Noname manuscript No.
(will be inserted by the editor)

Personality Driven Task Allocation for Emotional Robot Team

Baofu Fang · Quan Zhang · Hao Wang · Xiaohui Yuan

Received: date / Accepted: date

Abstract The task allocation of emotional robot is a new and valuable issue. There are many allocation algorithm in rational robot but only a few in emotional robot. Emotional robot is neoteric and meaningful although it is complex. In this paper, we reference to the previous research, propose emotional robot pursuit problem, build a mathematical model of emotional stimulation base on personality in task allocation and use this model propose an emotional robot pursuit task allocation algorithm. Different with other algorithm, our algorithm allocate different personality pursuers through emotional change after stimulation by allocation. The experiments reflect the influence and the positive role of personality in allocation, also show the algorithm reduces the total pursuit time and avoids the worst case scenario. This algorithm not only solve the emotional robot pursuit problem base on personality, but also shorten and stabilize the total pursuit time.

Keywords Multi-robot system · Task allocation · Emotional robot · Cost calculation · Personality

1 Introduction

The task allocation for multi-robot systems [1] is an important issue. The methods based on behavior enable coordinated team behaviors and complete the mapping from perception to behavior and synthesize multi-robot system [2]. Dimitri [3] developed an efficient method based on the market auction strategy to allocate resources. Reinforcement learning [4] gradually learned the optimal behavior strategy to assign tasks through interactions. To satisfy

Department of Computer Science and Technology Hefei university of Technology Hefei, China Email: fangbf@hfut.edu.cn
Department of Computer Science and Engineering University of North Texas, Denton, TX, U.S.A.

the practical needs, advanced task allocation methods have been devised [5] with improved operating efficiency [6].

Minsky [7] points out that "The question is not about whether there is emotional intelligence body, but rather when the machine can't have emotion while realizing intelligence." Therefore, to make the robot as intelligent as human beings, emotional factors must be taken into account. There exist many open issues when task allocation is realized in coordination of multi-emotional robots. The performance of task allocation methods designed for rational robot degrades due to the self-interest from each robot[8]. In addition, variation of emotional thinking of robots from their personalities greatly increases the complexity of the problem, and the conventional methods face challenges because of the absence of an emotional model to compute the effect of cooperation of each emotional robot in task allocation. Hence, they are unable to handle the impact produced by emotional factors in the task allocation process. When personality is introduced into robots, the results from those allocation algorithms are far from satisfactory [9-11].

In our previous studies, we proposed emotional cooperation factors [12] to evaluate the robot's willingness to cooperate, and design the task allocation algorithm of considering the emotional robot in multi-robot pursuit problem. We devised the maximum similarity matching emotion model [13] to establish the relationship between the cooperation willingness and the emotional stimulation. Yet, there exist two open issues in task allocation: (1) personality factors are not fully accounted for; (2) the process of emotional cooperation factors is simple and could make the robot close to an unassigned pursuit target, which makes the time of pursuit unstable. In this paper, we present a task allocation algorithm based on personality. The personality factors are taken into account in the emotion to achieve improved result and easily adoptable to other emotional robot task allocation problems.

2 Related work

Psychology model of emotional robot task allocation is mainly constructed by emotion model, personality model, mood model, and update model[14]. Emotion [15] in psychology is personal experience whether objective things satisfy their needs. It is transient psychology with instability, easily changes with environmental factors, and decays over time. Sentiment classification methods described herein using continuous variables, the use of N-dimensional coordinate system will be divided into N sub-emotional space, each of which corresponds to a basic emotion. We use E_t to express the emotion of a robot as follows:

$$E_t = [e_1, e_2, \cdots, e_n], \tag{1}$$

where E_t denotes the emotional state in time t and each e_i is the magnitude of a basic emotions (such as joy, sad, and angry), where $e_i \in [0, 1]$ and a greater value indicates a stronger emotion.

Different from emotion, personality is an unique and comprehensive description of a person, which can distinguish one person from another [16]. It is the tendentious, stable, intrinsic psychological characteristics. It remains mostly unchanged in a short period. The widely used method to represent personality is OCEAN model [17] (a.k.a. the Big Five personality model). The personality P consists of the robot personality attributes and is expressed as follows [18]:

$$P = [O, C, E, A, N], \tag{2}$$

where O stands for openness, C is cautious, E is extraversion, A is agreeableness and N is nervousness. All attributes are in the range of $[-1, 1]$.

Mood is between emotion and personality [19][20] and is expressed as a tuple of pleasure, arousal, and dominance as follows:

$$M = [P, A, D], \quad \text{and} \quad P, A, D \in [-1, 1] \tag{3}$$

where P for the degree of pleasure and a large value implies a positive mood; A denotes arousal and a large value implies an unstable mood; D is the degree of dominance and a large value implies great initiative.

Emotional collaboration factor expresses the willingness of robot to participate in a task. It is influenced by emotion and personality. Emotional collaboration factor f is expressed as follows:

$$f = E_t M_t (w_1, w_2, w_3), \tag{4}$$

where E is the emotion of a robot. M_t is transformation matrix of the basic emotions space to the PAD mood space. $w_i (i = 1, 2, 3)$ is the weight for the three dimensions for PAD and $\sum_i w_i = 1$. The higher emotional collaboration factor means that the thinking and behavior of robot are more active, and, hence, the robot takes an active part in the task. On the other hand, a robot moves slower with a lower value of emotional collaboration factor, and participates in the task passively.

Emotional update model includes emotional stimulation model and emotional decay model. Emotional stimulation considered the personality factors is a complex circumstance. Wang [21] simulated the emotion and the personality of the robot, defined the representation of stimulation and stimulation matrix. Emotional stimulation model can be expressed as quintuple:

$$\lambda = (E_t, S, \pi, A, B) \tag{5}$$

where E_t is the emotion of a robot, S is a set of stimulation: $S = (s_1, s_2, \cdots, s_n)$, where s_i, $s_i \in [-1, 1]$, is the stimulation of a basic emotion and n is dimensional of basic emotion E_t. π is the state probability at the beginning and $\pi = (\pi_1, \pi_2, \cdots, \pi_n)$. A is a n by n matrix and denotes the spontaneous transition probability of the emotional states. In A, an element a_{ij} means the probability of a basic emotion e_i transferring to a basic emotions e_j. B is also an n by n dimensional stimulation matrix, and b_{ij} is the emotional stimulation at robot's e_j basic emotion.

Psychological research shows that emotion decay over time[22]. According to emotional intensity third law (a.k.a. the emotional intensity attenuation law), the emotional decay can be expressed as follows:

$$E_t = E_{t-1} e^{-\lambda t} \tag{6}$$

where E_t is the basic emotion at moment t; E_{t-1} is basic emotion at previous moment; t is time period to detect the emotion; λ is an emotional decaying factor influenced by personality.

3 Personality of Emotional Robot

In an unbounded two-dimensional plane, there are M pursuer robots to pursue N evader robots. Pursuer and evader appear in arbitrary locations and move toward arbitrary direction. When the distance between pursuer and evader is less than capture radius, the evader is assumed captured successfully. The pursuers can then chase another evader until all evaders are captured. An evader has the attribute of position, capacity, and reward. The higher capacity of an evader, the higher reward a pursuer receives [23]. A pursuer has attributes of capacity, wage, personality and emotion. The capability of pursuer team is greater than or equal to the evaders. Assume that T_{start} is the time of evader i begin to escape, T_{end} is time of capture, the objective function is to minimize the total maximum pursuit time:

$$T_{min} = min(\sum_{i=1}^{n}[max(T_{end}) - T_{start}]_i), \tag{7}$$

where T_{min} is the least time to complete all tasks.

3.1 Basic Emotions

In Eq. (1), n implies complexity and is usually set ot 3 or 6 [24]. When n is 3, the basic emotions consist of Joy, Fear, and Anger; when n is 6, the basic emotions consist of Joy, Sadness, Anger, Surprise, Fear, and Disgust. Given the basic emotions, the transformation matrix can be defined [15][24].

Evaders defined as $E = \{E_1, E_2, \cdots, E_m\}$. E_i is a triad $E_i = (Pos, Cap, R)$. Among them:

- Pos stands for the current position of the evader, represented by coordinates (Pos_x, Pos_y) in the two-dimensional space.
- Cap stands for the capacity of evader. The bigger the capacity of evader is, the harder the task is, and the higher the risk is.
- R represents reward of successful capture, the greater the value is, the more rewards got.

Pursuers defined as $P = \{P_1, P_2, \cdots, P_m\}$, P_i is a six-tuple $P_i = (Pos, Cap, Wage, E_t, Per, f)$, where:

- Pos is the position of the evader, same as the evader's.
- Cap is the capacity.
- $Wage$ is wage of recruiting.
- E_t is the emotion defined in section 2.
- Per is the personality.
- f is emotional collaboration factor that represents collaboration willingness.

For example, $P_i.Per$ represents the personality attribute of the ith pursuer.

3.2 Stimulation

The external environment stimulation is the main source of the emotional changes. External stimulation can be divided into object, event and action stimulation[15]. Object refers to the impact of emotional robot to the other robots. A evader e generates a stimulation to a pursuer nearby even if the evader take no actions. Events refers to the impact of events around the emotional robot. For example when assigned a lucrative task, it makes a stimulation of Joy to the pursuer. The more the reward is, the stronger the stimulations are. Action refers to the impact of behavior on robot itself. Such as a pursuer have captured an evader successfully, then it makes a stimulation of Joy. The external stimulations adopted in our method are listed in Table 1.

Table 1 Stimulation effect on emotion

	Stimulation	Example	Joy	Anger	Fear
Object	Object 1	A dangerous robot	0	0	1
		...			
	Object i	an uncooperative robot	0	0.5	0.5
Event	Event 1	Allocate a risk task	0	1	1
		...			
	Event j	Allocate a reward task	1	0	0
Action	Action 1	Pursue successfully	0.5	0	0
		...			
	Action k	Pursue failed	0	0	0.5

For example, if we allocate an uncooperative robot, it generates a negative object stimulation $S = (0, 0.5, 0.5)$. When a risky task is allocated to it, it generates a negative event stimulation $S = (0, 1, 1)$. If, on the other hand, a high reward task is allocated, it generates a positive event stimulation $S = (1, 0, 0)$. When a pursuit succeeds, the robot produces a weaker positive action stimulation, e.g., $S = (0.5, 0, 0)$. The update model of emotional collaboration is depicted in Fig. 1.

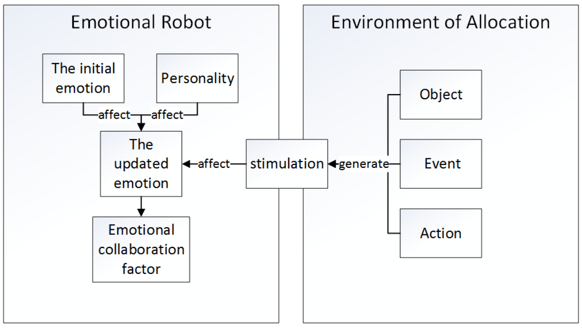


Fig. 1 The update model of emotional collaboration factor.

4 Emotional Robot Task Allocation

Factors such as distance and pursuer's ability affect the task allocation and their psychological factors play an important role. For example, a mission assigned to a robot with a positive mood is usually better performed than if it is assigned to robot with a depression mood. Risky tasks assigned to an adventurous robot is better than assigned to a conservative one [25]. So task allocation that takes the practical and psychological factors into consideration is a complex problem. We need to build an emotional task allocation model to calculate the distribution matrix.

In our method, the cost matrix includes the task cost and emotional cost. The dimension of the cost matrix is determined by the number of pursuers and evaders. The allocation problem can be either balance or unbalanced allocation problems [26]. In the balance allocation problems, there are equal number of pursuers and evaders and the cost matrix is as follows:

$$Cost = \begin{bmatrix} e_{11} & \cdots & e_{1j} & \cdots & e_{1n} \\ \vdots & \ddots & & & \\ e_{i1} & & e_{ij} & & \vdots \\ \vdots & & & \ddots & \\ e_{n1} & & \cdots & & e_{nn} \end{bmatrix} \tag{8}$$

where n is the number of pursuers and evaders, e_{ij} is the cost of pursuer i to capture evader j. In dealing with unbalanced allocation problems, "virtual variables" is used to balance the number of pursuers and evaders. That is, the corresponding rows (columns) of the cost matrix for the virtual pursuers (evaders) are initialized to the maximum cost.

The cost matrix includes the pursuit cost and emotional cost. The pursuit cost depends on factors such as the distance between the pursuers and the evaders, the wage of recruiting pursuers. The emotional cost is the pursuer's willingness to join the task. Cost expressed as follows:

$$Cost = \lambda_1 C_R + \lambda_2 C_E \tag{9}$$

where C_R is the pursuit cost and C_E is the emotional cost. λ_1 and λ_2 are the weights. C_R is the weighted sum of the normalized distance between the pursuers and evaders and the normalized wage of pursuers as follows:

$$C_R = \mu_1 Dis + \mu_2 Wage. \tag{10}$$

The initial state of emotion, stimulation of emotion, and the decay are considered for calculating C_E as follows:

$$C_E = f(E.risk_{ij}, E.rew_{ij}). \tag{11}$$

$E.risk_{ij}$ represents the emotion after event stimulation from evader j. It is influenced by the capacity and the personality of pursuer:

$$E.risk_{ij} = HMM(P_i.E_t, P_i.Per, S.risk_{ij}), \tag{12}$$

where $P.E_{t_i}$ is the current emotion of the pursuer i. It is affected by the emotional decay and the stimulation of the previous time, and gives the initial emotion. $risk_{ij}$ is defined for describing the risk of pursuer i to pursue evader j, calculated as $E_j.cap - P_i.cap$. $Normrisk_{ij}$ is the normalization of $risk_{ij}$. $S.risk_{ij}$ is the stimulation of risk, calculated as $S.risk_{ij} = Normrisk_{ij} \cdot (s_1, s_2, s_3)$. $P_i.Per$ represents pursuer' personality and decides the probability π.

$E.rew_{ij}$ represents the emotion after stimulation from pursuer i influenced by rewards. Similarly:

$$E.rew_{ij} = HMM(P_i.E_t, P_i.Per, S.rew_{ij}) \tag{13}$$

Because the process is the same as $E.risk_{ij}$, it describes the calculation of rew_{ij}. For an evader, the reward stimulation $S.rew_{ij}$ is $Normrew_{ij} \cdot (s_1, s_2, s_3)$. f is the function of Emotional Cooperation Factor and is used to compute C_E.

4.1 Task Allocation

The cost matrix is computed as follows:

1. Determine the stimulation vector S generated in task allocation.
2. Calculate the stimulation matrix S.
3. Calculate the emotional cooperation factor of each pursuer after stimulation.
4. Obtain $Cost$.

The capacity of a team of pursuers is no less than that of the evaders:

$$\sum_{i=1}^{n} P_i.Cap \geq E.Cap \tag{14}$$

Following the allocation algorithm, we obtain the allocation matrix T. Fig. 2 gives the flow chart of our algorithm.

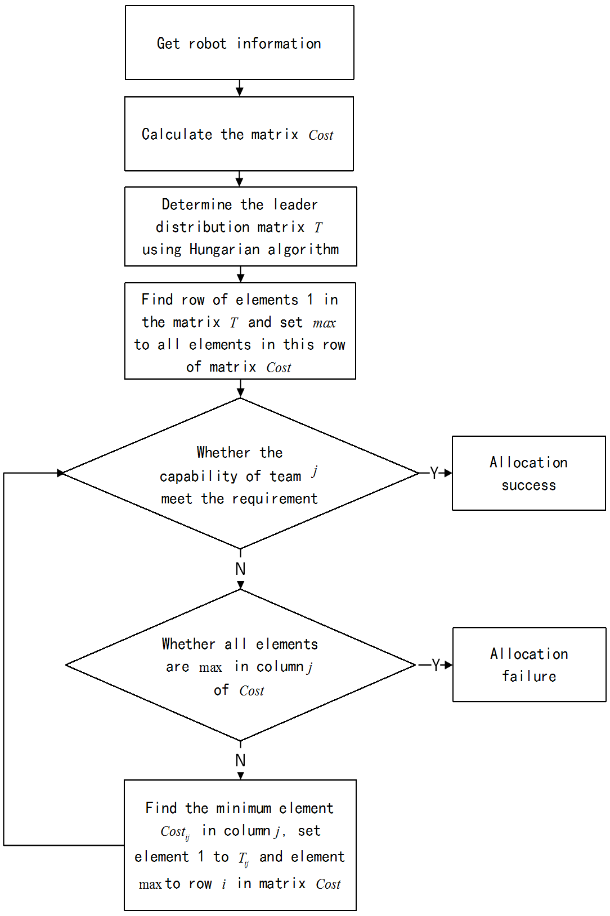


Fig. 2 Process of allocation

Assume that there is a virtual force field in the pursuit process. The force of pursuers to the evader is repulsive and that of evader to pursuers is attractive. The magnitude of attraction F_a and repulsion F_r is proportional to the distance as follows:

$$F_a = \gamma \frac{1}{E_{d_i}}, \tag{15}$$

$$F_r = \gamma \sum_{i=1}^{n} \frac{1}{P_{d_i}}, \tag{16}$$

where γ is scale factor, E_{d_i} is the distance from the pursuer to the evader E_i, P_{d_i} is the distance from each pursuer in pursuit team to its own evader.

Assume a unit circle centered at an evader. Split this circle into h parts on the circumference and the direction of the evader is chosen from the h directions which come from the center to the h dividing points. Calculate the repulsion F_r of the evader to get to each of the divisions; choose the direction with the least repulsion F_r as the motion direction. In the same way, choose the direction with the maximum attraction F_a as the motion direction for a pursuer[27].

Use f_d as the capturing distance to predict if an evader is captured or not:

$$f_d = \begin{cases} 1, \exists E_{d_i} \leq k \\ 0, \forall E_{d_i} > k \end{cases} \tag{17}$$

where k is the available distance for capture.

As the pursuit progresses, the task needs to be re-allocated. Reallocation must recalculate the cost matrix and assignment matrix. It has two trigger conditions.

Time Period: Due to the position and emotion decay, the cost of the previous cycle is no longer in line with the current situation. After a certain time period, tasks are reallocated.

Pursuit success: When an evader was captured, the pursuit team disbands. So after an evader is captured, task reallocation is performed.

5 Experimental Results

In our experiments, we used joy, anger, and fear as the basic emotions. Supposing pursuers speed is slightly faster than the evaders, but the field is unbounded. The initial emotion of all pursuers are the same.

5.1 Impact of Personality

In our simulation, two pursuers and two evaders were initialized. Due to the small-scale pursuit, we ignored the requirement of team's capacity must exceed the evader's. Only event stimulation were considered. Fig. 3 shows the initial positions of the evaders and pursuers. All attributes of the pursuers are the same except their personality as listed in Table 2. The weight of pursuit cost is the same as emotional cost. Therefore $\lambda_1 = \lambda_2 = 1$ in formula (9). Similarly $\mu_1 = \mu_2 = 0.5$ in formula (10).

Because of the same distance and wage, our calculation arrive at $C_R = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$. But the risk and rewards are different $risk = \begin{bmatrix} 4 & 6 \\ 4 & 6 \end{bmatrix}$,$rew = \begin{bmatrix} 200 & 230 \\ 200 & 230 \end{bmatrix}$, their stimulation sequence are different too. Based on the definition of stimulation, if we assign a risky task, it will produce a negative event stimulation sequence $s = [0, 1, 1]$, If we assign a high rewards task, it will produce a positive event stimulation sequence $s = [1, 0, 0]$. We get the stimulate matrix $S.risk = \begin{bmatrix} [0,0,0] & [0,1,1] \\ [0,0,0] & [0,1,1] \end{bmatrix}$ $S.rew = \begin{bmatrix} [0,0,0] & [1,0,0] \\ [0,0,0] & [1,0,0] \end{bmatrix}$.

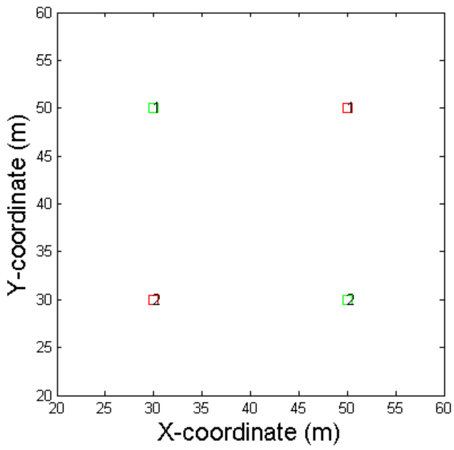


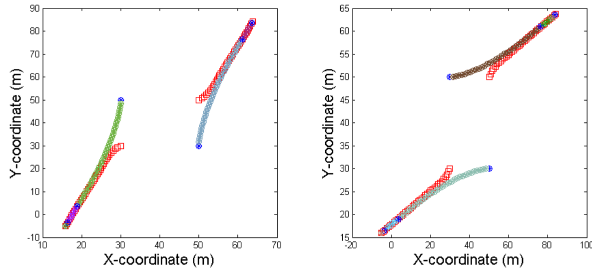
Fig. 3 The initial position of evaders and pursuers

After pursuer robots were stimulated, their emotion changed to $C_E = \begin{bmatrix} 0.1736 & 0 \\ 0.8402 & 1.0000 \end{bmatrix}$. Because C_R is initialized as a zero matrix, the cost and the allocation matrices are $Cost = \begin{bmatrix} 0.1736 & 0 \\ 0.8402 & 1.0000 \end{bmatrix}$ $T = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$.

Table 2 The attributes of evaders and pursuers

	Evader 1	Evader 2	Pursuer 1	Pursuer 2
Pos	50, 50	30, 30	30, 50	50, 30
Cap	8	10	4	4
R or W	200	230	1	1
E_{init}			[0.8134,0.6662 ,0.6225]	[0.8134,0.6662, ,0.6225]
Per			[-0.2373,-0.6777 ,0.5162,0.7422 ,-0.2984]	[0.9759,-0.6591 ,-0.4844,-0.2064 ,-0.8520]

According to OCEAN model, a robot with greater extraversion is more adventurous. In our experiment, pursuer 1 preferred higher risk tasks with greater rewards. Therefore, Pursuers 1 was chasing Evader 2 and Pursuers 2 was chasing Evader 1. The pursuit process is illustrated in Fig. 4. Our allocation(TA_P) method closely model the human behavior, which is not considered in the Task Allocation Based on Emotional Cooperation Factor(TA_ECF) algorithm.



(a) (b)

Fig. 4 Pursuit process. The pursuit ended when a pursuer is within a predefined distance to an evader.

5.2 A Comparison of Emotional and Rational Robots

In this experiment, we simulated 10 pursuers and 5 evaders and the initial positions of robots are shown in Fig. 5.

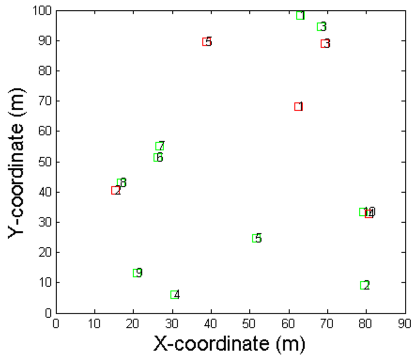


Fig. 5 Initial position of evaders and pursuers in experiment 2

In simulating rational robots, the weight of emotion cost is 0 but others are same. In Fig. 6, most of the robot assignments are the same except who pursue evader 1. In Fig. 6(a), to pursue evader 1 is pursuer 10 but in figure Fig. 6(b) is pursuer 5. The reason of the difference is the emotion stimulation, which from pursuer 10 catch evader 4 successfully although the distance to evader 1 is far than pursuer 5. In the final result, the total time of emotion robots is less than general robots. In Fig. 6(a), the pursuit completed in a smaller range than that of Fig. 6(b).

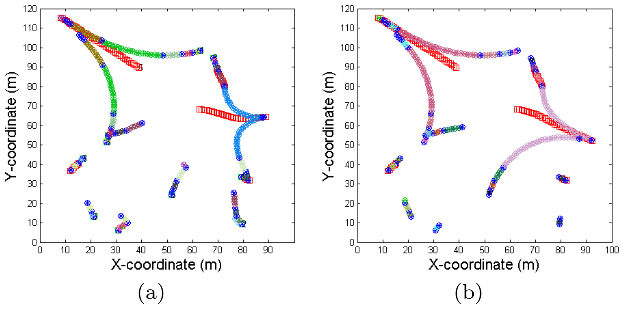


Fig. 6 Pursuit process with emotional robots (a) and rational robots (b).

5.3 Efficiency Analysis

Fifty experiments were conducted with the same scenario. Position, capacity, rewards, wage, emotion, personality were randomly initialized and all weights are same. Fig. 7 depicts the pursuit time in seconds using our method and TA_ECF method. It is clear that TA_P completed the pursuits in a shorter time in most cases.

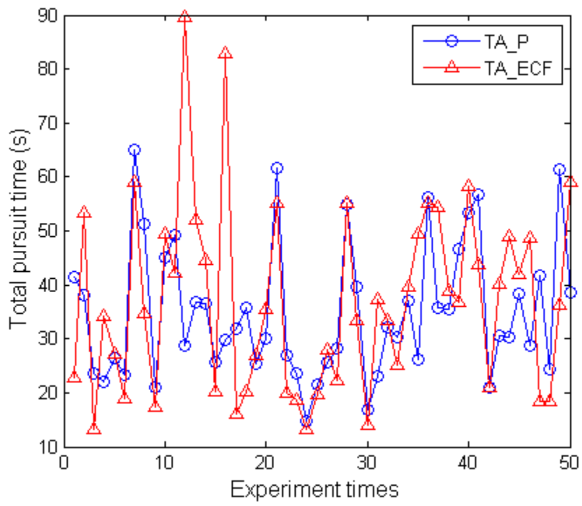


Fig. 7 Time used in pursuit tasks.

Table 3 presents the average time used by TA_P and TA_ECF. TA_P improved the average time by 5.6%. It is evidential that TA_P not only solved the complex allocation problem that take into consideration of personality, but also reduced the amount of pursuit time. Also, the variance of TA_P decreased by 46.02%, which implies that TA_P is a more stable allocation algorithm. The processing of the emotional coordination factor in TA_ECF is strict. In case of insufficient number of pursuers, no pursuers are excluded despite that their emotional factor is low.

Table 3 Average pursuit time of our method TA_P and TA_ECF

	TA_P	TA_ECF
Average time	34.98	36.92
Variance	156.495	305.155

6 Conclusion

In this paper we propose a task allocation algorithm for emotional robot pursuit. We allocate pursuers through the different emotion change after stimulation instead of transforming personality to emotion through a transform matrix. We build a mathematical model of emotional stimulation in task allocation. Our experiments simulated various cases and demonstrated the influence and the positive role of personality in task allocation. In comparison with the state-of-the-art task allocation algorithm TA_ECF, our algorithm considers personality, reduces the total pursuit time, and avoids the worst case scenario. In our future work, we plan to explore the scalability of our algorithm to large scale task allocation problems and conduct in-depth studies with more stimulations of complex circumstances.

Acknowledgements This work is supported by the National High Technology Research and Development Program of China (863 Program) under grant 2012AA011005, Natural Science Foundation of Anhui Province (1308085QF108), Science and technology support project of Sichuan Province (2016GZ0389), Doctorate Personnel Special Fund of Hefei University of Technology (JZ2014HGBZ0014).

References

1. Burgard W., Moors M. and Fox D., Collaborative multi-robot exploration, IEEE International Conference on Robotics and Automation (ICRA 2000) San Francisco, California, USA, 2000.
2. Zhou Q. and Mu D., Study of multi-robot system on task allocation, Journal of Northwest University(Natural Science Edition), China, 2014, vol.3, pp.403-410.
3. Moore K. and Lucarelli D., Decentralized adaptive scheduling using consensus variables, International Journal of Robust and Nonlinear Control, 2006, vol.17(10), pp.921-940.
4. Kwok K.S. and Driessen B.J., Analyzing the Multiple-target-multiple-agent Scenario Using Optimal Assignment Algorithms, Journal of Intelligent and Robotic Systems, 2002, vol.35, pp.111-122.
5. Zhu Q. and Cao X., An improved self-organizing map method for multiple autonomous underwater vehicle teams in dynamic task assignment and path planning, Control Theory Applications, 2015, vol.6, pp.762-769.

6. Wang H., Ding L., Fang B.and Yao H., Pursuers-Coalition Construction Algorithm in Multi-robot Pursuit-Evasion Game, China: Robot, 2013, vol.2 , pp.142-150.
7. Minsky M., The Society of Mind, New York, USA:Simonand Schuster, 1988.
8. Lou J., Resource Allocation among Multiple Selfish Agent, University of Science and Technology of China, 2014.
9. Joubertb M. and Poalses J., The influence of emotions and personal values on packaging preference decisions, The Retail and Marketing Review, 2014, vol.10 , pp.59-67.
10. Cheng H. and Chen W., The Impacts of Emotion Regulation on Job Burnout, China, Advances in Psychological Science, 2010, vol.6 , pp.16.
11. Wang H., Luo C. and Fang B., An alliance generation algorithm based on modified particle swarm optimization for multiple emotional robots pursuit-evader problem, China, Fuzzy Systems and Knowledge Discovery (FSKD), 11th International Conference, 2014.
12. Fang B., Chen L., Wang H., Dai S.and Zhong Q., Research on Multirobot Pursuit Task Allocation Algorithm Based on Emotional Cooperation Factor, The Scientific World Journal, 2014.
13. Wang H., Zhang Q., Fang B. and Fang S., Maximum similarity matching emotion model based on mapping between state space and probability space, China, Pattern Recognition and Artificial Intelligence, 2013, vol.26(6), pp.520-560.
14. Niu G., Hu D. and Gao Q., Robot Emotion Generation and Decision-making Model Construction Based on Personality, China, Robot, 2011, vol.33(6), pp.706-711.
15. Chen W., Research on the Cognitive Behavior Modeling of Emotional Agent, China, National University of Defense Technology, 2011.
16. Damasio A., Descartes' Error: Emotion, Reason and the Human Brain, Bulletin of the American Meteorological Society, 2002, vol.83: pp.742.
17. Digman M., Personality structure: Emergence of the five factor model, Annual Review of Psychology, 1990, vol.41(1): pp.417-440.
18. Vlad T., Christopher J., Gualtiero C., Martin C., Stuart A. and Roger W., The Personality of Venues: Places and the Five-Factors ('Big Five') Model of Personality, 2013 Fourth International Conference on Computing for Geospatial Research & Application, 2013, pp.76-81.
19. Gratch J., Marsella S., Evaluating a Computational Model of Emotion, Autonomous Agents and Multi-Agent Systems, 2005, vol.11, pp.23-43.
20. Maurizio M. and Catherine P., Generating distinctive behavior for Embodied Conversational Agents, Journal on Multimodal User Interfaces, 2009, vol.3, pp.249-262.
21. Wang G., Teng S. and Fu K., Simulating Emotion and Personality for Intelligent Agent, The International Conference on Intelligent Computation Technology and Automation, Changsha, China, 2010, pp.304-308.
22. Jon E., Urgency, Inquiry (An Interdisciplinary Journal of Philosophy), 2009, vol.52, pp.399-412.
23. Fang B., Research on key technologies of multi robot pursuit, Harbin Institute of Technology, 2013.
24. Mehrabian A., Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in Temperament, University of California, 1996, vol.14, pp.261-292.
25. Hu J., Yin Q., Chen W. and Zha Y., Research on Human Cognitive Behavior Modeling Under Influence of Emotion, Journal of System Simulation, China, 2012, Vol.3, pp515-520.
26. Kartik S., Praveenkumar R. and Vairamuthu S., Improvement in Hungarian Algorithm for Assignment Problem, Artificial Intelligence Evolutionary Algorithms in Engineering Systems: Proceedings of ICAEES 2014, 2015, Vol.1, pp1-8.
27. Lumelsky V. and Stepanov A., Dynamic Path Planning for a Mobile Automation with Limited Information on the Environment, IEEE Trans on Automatic Control, 1986, Vol.31(11), pp.1057C1063.