the expressiveness and susceptibility: incentive, empathetic, frank and indifferent. It can be further expanded on this basis in view of the complexity and emphasis of different problems. In this paper, the parameters of each personality type are as follows (see Table 3).

(1) *Effect of emotional attenuation on robots of different personality*

The robot is divided into four different types according to the personality. The initial emotion of different type of robots is 0.9. When there is no emotional contagion between robots, the intensity of emotion changes respectively to 0.21, 0.08, 0.02 and 0.01 after 50 unit times in Fig. 4.

In this experiment, the change in emotion is mainly caused by emotional attenuation, which is mainly related to the extroversion component of personality. The weaker the extroversion is, the lower the degree of emotion catharsis and the slower the emotional attenuation. Among them, the indifferent robot with the minimum extroversion has the longest duration of emotional
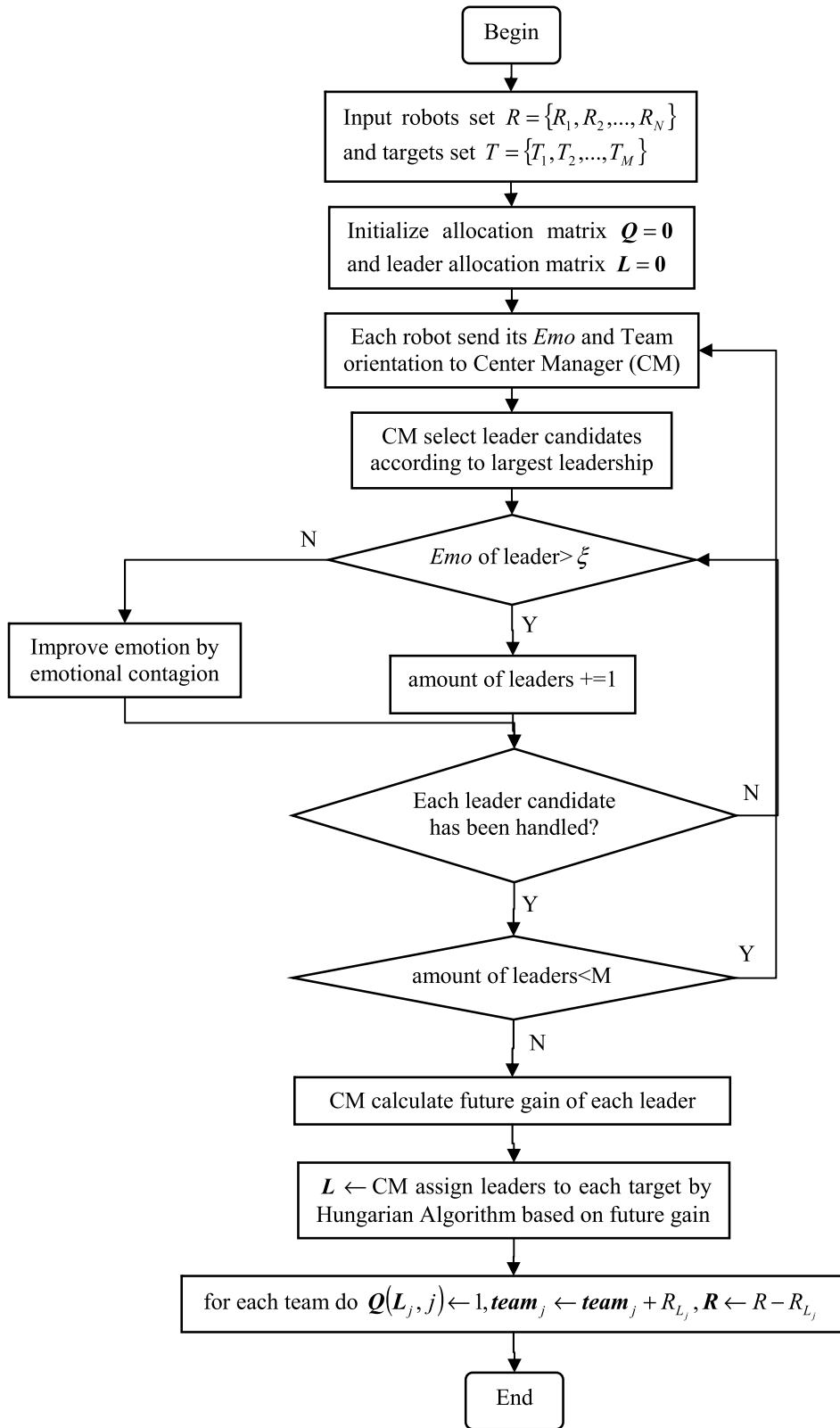
Fig. 2. The flow chart of the selection of the team leader.

intensity, while the incentive robot with the largest extroversion has the shortest duration.

(2) *Effect of emotional contagion to robots of different personalities*

The emotions of robots in the group are mainly influenced by the emotional contagion when there is emotional contagion. The initial value of emotional states of the four types of robots is 0.5. Given a special robot which personality components $P_O = 0.1$, $P_E = 0.9$ its emotional state is increased from 0.1 to 1. We study the influence degree of emotional contagion on the robots with different personalities through those four robots.
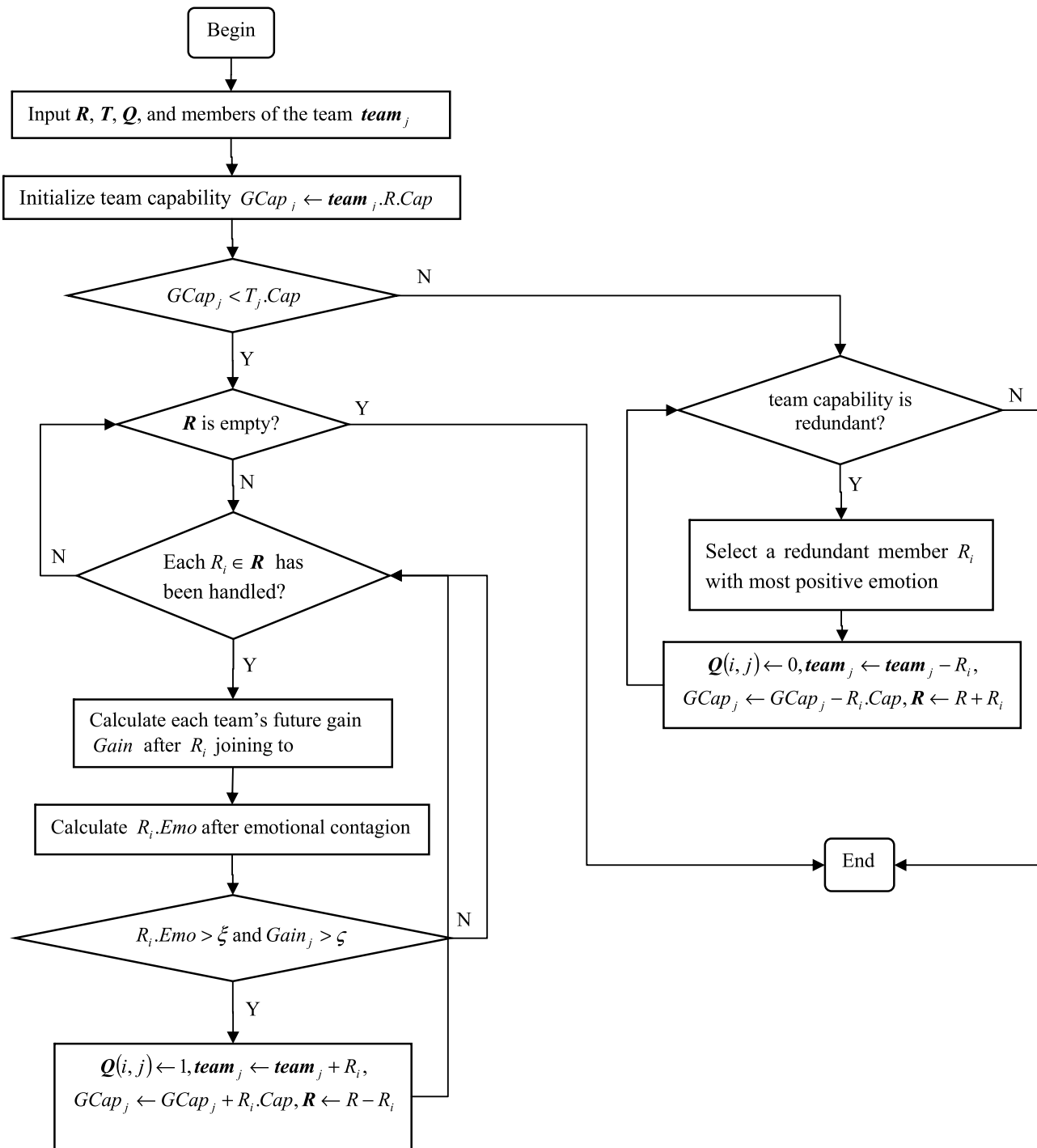
Fig. 3. The flow chart of the selection of collaborators.

When there is emotional contagion among robots, the changes in emotion is decided by emotional contagion. As shown in Fig. 5, the emotional changes of indifferent and frank robots are relatively stable, while the fluctuation of incentive and sympathetic robots' emotion are relatively large, the reason is that the sympathetic robot is better at capture emotion of others and incentive robot is more likely to motivate others.

(3) *Effect of different personality robots on the group*

There is a group of 100 random robots. The value of emotional states was random and obey normal distribution N (0.5, 0.1). The expectations of expressiveness and susceptibility are 0.5. The initial number of positive robots in the group is 44. After joining

different personality robots, the number of positive robots in the group is changed as shown in Fig. 6.

When the same number of different personality robots joins into the group, we can see that the most important contribution of robots to the group is the frank type and followed by the incentive robots, while the sympathetic robots and the indifferent robots almost have no effect on the group.

This phenomenon has become more obvious since the number of robots joined group reached 10. The number of positive robots respectively change to 62, 76, 45, and 41 when 10 incentive, frank, sympathetic and indifferent robots respectively join the group. Because the incentive and frank robots with stronger expressiveness

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Algorithm 1: Selection of the team leader

Input affective robots set $R = \{R_1, R_2, ..., R_N\}$ and targets set $T = \{T_1, T_2, ..., T_M\}$

Output allocation matrix $\boldsymbol{Q}$ and team member set $\boldsymbol{Team} = \{\boldsymbol{team}_1, \boldsymbol{team}_2, ..., \boldsymbol{team}_M\}$

Begin

    Initialize leader allocation matrix $\boldsymbol{L} \leftarrow \boldsymbol{0}, \boldsymbol{Q} \leftarrow \boldsymbol{0}$

    Each robot send its emotional state Emo to Center Manager(CM)

    while (amount of leaders < M) **do**

        CM calculates the leadership of each robot

        CM selects leader candidates according to largest leadership

        for each leader candidate **do**

            if $Emo < \xi$ **then**

                Improve the emotion of the leader candidate by emotional contagion

            else then

                amount of leaders $\leftarrow$ amount of leaders +1

    CM calculates the future gain of each leader

    $\boldsymbol{L} \leftarrow$ CM assigns leaders to each target by the Hungarian algorithm based on the future gain

    for each team **do**

        $Q(L_j, j) \leftarrow 1, \boldsymbol{team}_j \leftarrow \boldsymbol{team}_j + R_{L_j}, \boldsymbol{R} \leftarrow R - R_{L_j}$

    return $\boldsymbol{Q}$ and $\boldsymbol{Team}$

End

Algorithm 2: Selection of collaborators for each team j

Input allocation matrix $\boldsymbol{Q}$, members of the team $\boldsymbol{team}_j$, affective robots set $\boldsymbol{R}$ and targets set $\boldsymbol{T} = \{T_1, T_2, ..., T_M\}$

Output allocation matrix $\boldsymbol{Q}$

Begin

    Initialize team capability $GCap_j \leftarrow \boldsymbol{team}_j.R.Cap$

    while ($GCap_j < T_j.Cap$) **do**

        if ($\boldsymbol{R}$ is empty) **then**

            return $\boldsymbol{Q}$

        Leader releases recruiting information to all free robots

        for each $R_i \in \boldsymbol{R}$ **do**

            Calculate future gain $Gain$ of each team after R_i joining to

            $R_i.Emo \leftarrow$ emotion after emotional contagion

            if $R_i.Emo > \xi$ and $Gain_j > \varsigma$ **then**

                $Q(i, j) \leftarrow 1, \boldsymbol{team}_j \leftarrow \boldsymbol{team}_j + R_i, GCap_j \leftarrow GCap_j + R_i.Cap, \boldsymbol{R} \leftarrow R - R_i$

    for each $\{R_i | R_i \in \boldsymbol{team}_j$, and sorted by emotion in descending order$\}$ **do**

        if $\left\lceil \dfrac{GCap_j - T_j.cap}{R_j.cap} \right\rceil > 1$ **then**

            $Q(i, j) \leftarrow 0, \boldsymbol{team}_j \leftarrow \boldsymbol{team}_j - R_i, GCap_j \leftarrow GCap_j - R_i.Cap, \boldsymbol{R} \leftarrow R + R_i$

    return $\boldsymbol{Q}$

End

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can influence other robots more greatly, while the sympathetic and indifferent robots with weaker expressiveness less influence other robots so that the number of positive robots in the group is almost no change. Therefore, the number of incentive or frank robots should be increased in order to lead the group to more positive.

4.2. The process of task allocation

In this experiment, the process of the proposed task allocation algorithm will be detailed. Set the number of pursuers N = 4, the number of targets M = 2. The radius of success captured ε is set as 0.8. The velocity of the target is 0.9, the basic velocity of pursuer is 1.2 and velocity will slow down under negative emotional state,

$$v = v_{bas} - \lambda \cdot v \cdot Emo/\xi,$$

where v_{bas} is the basic velocity; $\lambda = 0.2$ is the proportionality constant, which represent the proportional relation between the velocity increment and basic velocity; Emo is current emotion state; $\xi = 0.5$ is a threshold of emotional state. We simulate the pursuit-evasion scenarios by MATLAB, and as shown in Tables 4 and 5, the attributes of robots and targets are generated with randomness which assures the universality of results.

The allocation of the pursuit task using the Task Allocation Based Auction Algorithm (TA_A) in [11] and PTA-EC is shown in Fig. 7.

In the task allocation phase, pursuit teams of the TA-A algorithm are $G_1 = \{r_1, r_2\}$ and $G_2 = \{r_3, r_4\}$, the pursuit time is 15.66, and the total gain is 128. The PTA-EC algorithm in this paper gets pursuer teams are $G_1 = \{r_1, r_3\}$ and $G_2 = \{r_2, r_4\}$, the pursuit time is 11.48, and the total gain is 161.
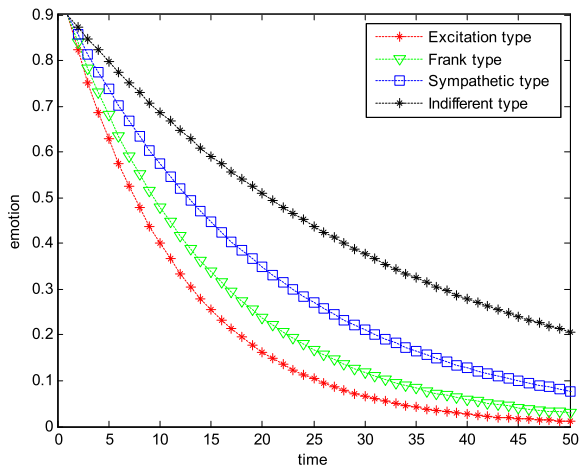
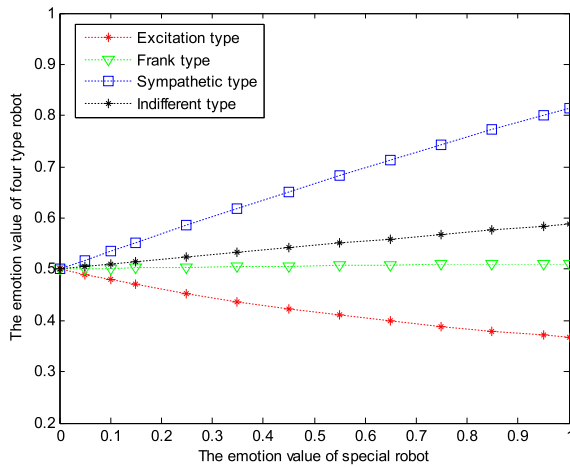**Fig. 4.** Emotional attenuation of robots with different personalities.

Fig. 5. Emotional contagion to robots with different personalities.
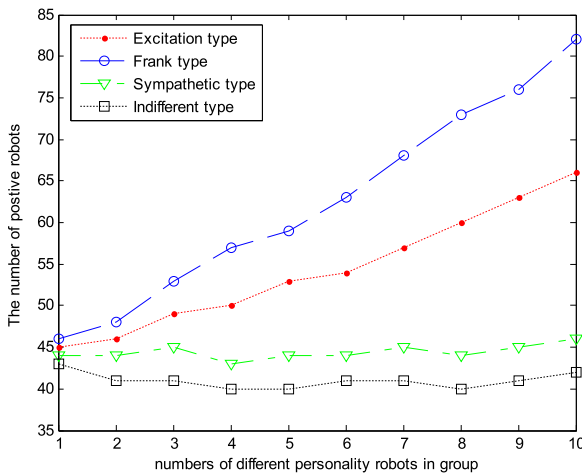

Fig. 6. The effect on the group of robots with different personalities.

The TA-A algorithm considers only the cost but no emotional mechanism, and recruits pursuers according to the principle of minimal cost. Thus the members of the team G_1 are r_1 and r_2 because they maximize the gain of G_1. The team G_2 can only choose r_3 and r_4 so that the team G_2 pursuit process is prolonged because of their weak cooperation willingness. The PTA-EC algorithm in this

Table 4
Initial information of the pursuers.

Pid	Posx	Posy	Emo	P_O	P_E	P_A	Cap
r_1	10	10	0.8	0.4	0.5	0.5	5
r_2	20	18	0.7	0.5	0.5	0.5	5
r_3	15	30	0.4	0.4	0.4	0.5	5
r_4	45	35	0.35	0.5	0.4	0.5	5

Table 5
Initial information on the targets.

Eid	Pos	Cap
e_1	10	9
e_2	30	8

Table 6
Comparison of time and gain.

	Time (s)			Gain		
	Max	Min	Average	Max	Min	Average
PTA-EC	117.8	65.79	81.86	351.8	233.7	287.3
TA-A	122.7	67.49	90.83	341.6	211.1	268.9

paper is different from the TA-A algorithm, this algorithm adds an emotion mechanism and determines team members through two stages. The first stage is selecting the team leader, that is r_1 and r_2, and respectively assign r_1 and r_2 to the team G_1 and team G_2 in view of maximizing the overall gain of the leader. The second stage is for the team leaders to select collaborators. Assign r_3 to the team G_1 and after emotional contagion, the emotional state becomes $Emo_1 = 0.6095$, $Emo_3 = 0.5524$; assign r_4 to the team G_2 and, after an emotional contagion, the emotional state becomes $Emo_2 = 0.5078$, $Emo_4 = 0.5038$. The emotional state of the two teams are both positive, so they achieve better experimental results. The results show that the proposed algorithm is better in the experimental scenario.

4.3. Comparison study

In this experiment, we will show the efficiency of the proposed method with compared to other methods. We conducted experiments using a large number of stochastic scenarios under the same conditions to evaluate the pursuit time and gain of each algorithm.

(1) Comparison of PTA-EC and TA-A algorithms

We generate 100 stochastic scenarios under the same conditions to evaluate the pursuit time and gain of TA-A algorithm and PTA-EC algorithm. Ten pursuers collaborate to serve four targets. The initial positions of robots are generated randomly in the range of 200 by 200. The total pursuit time and gain are shown in Fig. 8 and Table 6.

Fig. 8 illustrates the comparison of the time and gain used in the execution of a task. The x-axis is the number of experiment cases. The time and gain of PTA-EC are sorted and those of TA-A correspond to each scenario of PTA-EC. The maximum time of PTA-EC is less than 120 s; whereas the maximum time used by TA-A is about 124 s. The Fig. 8(a) clearly shows that our proposed method used much less time on average to complete the tasks. The time used by the PTA-EC algorithm is less than that of the TA-A algorithm in 81% of the experiments. Fig. 8(b) depicts the total gain of the task executors and the gain of the PTA-EC is greater than the gain of the TA-A in 74% experiments. One of the reasons that poor performance of PTA-EC in some experiments is that the experiments scenarios are extreme cases, e.g. each target is very close to a pursuer, our method considers affective factors so that the weight of the distance factor is less than TA-A which only considers distance and future gain.
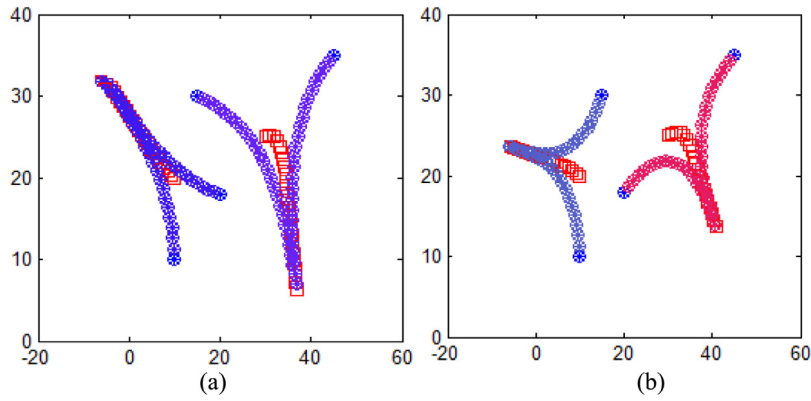
(2) Comparison of PTA-EC and TA-GOA algorithm

Fig. 7. Task allocation and performing of (a) TA-A Algorithm; (b) PTA-EC Algorithm.
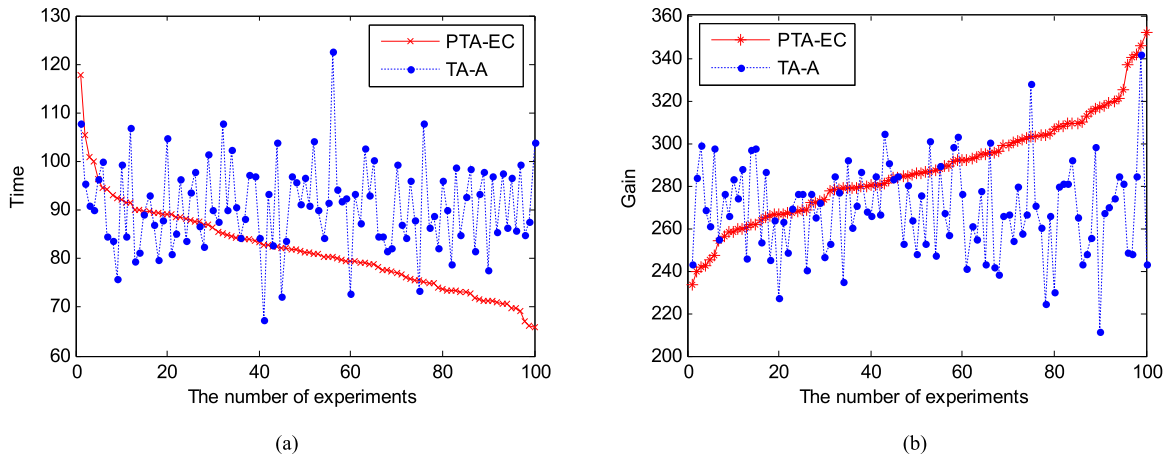

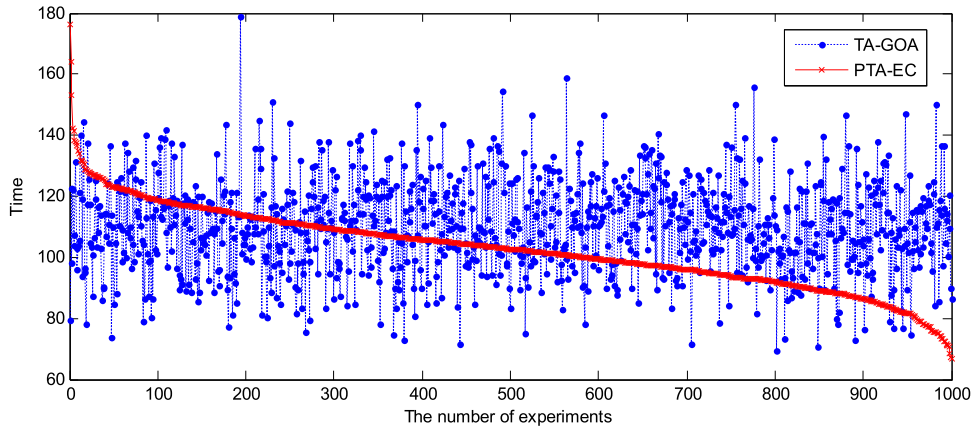**Fig. 8.** Total capture time and gain of the PTA-EC and TA-A.

Fig. 9. Total capture time of the PTA-EC and TA_GOA.

To further evaluate the effectiveness of the PTA-EC algorithm, we conducted 1000 experiment with random scenarios using our PTA-EC algorithm and instantaneous greedy optimal auction algorithm (TA-GOA). We evaluate the total pursuit time and gain, which are shown in Figs. 9 and 10, respectively (see Table 7).

In comparison with TA-GOA, PTA-EC spends less time in 75.4% of the testing cases and gets a higher gain in 80.3% of the testing cases, PTA-EC gets a greater gain. Because in the task allocation process, each pursuer of TA-GOA is self-interested and they choose the team with maximum gain, which could lead to a team formation

that some teams are formed with members that collectively possess abilities exceeding the minimum requirement whereas other teams fail to get capable members. In addition, PTA-EC allocates
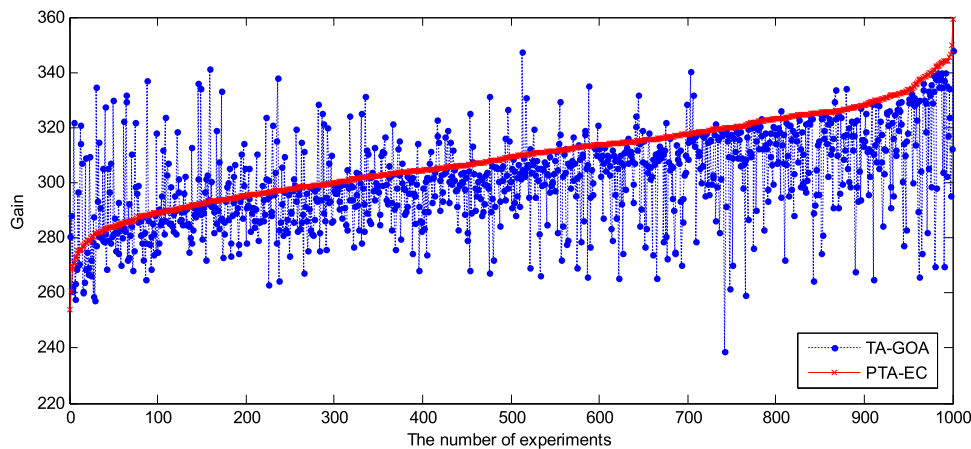
Table 7
Comparison of time and gain.

	Time (s)			Gain		
	Max	Min	Average	Max	Min	Average
PTA-EC	176.4	66.85	102.7	359.3	253.8	309
TA-GOA	178.8	69.56	110	348.1	239	301

Fig. 10. The total gain of the PTA-EC and TA_GOA.

tasks to leaders following the Hungarian algorithm that ensures that the allocation result is better than that of the TA-GOA method.

5. Conclusions

The paper presents a multi-robot task allocation algorithm for affective robots, defines emotion robot's personality, behaviors in task environment and the mapping from personality to behavior, and describes emotional contagion for robots' emotional interaction which is combined with MRTA. The paper then analyzes the impact of expressiveness and susceptibility of robots in the group. This paper proposed a novel method for scheduling collaborative robots to maximize outcomes and efficiency. The interconnected robots leverage emotion and personality to better communicate and synergy. We improved performance in comparison to the state-of-the-art methods and demonstrated promising results for healthcare applications.

This emotional multi-robot cooperative model can be applied to virtual or physical robots for healthcare and can further applied to other robotics interactions that involve a higher level of intelligence. The affective model in this work is simple relatively, and affective factors, such as personality, emotional state, and emotional attenuation, can be future optimized to better orient to the tasks. The type of personality can be extended from researches of human–human interaction and explore more combinatorial possibilities for better performance of task allocation.

Acknowledgments

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Baofu Fang, received Ph.D. degree in Computer Application Technology from Harbin Institute of Technology, China in 2013. He joined Department of Computer Science and Technology, School of Computer and Information, Hefei University of Technology in 2000, and An Associate Professor in 2010, and Master's Supervisor in 2011. His current research interests include multi robot/Agent system, emotion/self-interest robot and machine learning. He is the Technology Chair of Anhui Robot Competition, Member of Standing Committee of China Association of Artificial Intelligence (CAAI) Young Committee, Member of Standing Committee of China Association of Artificial Intelligence (CAAI) Robot and Culture Committee. He has published over 60 research papers in Journals and conferences.

Xiaoping Guo, received her BE degree in Computer Science and Technology from HuaZhong Agricultural University, China, in 2016. She is currently pursuing her ME in Computer Technology in the School of Computer and Information, Hefei University of Technology, Hefei, China. Her research interesting is multi-robot systems and affective computing.

Zaijun Wang, received her M. Eng. degree in Materials Science and Engineering from the Xihua University, China, in 2008. She is an Associate Professor of the CAAC Academy of Flight Technology and Safety, Civil Aviation Flight University of China. Her research interests include multi robot task allocation, artificial intelligence and data mining.

Yong Li received his M. Eng. degree in computer science and technology from Hefei University of Technology China. His research interests include multi robot system and emotion Robot.
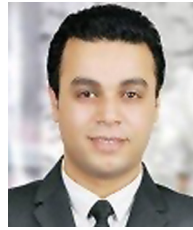
Mohamed Elhoseny received the PhD degree in Computer and Information from Mansoura University, Egypt (in a scientific research channel with Department of Computer Science and Engineering, University of North Texas USA He is currently an Assistant Professor at the Faculty of Computers and Information, Mansoura University. Collectively. He serves as the Editor-in-Chief of Big Data and Cloud Innovation Journal and Frontiers of Supercomputing. Besides, he is an Associate Editor of several journals including IEEE Access, and PLOS One journal. He guest-edited several special issues at journals published by IEEE, Hindawi, Springer, Inderscience, and MDPI. Moreover, he served as the co-chair, the publication chair, the program chair, and a track chair for several international conferences published by IEEE and Springer.

Xiaohui Yuan, received the B.S. degree in electrical engineering from Hefei University of Technology, China in 1996 and Ph.D. degree in computer science from Tulane University in 2004. After his graduation, he worked at the National Institutes of Health till 2006. He is currently an Associate Professor at the University of North Texas. His research interests include computer vision, data mining, machine learning, and artificial intelligence. Dr. Yuan is a recipient of Ralph E. Powe Junior Faculty Enhancement award in 2008 and the Air Force Summer Faculty Fellowship in 2011, 2012, and 2013. He is a senior member of IEEE.