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Task Allocation for Affective Robots Based on Willingness

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ABSTRACT Affection is regarded as a new solution to coordinate task allocation problems in the multi-robot system. In this paper, we proposed an interpretable and computational affection model based on willingness and a new personality model named CASE to measure the heterogeneity of the robot. Emotion contagion model is used to calculate affective interaction among robots, and we use willingness to quantify the impact of affective factors on task allocation and as an important factor for task allocation. Task allocation algorithm is designed for affective robots, and simulate the application of the affection model at task allocation by a typical example. It displays the characteristics and novelty of affection in task allocation and to verify the correctness, effectiveness, and novelty of affective robot task allocation algorithm. The result of the simulation experiment shows that affective robots in multi-robot cooperation systems obtain a better solution than rational robots and express the state of the art of task allocation for effective robots.

INDEX TERMS Affection model, emotional contagion, multi-robot system, task allocation, willingness.

I. INTRODUCTION

Affection plays a significant role in human life. Affective computing has gained much attention. One purpose that the robots are endowed with affection is to build software interface that allows users to experience naturalistic communication with the robot [1], especially in human-robot interaction [2]. A robot is capable of recognizing emotion and express emotion through the established emotional model. Some research-based robots are endowed with affection in order to study how affection is generated and act, for example, the interplay between affection and behavior [3] or thinking [4]. Affection has a role among multiple robots, which is yet to be explored.

Multi-robot system (MRS) has attracted academic and industrial attention and is widely used in many pertinent areas of industry and commerce such as demining [5], pursuit-evasion [6], search and rescue [7], environmental monitoring [8], and patrolling [9]. Multi-robot task allocation (MRTA) studies how to efficiently organize robots to perform the task with limited resources, which is one of the most challenging problems of MRS [10]. The goal of task allocation for the rational robot is to find the optimal solution. In communities, there are some behaviors such as cooperation and competitions among individuals. Thus, a common problem is the conflicts between the maximization of individual interests versus collective interests [11]. Besides, there are conflicts of interests between individuals. The focus should be balancing the needs of an individual and the group, and the affection will be a good solution. Currently, the main methods for multi-robot task assignment are behavior-based assignment methods, market mechanism methods, group intelligence methods, linear programming-based methods, and idle chain-based methods.

In addition, emotional recruitment-based methods for multi-robot task assignment. Affection has a significant effect on robot's behaviors. It regulates the social behavior and is a driving force of communication means [12]. Affection renders robot and robot team more autonomous and efficient [13]. Emotion is often the driving force of motivation, whether positive or negative [14]. The affective robots task allocation is a new combinatorial optimization problem with

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affective constraints and its goal is to find a balanced optimal solution.

Affective robots interact with task environment and each other. So how does the affection influence the decision-making of task allocation, and how does it change by the internal and external factors? We explore an interpretable and computable affection model based on willingness for the application of affection in robot cooperation. In this model, New personality model named CASE measures the heterogeneity of the robot and affection is modularized and quantified to measure the interplay with the task environment. The modules of affection model are integrated organically to MRTA. We simulate the affective interaction among robots. This paper systematically defines the key elements of an effective robot model and shows the impact of external stimuli, emotional contagion, and emotional attenuation to affection change and affective interaction between robots.

The key contributions of this paper are:

(1) An interpretable and computational affection model is designed for robot-robot interaction in cooperation system.

(2) the Conscientiousness, adventurousness, susceptibility, expressiveness (CASE) personality model is employed based on the OCAEN personality model to embody the heterogeneity of robots in task allocation.

(3) Emotion contagion model is used to calculate affective interaction among robots, and we use willingness to quantify the impact of affective factors on task allocation and as an important factor for task allocation.

(4) The result of the simulation experiment shows that affective robots in multi-robot cooperation systems obtain a better solution than rational robots and express the state of the art of task allocation for effective robots. The algorithm proposed in this paper was able to reduce the total experimental pursuit time significantly and the total gain were higher than the IGPA algorithm.

The rest of this paper is organized as follows. Section II reviews related work of affective computing and multi-robot collaboration. Section III presents our proposed model and details of affection updates including emotional attenuation, emotional contagion, and stimulation. Section IV introduces the algorithm of affective robot task allocation and experiment scenarios and instantiates the affection model in this scenario. Section V. discusses simulation experiments, and Section VI. concludes.

II. RELATED WORK

A. AFFECTIVE COMPUTING

Personality is a unique overall mental disposition with lasting and stable nature, which distinguishes the individual from others. The OCEAN model [15]–[17] is the commonest personality models, which has five factors: Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism, where Openness describes the degree of curiosity, creativity, and acceptance of new things; Conscientiousness reflects the organization and reliability; Extroversion represents the degree of interaction between the individual and the outside world; Agreeableness describes the tendency of friendliness of the individual to others; Neuroticism reflects the stability of affection and the control of compulsion.

Emotion is classified and described by many models. The discrete emotion theory states that there are several innate basic emotions. A popular example is the six basic emotions: anger, disgust, fear, happiness, sadness, and surprise concluded by Ekman [18]. The dimension method expresses emotion as a point in multi-dimensional space [19]. Pleasure, Arousal, Dominance (PAD) [20] is a typical dimensional method to describe and measure emotion state, which is defined as a space composed of three numerical dimensions: Pleasure, Arousal, and Dominance. The Pleasure measures how positive or negative the emotion state is; the Arousal indicates the degree of physiological arousal of emotion; the Dominance denotes the subjective control degree of emotion. The synthesis method divides the multi-dimensional space into regions, which combines the basic emotion theory and the dimensional method. The three-dimensional emotion structure proposed by Plutchik [21] is a typical synthetic method.

Individual's emotion is changed by internal and external influences, spreads between individuals and impacts on the performance of individuals. The process that individuals spread emotions to each other during their interaction is defined as emotional contagion [22]. In the process of interaction, individuals catch emotions from others through expressions, gestures, and language in real-world or social media [23], and express their own emotion, thus impact on their own and other individuals' emotional changes [24]. Bosse *et al.* [25], [26] established an emotional absorption model based on emotional interaction. The model considered emotion as an attribute of a group, emphasized the emotional interplay between members, and was simulated in a multi-agent community. Then the emotional contagion in the group was formalized and simulated, and the computational model was applied to the team collaboration [27]. Liu and Jin *et al.* [28] proposed the emotional contagion model in crowd scenes, studied the behavior of individuals under the influence of emotion, and emphasized the positive effect of managers on emotional contagion in crowded people. In our previous work [29] the emotional contagion was introduced into the task allocation of affective robot and validated the rationality and validity of the model by simulation experiments.

External stimulation is also one of the main causes of affection change. External stimuli cause individual affection change, and different types and intensities of stimuli may cause different changes in affection under the influence of different personalities. In previous work [30], a maximum similarity matching affection model was proposed to simulate the transfer of emotion state under the influence of stimulation by hidden Markov model (HMM) [31], the process of stimulation is elaborated in detail but the generation of stimuli is not mentioned.

B. MULTI-ROBOT TASK ALLOCATION

Task allocation is an essential research to the multi-robot cooperative system that is an allocation of subtasks in the system to an appropriate robot or robot alliance according to certain rules. Current multi-robot task assignments are based on three main areas:

1) Single-Task Robot (ST) vs. Multi-Task Robot (MT).

ST means that each robot can perform at most one task, while MT is that some robots can perform multiple tasks at the same time.

2) Single-Robot task (SR) vs. Multi-Robot task (MR).

SR means that each task requires only one robot to complete, while MR means that some tasks require more than one robot to complete.

3) Immediate assignment (IA) vs. Extended assignment (TE): IA is the immediate assignment of tasks to robots based on the information available about robots, tasks, and the environment, without planning for future assignments. TE, on the other hand, has more available information, such as the set of all tasks to be assigned or a model of how to obtain the tasks.

The main issue addressed in this paper is ST-MR-IA. Gerkey and Mataric [32] defined MRTA as there are given some robots and tasks. Each robot is capable of executing one task and each task requires one robot. The objective is to assign robots to tasks in such a way so that maximized overall performance can be achieved. There are many restrictions in task allocation, such as networks, energy, communication, real-time, and dynamic environment [33]–[35], and robots are mostly heterogeneous [36]–[38], which greatly increase the complexity of MRAT. Task allocation is an important foundation for efficient collaboration of robots, and its importance increases with the increase of system size and complexity.

Task allocation algorithm can be divided into centralized and distributed method according to the management mode. In centralized task allocation, there is a central control unit, which is responsible for centralized planning such as task release and robot recruitment. The auction algorithm [39] is a typical centralized allocation method. We [40] have applied a contract-based method to assign tasks, and a virtual central administrator is in charge of collecting task information, inviting bids, and authorizing contracts. Das *et al.* [41] proposed a market-based multiple tightly couple multi-robot tasks allocation algorithm simultaneously, which makes multiple tasks allocated at the same time and makes robots more evenly distributed to the team. In distributed task allocation, robots allocate task without central control unit. They make decision autonomously according to the real-time circumstance and communication with each other, for example, threshold response [42], swarm intelligence method [43], [44], and neural network method [45], [46]. Wang *et al.* [44] allocated the robots with a high cooperation intention by the modified particle swarm optimization (PSO) alliance generation algorithm to generate the pursuit alliance. Sun *et al.* [45] proposed a self-organizing algorithm based on self-organizing map neural network and integrated task allocation into the training process of the network. Lee [47] proposed a resource-based task allocation algorithm for multi-robot system enables the robots to reduce unnecessary wastage of time and resources during the mission. Mayya *et al.* [48] designed a decentralized mechanism to allocate tasks to each robot by using the spatial interactions that occurs when the robots move in the domain. Pang *et al.* [49] introduced the traffic flow density and the amount of obstacle avoidance together to build a task allocation model for adjusting the number of working robots autonomously in a swarm of foraging robots. Wei *et al.* [50] proposed a two-step scheme consisting of task partitioning and autonomous task allocation to overcome the difficulties of the bootstrapping problem and deception. Li *et al.* [51], [52] analyze a two-stage game in which leadership group members contribute before following the group and propose an accurate metric, leadership, to characterize key leaders. Then an efficient dynamic system is used to ensure that the cluster configuration converges to an optimal state. The distributed task allocation method is used widely because it is more practical, robust, and real-time.

III. AFFECTION MODEL BASED ON WILLINGNESS

Our proposed affection model, as shown in Fig.1, includes three components (personality, emotion, and willingness) and three relations (emotional attenuation, emotional contagion, and stimulation). Personality, emotion, and willingness are the fundamental components of the affection model. The relations update the states of affection.

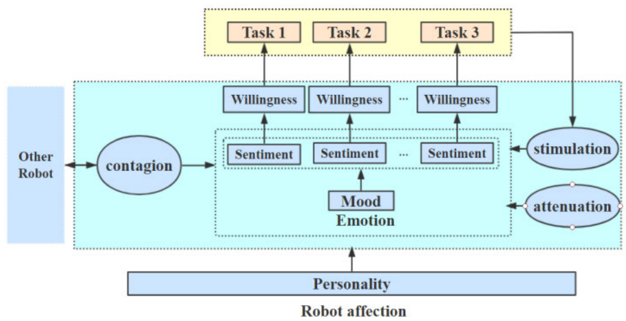

FIGURE 1. The affection model of the robot in task allocation which includes three components which are personality, emotion, and willingness and three relations include emotional attenuation, emotional contagion, and stimulation.

Personality is a long-term and stable psychological disposition and characters and is the main factor of distinguishing individuals from others. Personality decides the overall trend of affection changes.

Emotion contains mood and sentiment, and the difference is the objective it directs at. The mood is the robot's internal state of mind, which is directed at the robot itself. The sentiment is a series of feelings for task objective, which is directed at task objective. A robot can concurrently hold different sentiments for each task. Emotion is influenced by personality and external factors.

Willingness is proposed for multi-robot task allocation, which estimates the degree of the desire of the affective robot to a task objective. It is calculated from robot's sentiment for the task objective. A key point of this model is associating the affective factors with rational task environment. The change of willingness reflects the influence of task environment on affection change.

Emotional attenuation is modeled according to the emotional intensity third law (emotional intensity attenuation law), which is that emotion attenuate over time. Emotional contagion represents that the emotional interaction between robots and changes the mood. Stimulation comes from the external environment, which can be divided into object, event, and action stimulation according to sources. Object stimulation originates from the entities that interact with the robot, which impact the sentiment. Event stimulation and action stimulation impact the mood.

A. THE KEY FACTORS OF AFFECTION MODEL

1) PERSONALITY

Personality is robot's inherent characteristic, which embodies the heterogeneity and diversity of robot in the community. Personality determines the overall behavioral and ideological tendency of an individual. For example, a bold robot is more likely to perform a risk task than a cautious one. The OCEAN model is most widely used to describe personality, which is expressed as:

$$\boldsymbol{per}_{\text{ocean}} = [o, c, e, a, n] \tag{3.1}$$

where o, c, e, a, n are openness-intellect, conscientiousness, extroversion, agreeableness, and neuroticism respectively, $o, c, e, a, n \in [-1, 1]$.

Our affection model, however, aims at multi-robot cooperation. The OCEAN model is of good versatility but not well meets the requirement of task allocation. Thus, we propose the CASE model to represent the personality of robots in cooperation system. The model consists of four characteristics: Conscientiousness, Adventurousness, Susceptibility, Expressiveness, which directly influence task allocation. Conscientiousness describes the responsibility of a robot for completing the task and show cautious, dutiful, and organized; Adventurousness determines the acceptance of a robot for high risk and high reward tasks; Susceptibility reflects the ability of a robot to be influenced by others' emotions; and Expressiveness describes the ability of a robot to express its own emotions. Therefore, the personality of cooperating affective robot is expressed as:

$$\boldsymbol{per}_{\text{case}} = [con, adv, sus, exp] \tag{3.2}$$

where con, adv, sus and exp denote conscientiousness, adventurousness, susceptibility, and expressiveness respectively. $con, adv, sus, exp \in [0, 1]$. $\boldsymbol{per}_{\text{case}}$ represents the CASE personality of robots in task allocation.

Considering compatibility and further expansion, the OCEAN model is still involved in emotional computing because of its versatility. Therefore, the transfer from CASE model to OCEAN model is necessary, so that the personality model not only meets the requirements of task allocation but also is convenient for affective computing.

Conscientiousness has a specific description of the OCEAN model, so the conscientiousness in the CASE model corresponds to that in the OCEAN model. Adventurousness is used to measure the acceptance of individual to the risky task, which is related to the openness, extroversion, agreeableness, and neuroticism in OCEAN model, high adventurousness corresponds to high openness, high extroversion, high neuroticism and low agreeableness. Susceptibility and expressiveness of individuals are related to openness, extroversion, and agreeableness in the OCEAN model. High susceptibility corresponds to high openness, low extroversion, and high agreeableness. High expressiveness corresponds to high agreeableness and high extroversion.

According to the above analysis, the transfer matrix from CASE personality model to OCEAN model is obtained:

$$M_{\text{per}} = \begin{bmatrix} 0 & 1 & 0 & 0 & -1 \\ 1 & 0 & 1 & -1 & 1 \\ 1 & 0 & -1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

where M_{per} is the transfer matrix. The personality of task allocation can be mapped to OCEAN personality model by this transfer matrix:

$$\boldsymbol{per}_{\text{ocean}} = Norm\left(\boldsymbol{per}_{\text{case}} * M_{\text{per}}\right) \tag{3.3}$$

where $\boldsymbol{per}_{\text{case}}$ is CASE personality in task allocation, which intuitively reflects the influence of personality on task allocation; Norm is the normalized function in [−1,1]. $\boldsymbol{per}_{\text{ocean}}$ describes personality in the OCEAN model.

2) EMOTION

In this work, emotion is described by the discrete emotion method:

$$\boldsymbol{emo}^t = [e_1, e_2, \ldots, e_N] \tag{3.4}$$

where $\boldsymbol{emo}^t$ is the emotional state (mood or sentiment) at time t, N is the number of basic emotion kind, e_i is the intensity of basic emotion i $(i = 1, 2, \ldots, N)$, $e_i \in [0, 1]$.

Moffat [53] defines that emotion is a brief, changeful, and focused (directed at an object) disposition, while sentiment is distinguished as a long-term, stable, and focused disposition. Eladhari [54] creates the Mind Model for characters in virtual game worlds referring to the model settings of Moffat. Similarly, we define sentiment as a brief, changeful, and focused affection, while the mood is brief, changeful, and global. The difference between two concepts is whether they are focused.

Mood: The mood is the internal psychological state and changed by inherent attenuation, external stimulation, and interaction with other individuals. The mood is represented as:

$$\boldsymbol{mood}_t = \left[e_m^1, e_m^2, \ldots, e_m^N\right] \tag{3.5}$$

where e_m^i is the intensity of basic emotion i component of mood state.

Sentiment: The sentiment is robot's affective connection to the task.

$$\boldsymbol{sent}_{ij}^t = \left[e_s^1, e_s^2, \ldots, e_s^N\right] \tag{3.6}$$

where $\boldsymbol{sent}_{ij}^t$ is the sentiment of robot i for task j, e_s^i is the intensity of basic emotion i component of sentiment state.

The sentiment of the robots for a new task is initialized by current mood state and changes in the interaction process. The current sentiment of the robot is decided by the previous moment sentiment, the external stimuli, and inherent attenuation.

3) WILLINGNESS

We put forward willingness to measure the desire of affective robot to task objective, which is determined by the sentiment of each task objective and varies with the difficulty, reward, and risk factors of the task. Each affective robot has a willingness to each task objective. Robot decides to perform a task or not mainly based on the willingness, and willingness is also impacted by stimuli in task environment, thereby the effective combination of affection model and task environment is realized.

Positive affection produces a greater willingness. Therefore, a model that represents the positive and negative aspects of emotion is necessary to calculate willingness. PAD model meets the requirement properly, where the dimension of pleasure can be used to show the positive and negative property of emotion (values range from -1 to 1). Suppose there are m tasks, the willingness of a robot i is:

$$\begin{aligned} W_i &= \{w_{i1}, w_{i2}, \ldots w_{im}\} \\ w_{ij} &= \boldsymbol{sent}_{ij} * M_{\mathrm{EP}} * \left[\lambda_p, \lambda_a, \lambda_d\right]^T \end{aligned} \tag{3.7}$$

where w_{ij} denotes the willingness of robot i for task j, $\boldsymbol{sent}_{ij}$ denotes the sentiment of robot i for task j; M_{EP} is the transfer matrix from basic emotion to PAD space [30], λ_p, λ_a, λ_d are the weights corresponding to three dimensions of PAD space, $\lambda_p + \lambda_a + \lambda_d = 1$, and are set as 0.7, 0.1, 0.2 following [40].

Willingness reflects the impact of affection on task allocation, and it varies with the change of sentiment. The change of sentiment is determined by the personality of robot and stimuli in task environment; therefore, the willingness is a foremost reference for task allocation which comprehensively reflects various influences.

B. AFFECTION INTERACTION AND CHANGE

Affection change mainly refers to the change of emotion, which is under the influence of personality. The main reason for affection change is the inherent emotional attenuation and external emotional contagion and stimulation. Emotional attenuation is mainly determined by the personality of a robot, emotional contagion comes from other robots interacted with it, stimulation generates from task objectives and the events and actions in interaction processes. Affection change is finally embodied through willingness and impact on task allocation and execution.

1) EMOTIONAL ATTENUATION

The third law of emotional intensity in psychology points out that the relationship between emotional intensity and duration is negatively exponential. Emotional attenuation rate varies with the personality of the individual, for example, the emotion of sadness will attenuate quickly if the individual is of optimistic personality, but attenuate relatively slowly if the individual is of negative personality. Emotional attenuation is represented as:

$$\boldsymbol{emo}_t = \boldsymbol{emo}_{t-1} \exp\left(-K_{\mathrm{type}} T\right) \tag{3.8}$$

where K_{type} is the attenuation rate for a type of personality and T denotes attenuation period. $\boldsymbol{emo}_t$ is the emotional state at time t.

2) EMOTIONAL CONTAGION

Suppose the mood state of the robot r_i at time t is $\boldsymbol{mood}_j^t = \left\{e_1^t, e_2^t, \ldots, e_N^t\right\}$, its expressiveness is exp_j, and susceptibility is sus_j. By emotion contagion, the amount of emotion that robot r_i receives after a period of ∇t is:

$$\boldsymbol{emo}_j^{\Delta t} = sus_j * \nabla t * \boldsymbol{emo}_{team_k} \tag{3.9}$$

where the robot r_i is the member of team k, $*$ refers to the products of a number and a vector, $\boldsymbol{emo}_{team_k}$ denotes the team emotion:

$$\begin{aligned} \boldsymbol{emo}_{team_k} &= \sum\nolimits_{i \neq j, r_i \in team_k} exp_i con_{ij} \omega_{ij} \boldsymbol{\nabla m} \\ \omega_{ij} &= \frac{exp_i con_{ij}}{\sum_{r_i \in team_k} exp_i con_{ij}} \end{aligned} \tag{3.10}$$

where $\boldsymbol{\nabla m} = \boldsymbol{mood}_i^t - \boldsymbol{mood}_j^t$, and con_{ij} is the strength of the connection between the robot r_i and r_j, $con_{ij} \in [0, 1]$, $con_{ij} = 1$ denotes there is a strong connection between them, and $con_{ij} = 0$ denotes there is no connection; ω_{ij} is the weight of robot r_i in the team, which represents its influence in the team when expressing its emotion.

According to the above formula, it can be seen that the highly expressive robots are better at expressing their emotions, and can express more emotions to team emotion. In addition, highly susceptible robots are better at absorbing others' emotions and are able to absorb more emotion from team emotion.

3) STIMULATION

The external stimulation is the one of the main cause of affection change throughout the task allocation and performance process. Stimulation is divided into object, event, and action stimulation according to the affection cognitive theory [55]. Object stimulation refers to the real-time impact from other entities on the affection of the individual. For instance, a task objective generates an object stimulus to a robot who performs this task. Object stimulation occurs in the whole process of the task allocation and execution. Event stimulation refers to the impact of events on an individual. For example, in MRTA, if a robot is selected as a team leader, it will be stimulated by a positive event stimulus. Action stimulation refers to the stimulation of the robot's own behavior. If a robot fulfills the task, the action "fulfilled task" will produce a positive stimulus to the robot, and a higher gain results in a stronger stimulus. Stimulation directly impacts the change of robots' affection, and further impacts the change of willingness. Thus, stimulation embodies the impact of the external environment to robots' affection.

There are many kinds of stimulus:

$$SV = \{\boldsymbol{sv}_1, \boldsymbol{sv}_2, \ldots, \boldsymbol{sv}_K\} \tag{3.11}$$

where SV denotes the set of stimulus kinds, $\boldsymbol{sv}_k$ is a fundamental stimulus ($k = 1, 2, \ldots, K$), which is defined as how much degree stimulus k impact emotion:

$$\boldsymbol{sv}_k = [sv_1, sv_2, \ldots, sv_N] \tag{3.12}$$

where sv_i represents the degree this stimulus impact on the basic emotion i and $sv_i \in [0, 1]$.

The definition of fundamental stimulus vector can be different with the system requirements, and the more kinds of the vector are defined, the more comprehensive system is, and the more complex corresponding calculation is. Therefore, stimulus and its calculation are versatile, which can easily extend to other systems.

The intensity of stimulus varies with its determinants, for example, the determinant of reward stimulation is the reward of the task, and the higher the task rewards, the stronger the stimulus is. The stimulus is calculated by the determinants and fundamental stimulus vector:

$$\boldsymbol{S}_k = \boldsymbol{st} \cdot \boldsymbol{sv}_k \tag{3.13}$$

where $\boldsymbol{S}_k (k = 1, 2, \ldots, K)$ denotes a stimulus; st is the strength of determinant, $\boldsymbol{sv}_k (k = 1, 2, \ldots, K)$ is the corresponding kind of fundamental stimulus vector. · refers to the dot products of two vector.

Different types of stimuli impact different modules of affection model. Object stimuli impact the sentiments of the robot for each task objectives because they relate to task objectives. Event and action stimuli, because generate from the robot itself, impact on the mood state. The stimulation process of emotion:

$$\boldsymbol{emo}_t = HMM\left(\boldsymbol{per}_{\text{case}}, \boldsymbol{emo}_{t-1}, S\right) \tag{3.14}$$

where $\boldsymbol{per}_{\text{case}}$ denotes personality used to calculate the limit probability distribution of emotional state, $\boldsymbol{emo}_{t-1}$ is the emotional state of the previous moment; S represents a stimulus. HMM is the emotion transfer model under external stimulation [30].

IV. TASK ALLOCATION BASED ON WILLINGNESS

In the process of multi-robot task allocation and cooperation, the influence on robot's behaviors should not only be rational practical factors (such as capabilities, resources, etc.), emotion also plays an important role. For example, robots with positive emotion state are more willing to perform tasks than robots with the negative emotional state, and bold robots more dare to accept high-risk tasks than cautious robots. There are many solutions to the task allocation problem in rational robots, but it cannot be simply applied to affective robots. We already constructed an affection model for multi-robot cooperation and put forward the willingness to reflect the impact of affection on task allocation while willingness is impacted by the external environment. Thus, we need to design a task allocation algorithm for affective robots.

Firstly, the formalized definition of multi-robot task allocation is provided as follows. In multi-robot task allocation, there are given n robots and m tasks. Each robot performs no more than one task and each task requires a certain number of robots. The objective is to assign robots to tasks in such a way so that maximized overall performance can be achieved.

The set of robots is defined as $R = \{R_1, R_2, \ldots, R_n\}$, R_i denotes the robot i and is represented as a triad, $R_i = \langle Info, Cap, Cost\rangle$, where:

— *Info* represents the identity information of robot, including ID, type, personality;

— *Cap* represents the set of capabilities of the robot, such as velocity, the range of the sensor;

— *Cost* represents the set of cost of robot work, such as energy consumption, communication bandwidth, etc.

The set of tasks is defined as $T = \{T_1, T_2, \ldots, T_m\}$, T_j denotes the task j and is represented as a triad, $T_j = \langle Info, Req, Rew\rangle$, where:

— *Info* represents the basic information of the task, such as position, type;

— *Req* represents the requirement of performing the task, that is the requirement of capabilities of robots;

— *Rew* represents the reward of fulfilling the task.

A. TASK ALLOCATION

In a task allocation, robots with the same task objective compose a team, and the number of teams is decided by the number of task objectives. To organize the limited resources effectively to complete the task [56], a leader should be chosen from the robot team. The personality of a leader should be confident, outgoing and expressive. Leadership is defined as the basis for the choice of leader, which is related to the robot's personality and the current emotion state.

Definition Leadership depends on the individual's mood, susceptibility, and expressiveness.

$$leadership = \boldsymbol{mood} * \boldsymbol{\lambda} \cdot sus^{-exp} \tag{4-1}$$

where $\boldsymbol{\lambda}$ is the coefficient vector, $\boldsymbol{\lambda} = \begin{bmatrix} \lambda_1 & \ldots & \lambda_i & \ldots & \lambda_N \end{bmatrix}^T$, $\lambda_i \in [0, 1]$; sus and exp are susceptibility and expressiveness, respectively. · refers to the

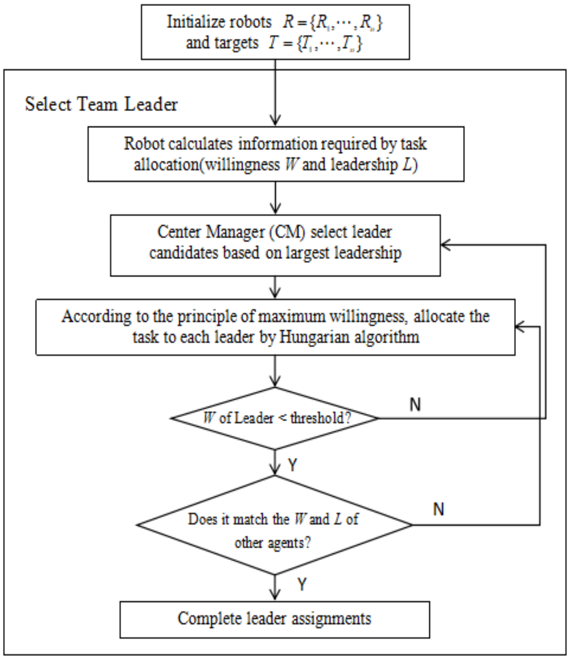

FIGURE 2. **The flow chart of the selection of the team leader.**

dot products of two vector. $*$ refers to the products of a number and a vector.

So, the leader of each team should be selected firstly, who then recruits members. 1) The algorithm for selecting a team leader, and the flow chart as shown in Fig. 2.

Step1: Object stimuli are generated from task objectives, and impact all robots. According to robot's affection impacted by simulation, each robot calculates information required by task allocation, such as willingness and leadership, and then send this information to other robots.

Step2: Each robot forms a global willingness matrix and a leadership list combining others information.

Step3: Choose robots with the highest leadership ability as the leader candidate, the number of leaders equal to tasks.

Step4: According to the principle of maximum willingness, allocate the task to each leader by Hungarian algorithm [57] and form a task allocation matrix of leader. If each leader's willingness to its task is higher than the threshold, continue; otherwise, if there is a willingness of candidate is lower, whose leadership in the list is set to 0, to Step3.

Step5: Leader candidates send candidate message to all robots. Each robot compares these messages with its own allocation matrix, if allocation results are same the robot will agree with the candidate as a leader; otherwise, the robot will resend the message.

Step6: If all robots agree that all candidates become leaders, the leader allocation is finished; otherwise, turn to Step2.

Algorithm 1 Selecting Team Leader

```
Input robot set R = {R1, R2, ..., Rn} and task set T =
{T1, T2, ..., Tm}
Output leader allocation matrix L
Begin
    Compute robots' emo after stimulation using (3.9)
    Compute robots' W using (3.2)
    Compute leadership using (4.1)
    while (L == NULL)
        Select m leaders from robots with maximum
         leadership
         L ← allocate m tasks to m leaders by
        Hungarian
algorithm
        for j ← 1: m
            if leader(j) · W(j) < threshold
                leadership(leader(j)) ← 0
                L ← NULL
    return L
end
```

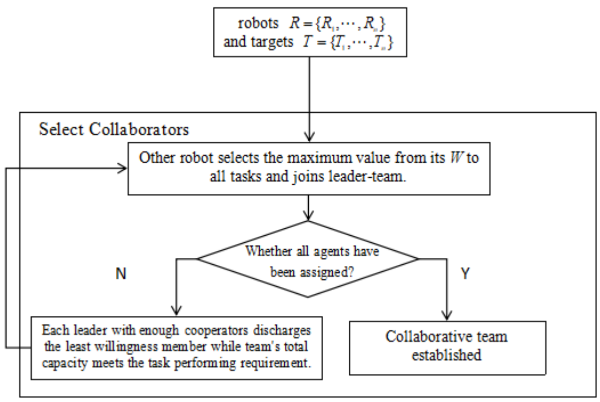

FIGURE 3. **The flow chart of the selection of collaborators.**

2) The algorithm of recruiting members, and the flow chart as shown in Fig. 3.

Step1: Each robot sets the column of all leaders in the willingness matrix as the maximum value to prevent reselection;

Step2: Each robot selects the maximum value from its willingness to all tasks, then automatically joins the corresponding team of the task.

Step3: If all teams meet the task performing requirement, the task allocation is finished. Otherwise, the leader who is short of cooperators sends a notice to other leaders.

Step4: Each leader with enough cooperators discharges the least willingness member while ensures that its team's total capacity meets the task performing requirement. The leader who is short of cooperators selects cooperators with the maximum willingness from free robots until the task performing

Algorithm 2 Recruiting Members

Input robot set $R = \{R_1, R_2, \ldots, R_n\}$ and task set $T = \{T_1, T_2, \ldots, T_m\}$
Output allocation matrix $\boldsymbol{A}$
Begin
  for $j \leftarrow 1{:}\ m$
    leader(j). $W(j) =$ MAXIMUM
  for $i \leftarrow 1{:}\ n$
    $j \leftarrow$ the index of the maximum willingness of robot i
    if $R_i.W\ (j) >$ threshold
      $A\ (i,j) \leftarrow 1, R \leftarrow R - R_i$ //robot i join the team j
  while$((\exists T_k) \sum_{R_l \in team_k} Cap_l < Req_k)$
    for $j \leftarrow 1{:}\ m$
      $i \leftarrow$ the index of the minimum willingness robot in team j
      if $\sum_{R_l \in team_j} Cap_l - Cap_i > Req_j$
        $A\ (i,j) \leftarrow 0, R \leftarrow R + R_i$ //discharges the robot
    for $j \leftarrow 1{:}\ m$
      while$(\sum_{R_l \in team_j} Cap_l < Req_j)$
      if $R ==$ NULL//team capability is insufficient but there
        are no free robots
        return NULL
      for $i \leftarrow 1{:}$ length(R)
        if $\boldsymbol{R_i.W\ (j)} >$ threshold
          $A\ (i,j) \leftarrow 1, R \leftarrow R - R_i$
  return $\boldsymbol{A}$
end

requirement is met. The rest of free robots rejoined the original team. If the task performing requirement is still not satisfied, task allocation fails.

B. TASK REALLOCATION

When a team fulfills the task, the emotional state of the team members will be enhanced positively. Then their willingness may be higher than other robots who are performing tasks, it will lead to reallocate tasks. In addition, during the process of performing tasks, the robot will quit the team when its willingness drops below the threshold because of emotional attenuation. If the team unable to fulfill the task because being short of capacity, it will lead to reallocate tasks. Frequent reallocations will reduce pursuit efficiency, we can reduce the frequency of task reallocation by adjusting the willingness threshold.

V. SIMULATION EXPERIMENT

Multi-robot pursuit-evasion [6] is a typical task allocation scene and in this work is used to simulate our affective model and algorithm. On an unbounded two-dimensional continuous plane, there are some evaders (task objectives) and pursuers (affective robot), all evaders and pursuers could appear in any coordinate and move in any direction with a default step size. Pursuers have a global view so that they can directly allocate task without searching [58]. Each pursuer selects an evader through task allocation as the task objective, and pursuers with the same task objective constitute a team. The evader is captured successfully on the requirement that the distance between the evader and pursuers is less than the default capture radius r and the total capacity of pursuers is greater than that of the evader. The pursuer who fulfills a pursuit task could continue to chase other evaders until all evaders are captured.

The set of evaders is defined as $E = \{E_1, E_2, \ldots, E_m\}$, E_i denotes the evader i and is a triad, $E_i = \langle \boldsymbol{pos}, cap, rew \rangle$, where:

— ***pos*** represents the position of evader in the two-dimensional pursuit scene $\boldsymbol{pos} = (x, y)$;

— *cap* represents evader's capacity. The greater the capacity, the higher the risk is, and the more difficult the task is;

— *rew* represents the reward of a successful capture.

The set of pursuers is defined as $P = \{P_1, P_2, \ldots, P_n\}$, P_i denotes the pursuer i and is a five-tuple, $P_i = \langle \boldsymbol{per}, \boldsymbol{emo}, \boldsymbol{pos}, cap, cost \rangle$, where:

— ***per*** represents the personality of pursuer;

— ***emo*** represents the emotion state;

— ***pos*** stands for the location of the pursuer;

— *cap* stands for the capacity;

— *cost* represents the cost of the pursuer for performing the task.

Definition f_{suc} is the judgment condition of successful pursuing, $f_{\text{suc}} = 1$ is success, $f_{\text{suc}} = 0$ is fail:

$$f_{\text{suc}} = \begin{cases} 1, & \exists\ dis_{ij} < r \\ 0, & \forall\ dis_{ij} > r \end{cases} \tag{5-1}$$

where dis_{ij} represents the distance from the j-th evader to the i-th pursuer in the corresponding team; r is the default capture radius. If there is a distance from the pursuer to the evader to reach the default capture radius, the evader is captured. The pursuit-evasion strategy is virtual force field [40], [58]

A. PARAMETER SETTING

The speed of pursuer and evader is set as 5 and 3 respectively, and the capture radius is 0.8. The basic emotion is Fear, Anger, and Joy, so both mood and sentiment are triad, correspondingly the stimulus is a triad. According to the previous work [30], [40], the transfer matrix from basic emotion to PAD space is:

$$M_{\text{EP}} = \begin{bmatrix} -0.64 & 0.60 & -0.43 \\ -0.51 & 0.59 & 0.25 \\ 0.40 & 0.20 & 0.15 \end{bmatrix}$$

The type and value of fundamental stimulus vector in this example are defined as Table 1, and compute instances of stimulus are as follows.

TABLE 1. Fundamental stimulus vector.

	Kind of stimulation	Fundamental stimulus vector				Influence model	Generation model
			Fear	Anger	Joy		
Object	Far evader	$\boldsymbol{sv}_{far}$	1	0	0	Sentiment	Real time
	Near evader	$\boldsymbol{sv}_{near}$	0	0	1		
	Reward of evader	$\boldsymbol{sv}_{rew}$	0	0	0.5		
	Risk of evader	$\boldsymbol{sv}_{risk}$	0.4	0.3	0		
Event	Become leader	$\boldsymbol{sv}_{leader}$	0	0.3	0.5	Mood	Trigger
Action	Successful Pursuit	$\boldsymbol{sv}_{capture}$	0	0	0.5	Mood	Trigger
	Failed Pursuit	$\boldsymbol{sv}_{fail}$	0.5	0	0		

1) OBJECT STIMULUS

The distance stimulation generated by the pursuit objective is:

$$S.dis_{ij} = \begin{cases} Norm(\left|dis_{ij} - \xi\right|) \cdot \boldsymbol{sv}_{far}, & dis_{ij} > \xi \\ Norm(\left|dis_{ij} - \xi\right|) \cdot \boldsymbol{sv}_{near}, & dis_{ij} < \xi \end{cases} \quad (5\text{-}2)$$

$$dis_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \quad (5\text{-}3)$$

where $S.dis_{ij}$ represents the distance stimulus to pursuer i from evader j; ξ denotes the distance threshold, the stimulus is positive when the distance is less than the threshold, otherwise it is negative; Norm is the normalized function ranged within [0,1]; $\cdot$ refers to the dot products of two vector. The nearer the distance between pursuer and evader is, the stronger the positive stimulus is, so that the pursuer's willingness is higher. Similarly, the farther the distance is, the stronger the negative stimulus is.

The reward of task objective will produce a reward stimulus for robots, which is related to evader's reward and pursuer's cost:

$$S.gain_{ij} = Norm(gain_{ij}) \cdot \boldsymbol{sv}_{gain} \quad (5\text{-}4)$$

$$gain_{ij} = rew_i - cost_j \quad (5\text{-}5)$$

where $S.gain_{ij}$ is the reward stimulus to pursuer i from evader j; Norm is the normalized function ranged within [0,1]. $gain_{ij}$ denotes the gain of pursuer i fulfilling the task (capturing evader j); rew_i denotes the reward of a successful capture of robot i; $cost_j$ denotes the cost of the pursuer for performing the task of robot i.; $\boldsymbol{sv}_{gain}$ is a fundamental stimulus, which is defined as how much degree stimulus *gain* impact emotion. Thus, the higher the reward of task objective is, the more positive the reward stimulus is, and the higher the willingness of pursuer is.

Similarly, the risk of task objective will produce a negative risk stimulus to the pursuer robot that is related to the capability of pursuer and evader:

$$S.risk_{ij} = Norm(risk_{ij}) \cdot \boldsymbol{sv}_{risk} \quad (5\text{-}6)$$

$$risk_{ij} = cap_j - cap_i \quad (5\text{-}7)$$

where $\boldsymbol{sv}_{risk}$ is a fundamental stimulus, which is defined as how much degree stimulus *risk* impact emotion; Norm is the normalized function ranged within [0,1]; cap_j denotes the capacity of robot j; cap_i denotes the capacity of evader i.

2) EVENT STIMULUS

When a robot is selected as a leader, there is a leader stimulus generated, and the actual stimulus is the same as that of fundamental stimulus vector.

3) ACTION STIMULUS

When an evader is captured, the pursuers in corresponding pursuit team will be stimulated by a positive action stimulus, and the intensity of stimulus is proportional to the gain of fulfilling the task.

$$S.capture_{ij} = Norm(gain_{ij}) \cdot \boldsymbol{sv}_{capture} \quad (5\text{-}8)$$

where $\boldsymbol{sv}_{capture}$ defined as how much degree stimulus evader was captured impact emotion.

Generally, the objective function of the pursuit-evasion problem is minimizing time and maximizing gains. In this work, because the pursuer is affective, we need to measure the rationality of allocation results under the premise of pursuit gains, which is whether the allocated task is suitable for robot's personality and emotional state.

$$S = max(\sum\nolimits_{i\in pursuer} \sum\nolimits_{j\in \text{evader}} (S.dis_{ij} + S.gain_{ij} + S.risk_{ij} + S.capture_{ij})) \quad (5\text{-}9)$$

B. THE PROCESSING OF AFFECTIVE COMPUTING IN TASK ALLOCATION

In this experiment, we show the process of affective computing in once task allocation.

1) INITIALIZING SCENE

There are 4 pursuers and 2 evaders, and their initial attributes are given randomly as shown in Fig.4 and Tables 2 and 3.

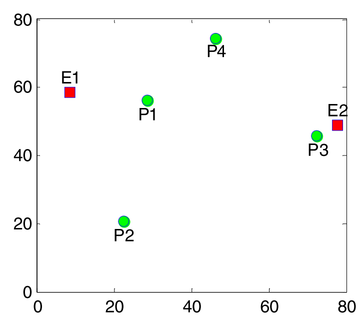

FIGURE 4. The initial positions of pursuers and evaders.

TABLE 2. The initial attributes of evaders.

	cap	*rew*
Evader 1	10	230
Evader 2	8	200

TABLE 3. The initial attributes of pursuers.

	mood	per	*cap*	*cost*
Pursuer 1	[0.16,0.55,0.57]	[0.21,0.62,0.69,0.72]	4	1
Pursuer 2	[0.12,0.54,0.38]	[0.22,0.76,0.60,0.66]	5	2
Pursuer 3	[0.17,0.11,0.64]	[0.31,0.71,0.79,0.87]	6	3
Pursuer 4	[0.22,0.45,0.31]	[0.13,0.65,0.57,0.19]	6	3

2) OBJECT STIMULATION

Each evader produces an object stimulus to pursuer which affects the sentiment of pursuer and further changes willingness (Table 4). Taking pursuer 3 as an example, before stimulation, the sentiment of pursuer 3 is initialized by its mood state:

$$\boldsymbol{sent} = \begin{bmatrix} 0.17 & 0.11 & 0.64 \\ 0.17 & 0.11 & 0.64 \end{bmatrix}$$

TABLE 4. Sentiment and willingness after object stimulation.

	Evader 1		Evader 2	
	sent	*w*	**sent**	*w*
Pursuer 1	[0.08,0.19,0.73]	0.66	[0.11,0.27,0.62]	0.56
Pursuer 2	[0.09,0.31,0.60]	0.59	[0.17,0.27,0.56]	0.39
Pursuer 3	[0.23,0.05,0.73]	0.32	[0.03,0.01,0.96]	0.85
Pursuer 4	[0.16,0.25,0.59]	0.42	[0.11,0.17,0.72]	0.58

To pursuer 3, evader 1 is far and evader 2 is near (Fig.4), so the distance stimulus of evader 1 and evader 2 is:

$$\boldsymbol{S}.dis = \begin{bmatrix} 0.30 & 0 & 0 \\ 0 & 0 & 0.88 \end{bmatrix}.$$

The reward stimulus and risk stimulus are:

$$\boldsymbol{S}.rew = \begin{bmatrix} 0 & 0 & 0.50 \\ 0 & 0 & 0.43 \end{bmatrix}, \quad \boldsymbol{S}.risk = \begin{bmatrix} 0.27 & 0.20 & 0 \\ 0.13 & 0.10 & 0 \end{bmatrix}.$$

After the object stimulation, the sentiment is:

$$\boldsymbol{sent} = \begin{bmatrix} 0.23 & 0.05 & 0.73 \\ 0.03 & 0.01 & 0.96 \end{bmatrix}.$$

And the willingness is calculated based on sentiment:

$$W = \{0.32, 0.85\}.$$

The willingness matrix is:

$$M_W = \begin{bmatrix} 0.66 & 0.59 & 0.32 & 0.42 \\ 0.56 & 0.39 & 0.85 & 0.58 \end{bmatrix}$$

3) TASK ALLOCATION

Willingness matrix is the main reference for task allocation. The first stage of task allocation is selecting leader based on leadership as Table 5.

Pursuer 1 and pursuer 2 are selected as leaders because of their greatest leaderships. The allocation result is calculated by Hungarian algorithm based on the willingness matrix: the evader 1 is allocated to pursuer 1, and the evader 2 is allocated to pursuer 2. Both leaders are stimulated by an event stimulus—-be a leader $S.beleader = \begin{bmatrix} 0 & 0.3 & 0.5 \end{bmatrix}$, their mood states change as Table 6.

TABLE 5. Leadership list.

	Pursuer 1	Pursuer 2	Pursuer 3	Pursuer 4
leadership	0.69	0.57	0.53	0.38

TABLE 6. The mood of leaders before / after the event stimulation.

	mood	
	Before	After
Pursuer 1	[0.16,0.55,0.57]	[0.12,0.14,0.73]
Pursuer 2	[0.12,0.54,0.38]	[0.12,0.19,0.68]

The second stage of task allocation is selecting team members according to the principle of maximum willingness, finally obtain an allocation matrix:

$$M_A = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix}$$

That is, the pursuit team members of evader 1 and evader 2 are $\{1, 4\}$ and $\{2, 3\}$ respectively.

4) EMOTIONAL CONTAGION

After successful allocation, emotional contagion occurs among the members of each task team. According to the personality of pursuers in Table 2, in team 1 the susceptibility and expressiveness of pursuer 1 is $[\,sus \;\; exp\,] = \begin{bmatrix} 0.69 & 0.72 \end{bmatrix}$ and the pursuer 4 is $[\,sus \;\; exp\,] = \begin{bmatrix} 0.57 & 0.19 \end{bmatrix}$.

After emotional contagion, in Table 7, the intensity of mood of pursuer 4 increase because of very low expressiveness. Correspondingly, the intensity of mood of pursuer 1 decrease due to its expressiveness is high and pursuer 4 express too little emotion.

TABLE 7. The mood of pursuers before / after emotional contagion.

		mood	
		Before	After
Team1	Pursuer 1	[0.12,0.14,0.73]	[0.06,0.07,0.30]
	Pursuer 4	[0.22,0.45,0.31]	[0.23,0.46,0.40]
Team2	Pursuer 2	[0.12,0.19,0.68]	[0.14,0.19,0.73]
	Pursuer 3	[0.17,0.11,0.64]	[0.14,0.11,0.55]

C. IMPACT OF SIMULATION OF TASK ALLOCATION

In this experiment, we verify the impact of external stimulation on task allocation using action stimulation as an example. The time performance and allocation result of this algorithm are compared with instantaneous greedy optimal auction algorithm for rational robots and multi-robot pursuit task allocation algorithm based on emotional cooperation factor [40].

In order to highlight the impact of stimulation, there is no emotional contagion. Emotional attenuation is an inherent property of affection, that is emotional intensity decreases over time. In addition, pursuers' personalities are identical, so personalities have the same influences on stimulation and emotional attenuation.

There are 9 pursuers and 3 evaders shown as Fig. 5. After the first task allocation, there are also twice reallocation in pursuit process because evaders are captured in sequence.

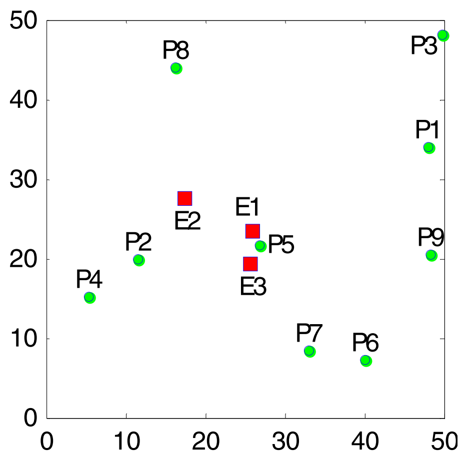

FIGURE 5. Chase scenes in which robots are reassigned tasks.

In Fig.5, task allocation of rational robots only relates to objective factors such as distance and reward. Each time allocation result of each pursuers is always its optimal choice, that is the nearest evader.

The pursuit process of the algorithm based on emotional cooperation factor is shown in Fig.6(a), allocation result of affective robots differs from rational robots because affective pursuer is not always choosing their optimal choice. But this algorithm did not thorough consider external stimulus, thus its allocation results is not flexible enough. For example, at the second reallocation the pursuit team of evader 1(orange dotted lines) — pursuer 1, pursuer 7, and pursuer 9— is same as the first reallocation (green dotted lines), but not choose the pursuers on the left-hand side to round up the evader, because pursuers of the team are still the most appropriate (maximum net income) of pursuing evader 1.

In Fig.6(b), we systematically consider external stimulus in task allocation and pursuit process. Taking the action stimulus as example, when the evader 2 is captured, pursuers of this team (purple dotted lines) — pursuer 2, pursuer 7, and pursuer 8— are stimulated by a positive action stimulus, so that their emotional states are lifted (Table 8).

Then at the second reallocation for the evader 1, the willingness matrix is:

$$M_w = [0.83, 0.82, 0.73, 0.62, 0.75, 0.82, 0.89, 0.84, 0.73]$$

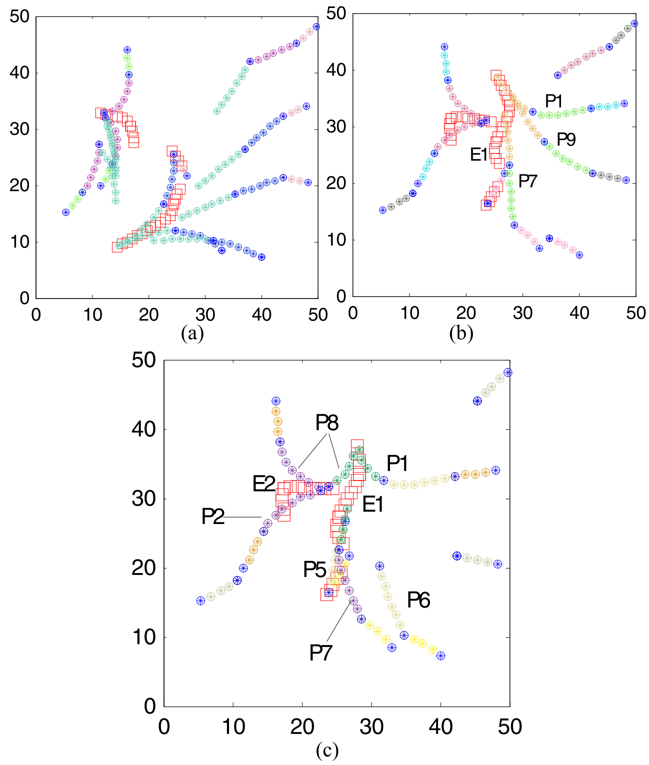

FIGURE 6. The comparison of pursuit process.

TABLE 8. The emotion of pursuit team members before / after capturing evader 2.

	mood	
	Before	After
Pursuer 2	[0.07,0.14,0.23]	[0.09,0.14,0.73]
Pursuer 7	[0.03,0.03,0.37]	[0.03,0.03,0.94]
Pursuer 8	[0.06,0.11,0.22]	[0.08,0.15,0.77]

Pursuer 7 and pursuer 8 replace pursuer 5 and pursuer 6 as the member of pursuit team (green dotted lines) because of their higher willingness. At this time, the pursuer 8 is near evader 1(Fig.6(c)), and the pursuit process is accelerated.

D. EMOTIONAL CONTAGION

This experiment shows the effect of emotional contagion on task allocation. There are 3 pursuers and 1 evader and their attributes are shown in Table 9. There is no stimulation, but the attenuation rate is 0.89.

TABLE 9. The attributes of pursuers.

	emo	per
Pursuer 1	[0.1,0.5,0.9]	[0.5,0.5,0.5,0.8]
Pursuer 2	[0.4,0.5,0.5]	[0.5,0.5,0.7,0.6]
Pursuer 3	[0.2,0.3,0.4]	[0.5,0.5,0.7,0.4]

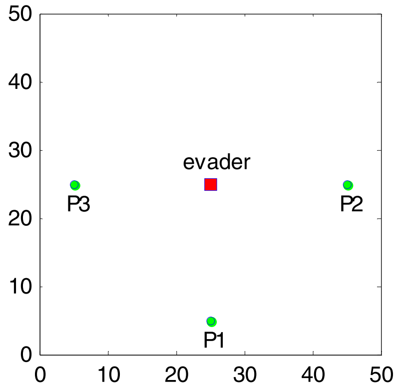

FIGURE 7. The comparison of pursuit process.

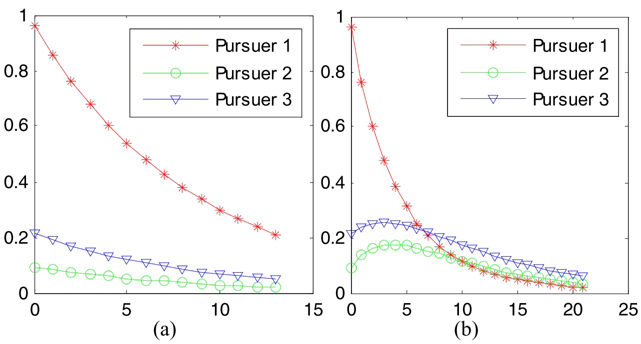

FIGURE 8. The pursuit process under (a) no emotional contagion; (b) emotional contagion.

Pursuer 1 is of positive emotion and stronger expressiveness. Pursuer 2 and pursuer 3 are of negative emotion and stronger susceptibility.

Pursuers' initial willingness are $w_1 = 0.96$, $w_2 = 0.09$, $w_3 = 0.22$. If there is no emotional contagion (Fig.8(a)), all pursuers' willingness decrease because of emotional attenuation, and the lowest willingness (pursuer 2) firstly drops below the threshold (set as 0.02) which leads to reallocation or failure to pursuit as shown in Fig.9(a). Pursuer 2 and pursuer 3 will give up because their emotions are down too low, which will result reallocation or the failure of pursuit.

In Fig.8(b), pursuer 1 expresses its positive emotion to pursuer 2 and pursuer 3 and the latter two willingness are driven by pursuer 1, so that the pursuit process has not been interrupted because of low willingness (Fig.9(b)).

E. INFLUENCE OF PERSONALITY TO TASK ALLOCATION

This experiment shows the influence of personality to task allocation through an eight-vs-three game (Fig.10). We compare the allocation results of two pursuit scenes which differ in whether pursuers are personalized or not, more attributes are shown in Table 10.

The pursuit process of two scenes is shown in Fig.11. The initial allocation results of both scenes are same, but in each reallocation (one evader is captured) appears the difference

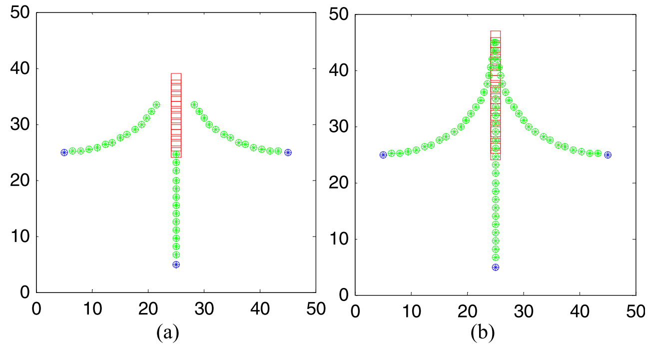

FIGURE 9. The pursuit process under (a) no emotional contagion; (b) emotional contagion.

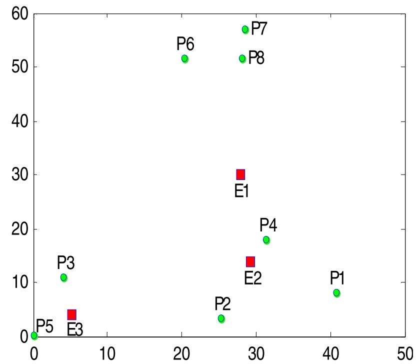

FIGURE 10. Initial position.

TABLE 10. Attributes of pursuers and evaders in both scenes.

	Pursuers			Evader 1	Evader 2	Evader 3
	per	emo	*cap*		*cap/rew*	
Scene 1	/	[0.2,0.4,0.6]	4	16/400	8/200	8/200
Scene 2	Random					

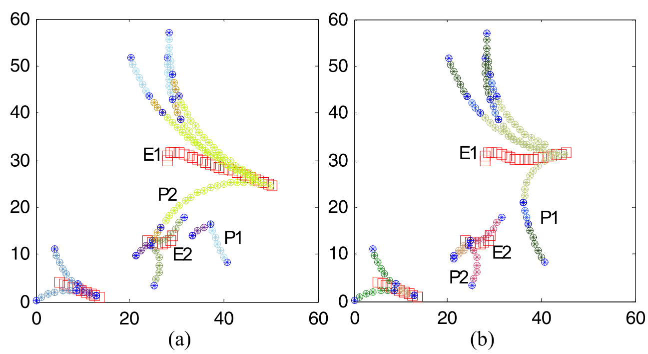

FIGURE 11. Pursuit process under (a) no emotional contagion; (b) emotional contagion.

between allocation results of two scene and the reason of the difference is pursuers' personality.

In scene 1 shown as Fig.11(a), pursuers are non-personalized and their willingness's changes relate to initial emotion and environment factors (evaders' distances, rewards and capabilities). Due to initial emotions are same, the allocation result of scene 1 is mainly determined by environment factors. At the first reallocation (evader 3 is captured), the willingness of pursuer 1 to evader 1 and evader 2 is $w_1 = \{0.79 \;\; 0.88\}$, and the willingness of pursuer 2 is $w_2 = \{0.73 \;\; 0.86\}$, both their willingnesses to evader 1 are lower because of its higher risk and farther distance. Due to the pursuit team of evader 1 lack of cooperators, pursuer 2 is discharged from the pursuit team of evader 2 because of its lower willingness to evader 2 and join the pursuit team of evader 1.

In scene 2 shown as Fig.11(b), pursuers are personalized and personality is also a determinant of allocation result. Pursuer 1 is adventurous and extroverted: $\boldsymbol{per}_1 = [0.09 \;\; 0.95 \;\; 0.02 \;\; 0.97]$, pursuer 2 is cautious: $\boldsymbol{per}_2 = [0.85 \;\; 0.20 \;\; 0.61 \;\; 0.54]$. At the first reallocation, the willingness of pursuer 1 to evader 1 and evader 2 is $w_1 = \{0.90 \;\; 0.88\}$, and the willingness of pursuer 2 is $w_2 = \{0.48 \;\; 0.86\}$. To the higher risk and reward evader 1, the willingness of adventurous pursuer 1 is higher and cautious pursuer 2 is lower. As a result, pursuer 1 chooses to chase evader 1, pursuer 2 chooses to chase evader 2.

The pursuit time and gains in both scene 1 are shown in Table 11. Under the influence of personality, the time and gains are better in scene 2.

TABLE 11. Pursuit time and gains.

	Time	Reward
Scene 1	13.60s	605.96
Scene 2	10.50s	626.58

F. EXPERIMENTAL AND RESULT

This experiment was conducted to test the effectiveness of the algorithm studied in this paper by comparing it with the IGPA algorithm [58]. In 1200 sets of comparison experiments under the same scenarios, the scene is set with a total of 5 Pursuers, 3 Evaders. The algorithm proposed in this paper was able to reduce the total experimental pursuit time in 83.58% of the scenarios and the total gain of 74.75% of the experimental pursuit teams were higher than the IGPA algorithm, as shown in Figure 12 and Figure 13. When using the IGPA algorithm to build pursuit teams, each robot is self-interested and will choose to join the team with the greatest benefit to itself, which may lead to some of the pursuit teams being over-capable and others being under-capable, which is not conducive to pursuit task allocation and leads to poor experimental results. In this paper, we consider both the emotional risk and benefit of the robot in the task assignment stage, use the robot willingness degree as the bid value, combine the two-step auction algorithm, consider the overall benefit in each task assignment, assign the optimal robot for each team, and calculate the actual emotional risk to derive the actual net benefit after the successful pursuit, eliminating the situation that the team's benefit is affected because of individual benefit. Therefore, using the algorithm in this paper can optimize the total chase time and the total chase team revenue.

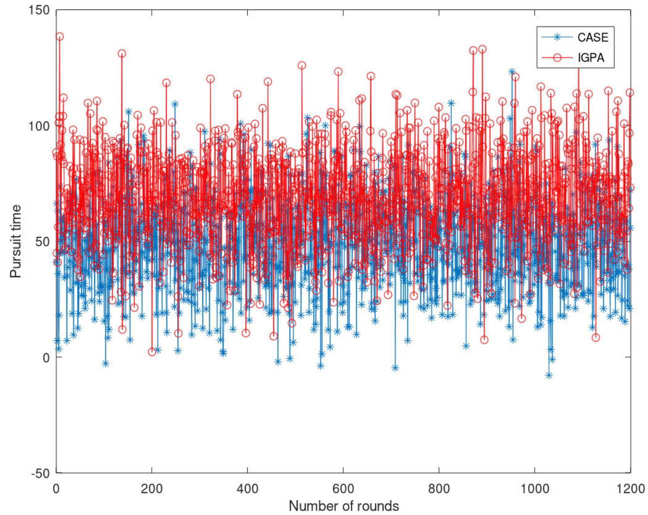

FIGURE 12. The comparison chart of total time for pursuing team.

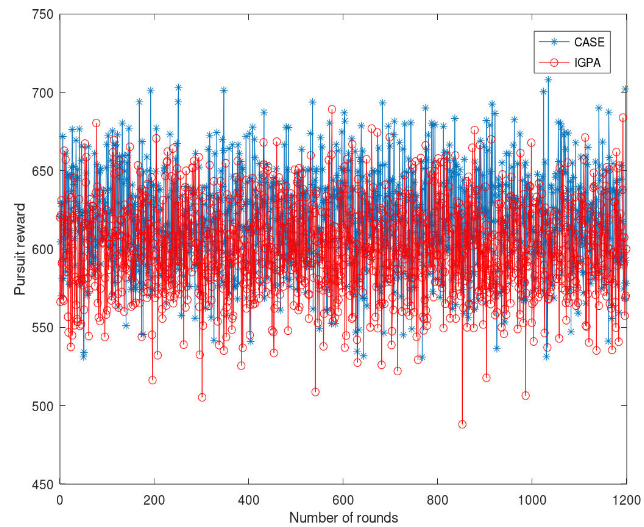

FIGURE 13. The comparison chart of total reward for pursuing team.

VI. CONCLUSION

This paper focuses on the impact of affection on multi-robot cooperation, for this problem, an interpretable and computable affection model is proposed. Then it was detailed each modules of the affection model and their relation and change, subsequently calculated the willingness to reflect the effect of affection on task allocation. The feasibility and reasonability of the model is proved by multi-robot pursuit task allocation. We elaborate a relatively complete theory in the interdisciplinary of affective computing and multi-robot cooperation, and realize it in multi-robot pursuit task environment. Thus, this work is of theoretical value and practical significance.

This algorithm has good versatility and flexibility. The versatility is embodied in the affection model. The affection model can be viewed as a black box; the influence of affection on cooperation can be quantified through willingness. The internal operation process of affection model does not have to understand while only set different kinds of external stimuli can result in different willingness. The willingness can be used as an important reference in most cooperative environments. Flexibility is particularly reflected in the choice of stimulus kinds according to the system requirements.

This affection model is an evolving framework, in which components are to be perfected. For example, the effect of personality can be expanded to emotional contagion and emotional attenuation. An optimistic individual tends to express more positive emotion, and its attenuation rate of positive emotion is slower than negative emotion. This affection mechanism can be further applied to social network.

This task allocation algorithm is a centralized method and relatively simple, because the focus of this paper is modelling affection. On the basis of this affection model, we can explore more efficient and appropriate task allocation algorithm combined with affection. Further, task type and environment can be changed to test the affection model,, multi-robot map exploration.

However, the emotion model in this paper needs to be refined. In terms of emotion infection, the degree of emotion infection that occurs when two individuals communicate with each other must be different, and for subsequent extensions we defined the existence of connection strength between two individuals. Also, emotional infection should be influenced by personality, for example, individuals with pessimistic personality are susceptible to negative emotional infection, while optimistic individuals are not susceptible to negative emotional infection. In terms of emotion attenuation, we consider calculating the attenuation coefficient based on personality values, so as to achieve the true sense of different by personality. Also, since the representation of emotions in this paper is the basic emotion method, each basic emotion should have an attenuation coefficient, which means that the attenuation coefficient should be a vector whose dimension corresponds to the emotion vector. This will completely represent the different effects of personality on the decay rate of different emotions.

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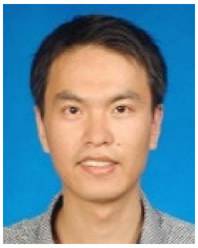

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