Introducing 'Personality' Into The Multi-Robot Cooperation

Ding Yingying, He Yan, Jiang Jingping
College of Electrical Engineering, Zhejiang University
Hangzhou, 310027, P.R. China
dingyying@sohu.com, heyan@cee.zju.edu.cn, eejiang@dial.zju.edu.cn

***Abstract*—How to enable the robots cooperative efficiently is one of the most important problems in multi-robot domain. Improving the cooperation diversity can give the system chance to fit more kinds of situation. In this paper, a concept 'personality' is introduced into the multi-robot system and help to improve the diversity of the system. The previously homogenous robots may possess different personalities and become heterogeneous ones. With personality changing, the value inclination of a robot is changing either, and the behave style of a robot appears to be different with before. And when the multi-robot system works in an unknown environment, their personalities may evolve through the labor division and cooperation process to try to enlarge the benefit. We bring different personality into the multiple targets observation problem and try to analyze the influence of personality in this problem.**

***Keywords*—Personality, Multi-robot system, Cooperation, Multiple targets observation, Evolution.**

I. INTRODUCTION

Diversity is one of the most important specialities that help the animal systems to adapt to the ever-changing nature environment. In a certain biology colony, although much commonness exists among all, there still remains some particular characteristic in each individual. And based on its own speciality, an individual makes a decision about which kind of competition and cooperation manner it will choose. Much difference results in more kinds of decision modes and then, more cooperation methods, and we can say the system is of more diversity.

In a really intelligent system, we want the robots can make different decisions not only considering the different situation but also taking into account the character of the current working robots contained in the task. We want a robot to express its own point of view which can reflect its value inclination when it is cooperating or competing with others. And what's more, we want more kinds of cooperation moods, for this is good to adapting to the complex and ever changing environment.

For these purpose, we introduce the concept of 'personality' into the multi-robot system. The personality of a robot can reflect the value inclination of it and will help to decide what kind of competition and cooperation relationship with others it will choose. Different robots in a system may have different personalities, even though they are structurally homogeneous. So, a multi-robot system may become heterogeneous when the robots in the system have different kinds of personalities. The cooperation method a robot will choose not only depend on its own personality but also on the personalities of the robots working together with it, this phenomenon enlarges the cooperation kinds a lot and enable the multi-robot system possessing more choice when facing an unknown environment.

Cooperative Multi-Robot Observation of Multiple Moving Targets (CMOMMT) problem is very important in many security, surveillance, and reconnaissance tasks and it is a main application area in multi-robot domain. How to maximize the total coverage of the sensors by moving the robots constantly is the key technique in this problem. Lynne Parker[2] did the most important work in this area. She designed the A-CMOMMT process in which the local force vectors of the targets and the other robots are calculated and then the actions are concluded based on the sum of all the vectors. She also uses weights to decrease the overlap observation area. Boyoon Jung and Gaurav S. Sukhatme[3] also studied the similar case. While they also investigate the effect of the environment occlusion.

Parker did much work to decrease the overlap observation in the CMOMMT problem, such as introducing the repulsive force between robots and a weight to attenuate overlap observation area. But she didn't point out to which degree should the overlap area be decreased to produce the best observation performance and did not explain how to set parameters to get better performance.

In out work, we discuss the performance when observing robots possess different personalities, and discuss how the different personalities influence the performance of the observation and how the system contrarily influencing the personality evolution process.

II. PERSONALITY OF THE MULTI-ROBOT SYSTEM

A. Exhibition of Personality in Multi-robot System

Personality represents the value inclination of a robot and will decide the representation a robot showing. We can say that a robot exhibits its personality by behaving in a particular way. Behaviors as the basis of the activity of

This work is supported in part by the Chinese National Science Foundation under Grant 60405012

robots may contain much information in them which also including the information about personality. Some behaviors may seem to be aggressive, while others seem humility; some seems to be selfish while other behaviors seems altruist. When a robot is making decisions about which behavior to choose, it does not only consider the current situation it is facing but also takes into account its own personality. And the decision it makes at last is of course based on the value architecture or we may say its personality.

For example, when two robots meet on the way, they will try to avoid each other, to reach this purpose, they may actively move away from the other one or they may choose to just stay at the current point to wait the other robot move away. We can say the first collision avoidance method is an active one while the second is a passive one. Correspondingly, a robot with active personality is more likely to choose the active obstacle avoidance behavior, while a robot with passive personality is more likely to choose the passive behavior.

From the above example we can see that when cooperation or competition occurs among robots, different personality can result in different behaviors and then different cooperation mood. And sometimes, this diversity will do good to the performance of the system. Even if it gains no more profit, more choices is provided and this is good to the adaptation of the multi-robot system.

B. Description of Personality

A robot can exhibit its peculiar personality by behaving in a particular way. But what determines this representation is the embedded value inclination. To a robot, we can use different parameters in their value function to get different value inclination. Different value inclination induces different decision making method and then result in different behaviors and different personalities is formed.

In the artificial system personality can be represented by the value function $E(\Phi,s,a)$, which evaluates the action effect. $\Phi=\{\alpha,\beta,\gamma,\ldots\}$ is the personality parameter set representing the personality orientation. s is the current state sensed by the robot, including the environment information and the state information of itself and other robots. a is the possible action the robot could take. $E(\Phi,s,a)$ can be defined as[1]:

$$E(\Phi,s,a)=\alpha E_1(s,a)+\beta E_2(s,a)+\gamma E_3(s,a)+\ldots \qquad (1)$$

Where α, β, γ are personality parameters, and E_1, E_2, E_3 are the value functions which have relationship with α, β, γ. All of the personality parameters are non-negative. We can select the action a for state s as following:

$$a^*=\text{argmax } E(\Phi,s,a) \qquad (2)$$

With different α, β, γ we can have robots with different personalities. When the α, β, γ changes, the value inclination of a robot is also changing, then the robot will form its behavior manner across a different way.

III. INDIVIDUAL BENEFIT AND INTEGER BENIFIT

The now existing multi-robot systems are usually distributed and parallel. A robot in such a system possesses great right to make its own decision. It has independent goals and chooses behaviors on the basis of these goals and the current situation. The behaviors a robot chosen are also based on the principle of maximizing the benefit according to their own value function.

On the same time, the multi-robot systems consists of multiple robots and the performance of the system is not the direct summation of all the single performance. Sometimes, the benefit of the whole system is consistent with the benefit of the independent robots, the system gains more advantage when all the robots try to maximize their own benefit; But there still exists many situations that the profit of the system can not be improved or even be damaged when the robots in the system are too ingressive and selfish. On the worst conditions, the excessive selfishness may even cause the system to a collapse condition.

If a multi-robot system contains n robots R_1, R_2, ……R_n, and the corresponding value functions are $E_1(s_1,a_1)$, $E_2(s_2,a_2)$,…, $E_n(s_n,a_n)$, where s_i is the situation faced by the *ith* robot and a_i is the action taken by *ith* robot. The value function of the whole system is:

$$E(\mathbf{s},\mathbf{a})=E((s_1, s_2, \ldots, s_n\,; a_1, a_2,\ldots, a_n)$$

In which **s** represents the situation the multi-robot system is facing and **a** represent the action series selected by the robots of the system.

The best policy $\pi^*(s_i)$ to robot R_i is the one to maximize its value function if only its own benefit is considered,

$$\pi^*(s_i)=\text{argmax } E_i(s_i,a_i)$$

And to the whole system, the best policy $\pi^*(\mathbf{s})$ is,

$$\pi^*(\mathbf{s})= \text{argmax } E(\mathbf{s},\mathbf{a}) \qquad (3)$$

Now the problem is that when all the single robots choose the best policies in their own opinion, the integrate policy $\pi(\mathbf{s})$ may not be the best one. While on the same time, it is almost impossible to make decision after considering the whole situation of the system because of the complex and dynamic of the multi-robot environment. So the best policy of the system $\pi^*(\mathbf{s})$ is usually unreachable. What we can do is try to get to a tradeoff between them.

Because of the dynamic, complex and usually unknown identity, it is almost impossible for a single robot to choose an action on the criterion of the value function of the whole system. At the same moment, if the performance of the whole system and other robots are not considered at all, many problems also exist. Usually, a robot will choose behaviors based on its own value inclination while on the same time considering the whole performance or the performance of the other robots to some extend, the value function are now rewritten as:

$$E_i^{'}(s_i, a_i) = \alpha E_i(s_i, a_i) + (1-\alpha)E(\mathbf{s}, \mathbf{a}) \quad (4)$$

$$\begin{aligned}\pi^*(s_i) &= \arg\max_{a_i} E_i^{'}(s_i, a_i) \\ &= \arg\max_{a_i}(\alpha E_i(s_i, a_i) + (1-\alpha)E(\mathbf{s}, \mathbf{a}))\end{aligned} \quad (5)$$

The parameter α decides the degree of altruist and selfish of a robot, and the robot will change the appearance with the α changing. In fact, many aspects of the personality can be concluded as the fact to which degree the robot is selfish or altruist, so, this parameter is very important.

IV. PERSONALITY EVOLUTION IN THE MULTI-ROBOT SYSTEM

When cooperation occurs, several robots are required to work together. But we can find that in most of the cooperation situation, the cooperation is not restricted in the homogeneous mood, that is, the individuals contained in the cooperation always locate in different estate, some may act as leading cooperators while others may act as assistant. The order is formed part because of the character of the robot itself and part because of the character of other robots involved in the cooperation. What's more, it may also form by chance, for example, when several people work together, the man who acts as leader the first time may take on this role in the following work.

The evolution of the personality is somewhat slower than the evolution of behavior selection process. Personality is to some degree steady, when the environment and situation do not change excessively and an individual does not experienced with great change, the value inclination will not change greatly as usual and the personality remains to be the same. Personality is also adaptive and may change through the cooperation process. We can see that a man with aggressive personality will learn to be humility if he met many times of frustration. By adjusting personality little by little through the cooperation process with others, each robot of a system form its own personality and all the robots together form a peculiar cooperation relationship which suits the now environment.

Personality evolution is accomplished in cooperation and has relation with the certain environment. But when the personalities of the robots in a certain multi-robot system are set temporarily, they influence the cooperation mood.

Personality evolution process may also be completed by reinforcement learning. But this layer of learning is not the same as the one in which behaviors are learnt. So, we can use a multi-layer reinforcement learning model to achieve this. In the algorithm, two layers of learning are embedded, the first layer is in charge of the behavior learning, and the second layer is in charge of personality learning(Fig1). When the personality is set temporarily, and the value function is set, a robot will learn to choose behaviors in this condition. On the same time, a robot still wants to try to modify its personality to see if a different personality will help it getting more profit.

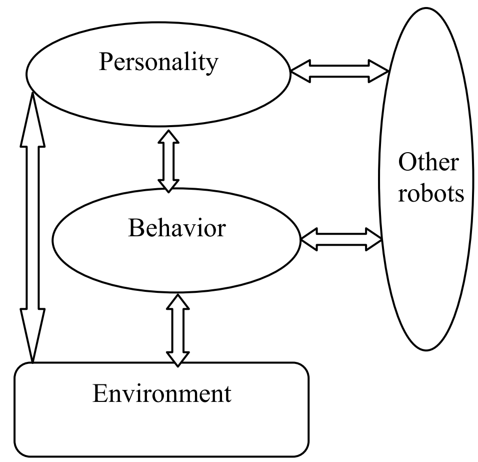


Fig1:Two layers reinforcement learning

V. CMOMMT PROBLEM DESCRIPTION

Since Parker's work is the basis of our study, we first introduce her approach to solve this problem.

A. Problem Description

The Cooperative Multi-robot Observation of Multiple Moving Targets (or CMOMMT for short) can be expressed as follow: In a space S, distributing M robots R_j(i=1,2,…,M), and N targets T_j (j=1,2,…,N). Define a $m \times n$ matrix A:

$$a_{ij} = \begin{cases} 1 & \text{If robot } i \text{ is observing target } j. \\ 0 & \text{If robot } i \text{ is not observing target } j. \end{cases} \quad (6)$$

we have $\overset{m}{\underset{i=1}{\vee}} a_{ij} = 1$ if $\vee i \quad a_{ij} = 1$

The goal is to maximize the following equation:

$$\sum_{t=0}^{T}\sum_{j=1}^{N}\overset{M}{\underset{i=1}{\vee}} a_{ij}(t)$$

That is, to maximize the observe rate of the N targets in the time duration T.

B. Local Force Vector Calculation

In order to successfully observe the local targets, Parker proposed the ***Local force vector*** method. The idea is: a robot is attracted by the adjacent targets to keep close enough to observe them and repulsed by other near robots to avoid observation overlap. The robot's next step action is based on the combination of all the local force vectors.

There are two sorts of local force: the local force $\boldsymbol{f}_{rt}$ between a robot and a target and $\boldsymbol{f}_{tt}$ between robot and robot. The value changes according to the distance between them.

C. Weighting The Local Force Vectors

Sometimes, two robots may observe the same area, we call this "*observation overlap*" phenomenon, see Fig 2. In Fig 2, robot 1 and robot 2 are both observing target 2, the overlap area is ΔS , and it is caused by target 2 which is near both of the robots. To decrease the overlap. Parker used a weight less than 1.0 to decrease the influence of target 2.

$$f_{rt}=w*f_{rt} \quad w<1.0 \tag{7}$$

Fig2 shows the result after weighting. We can see that the overlap area decreased. If now, a target 5 is just near the

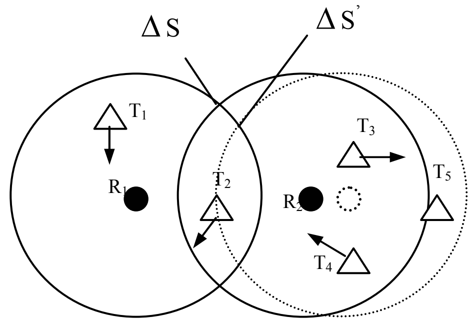


Fig 2: Overlap observation situation after weighting the local force vectors

previous area, robot 2 can observe more targets and the observation rate is increased.

D. Factors Influence The Observation Performance

When the task space S is much greater than the total area of all the robots' sensor coverage together, denoted as:

$S>>S_1+S_2+\ldots S_M$

Where S_i is the coverage area of sensor R_i. Define the efficient observation area $\overline{S}_i$, which is the sensor coverage area subtracted the equally divided overlapped area. For example, in Fig 2, the efficient coverage area of R_1 is:

$$\overline{S}_i = S_i - \frac{1}{2}\Delta S \qquad i=1,2,\ldots,M$$

where ΔS is the overlapped area. If the targets are distributed evenly, the distributing density of the targets is ρ. Now, if we want to maximize the observed targets at time t, we should maximize the sum of the sensor coverage area of all the robots, formulated as:

$$\max(observe\_num) = \max\left(\sum_{i=1}^{M}\overline{S}_i\rho\right) = \left(\max\left(\sum_{i=1}^{M}\overline{S}_i\right)\right)\rho \tag{8}$$

But in usual situations, the targets density is not always the same everywhere, it's usually different at different places, and now we have:

$$\max(observe\_num) = \max\left(\sum_{i=1}^{M}\overline{S}_i\rho_i\right) \tag{9}$$

It can be learned that, at time t, if we want to observe the most targets, the following two conditions should be satisfied, that are:

1) The overlap between the robots is minimized;

2) The robots try to observe the area with highest targets density.

From the former discussion it can be seen that when overlap observation occurs, some technique is taken to decrease it, the center idea is to enlarge the total observation area and to improve the total observation rate of the whole system. But it can also be seen that when the total observation area increases, the cost is the sacrifice of observation targets number of some of the robots. So, this problem is a one of the benefit coordination between single one and the whole system. And to which extend will a robot weight the forces of the targets in the overlap observation area is also depend on the personality aspect on altruism of that robot.

VI. PERSONALITY IN THE CMOMMT PROBLEM

Personality may have many aspects, such as altruism or selfish, aggressive or modest, initiative or passive. Each aspect can be exhibited in the value function of the robot and will influence the behavior selection of the robot.

All the relationship among animals and human beings can be concluded as competition and cooperation relationships. And the focus of this kind of relationship is to which degree a single individual permits to sacrifice its own benefit to conserve benefit of others.

Parker did not explain in detail how to adjust the parameters to get the best observation performance, and in fact it is hard to decide for the best policy has much to do with the environment settings. The policy that perform well in a situation with many robots in a small room may not suits the big room with little robots, and vice versa.

So, if we do not possess the information of the environment in advance, it is very difficult to decide the best parameters. We assign robots with different personalities, some are more selfish, and consider their own profit more important; while some of the robots are more altruistic, and are willing to sacrifice some of its own benefit to retain the interest.

Since in the CMOMMT problem, the weight $\boldsymbol{w}$ can reflect the degree a robot is willing to give up its value, so, robots using different value of $\boldsymbol{w}$ can be seen as possessing different kind of personality. A robot with a high $\boldsymbol{w}$ can be seen to be more selfish, for it is not willing to sacrifice its own benefit to improve the integer benefit; on the contrary, a robot with a small $\boldsymbol{w}$ can be seen as an altruist one, for it will not be pleasure to give up some of the targets in its observation area although this will help to increase the total observation area of the whole system.

When we use different $\boldsymbol{w}$ in a multi-robot system we can say this system is of multiple personality diversity, and will cooperatively working in many moods.

VII. SIMULATION

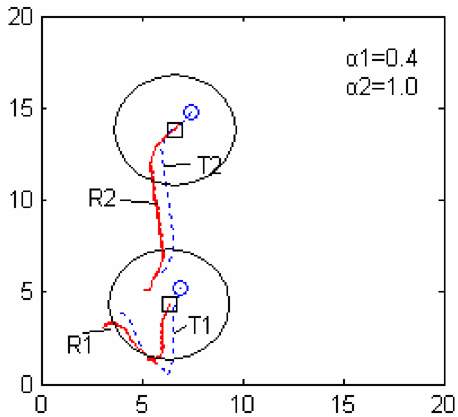
The robots used in this simulation have two behaviors, go ahead and turn randomly between 45^0 and -45^0. The robots have an omnidirectional view, and the sensor range is 3m; The velocity of targets is 0.1m/s; The velocity of the robots is 0m/s-0.3m/s; Simulation environment is a square room with each side of 20m. The local force vector parameters defined by Parker[2] are set as following:

do1=0.5m; do2=1.0m; do3=3.0m; predictive_range=4.0m;

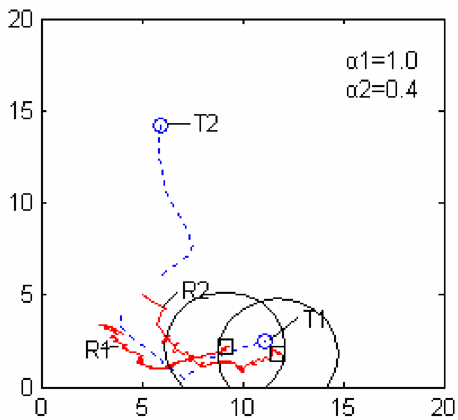
dr1=1.0m; dr2=2.5m;

$\boldsymbol{w}_{max}$=1.0;$\boldsymbol{w}_{min}$=0.2.

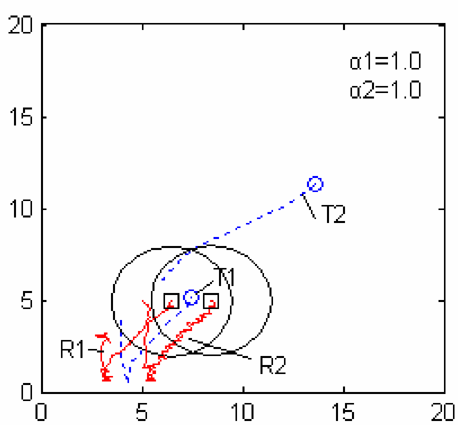
The first simulation tests the performance when the robots with different personalities are working together. Target T1 is in the observation area of both robot R1 and robot R2, while target T2 is only in the observation area of robot R2. We give robot R1 and R2 different personalities parameters and watch the cooperation results(Fig 3).



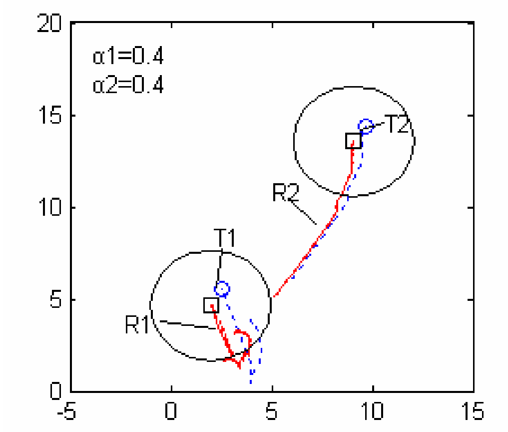
(a) Tracking results with α1=0.4, and α2=1.0



(b) Tracking results with α1=1.0, and α2=0.4



(c) Tracking results with α1=1.0, and α2=1.0



(d) Tracking results with α1=0.4, and α2=0.4

Fig3. Tracking results with different personalities

The different status and the separate results are:

Status 1: α1=0.4, and α2=1.0, R1 keep tracking T1 while R2 keep tracking T2;

Status 2: α1=1.0, and α2=0.4, R1and R2 both lost tracking of T2 and both keep tracking T1;

Status 3: α1=1.0, and α2=1.0, R1and R2 both lost tracking of T2 and both keep tracking T1;

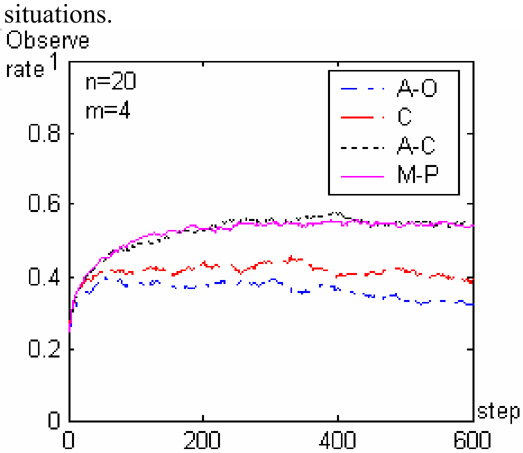
Status 4: α1=0.4, and α2=0.4, R1 keep tracking T1 while R2 keep tracking T2.

From the above results we can see that, when the personality is set, it cannot always obtain good performance. But it can also be concluded that when the robots in a system possess multiple personalities, they also possess the chance to form more kinds of cooperation moods. Although in this simulation not all the combination of different personalities works well and produce perfect results but each of the combination may fit some certain environment and so, personality diversity may help the system to adapt to more kinds of situation.

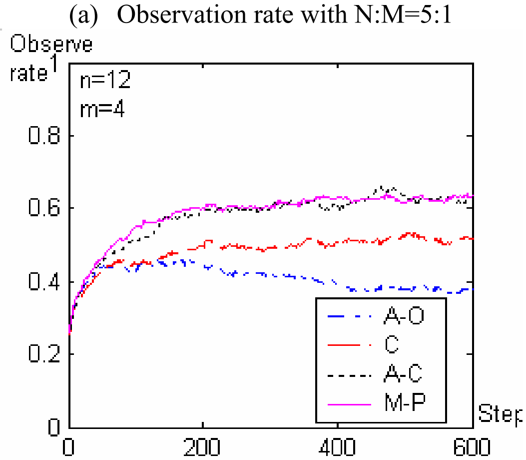
In the second simulation, four robots and N targets scatter in the room, their initial situations are randomly set. N is set to 4,8,12,20 separately, that is, N:M is 1:1, 2:1, 3:1, 5:1 separately.

This simulation is done to test the performance of the Attract-Only (A-O), CMOMMT(C), A-CMOMMT(A-C) and Multiple Personalities (M-P) method. Each simulation went on for 10mins, and the average observation rate across the simulation period is taken to judge the performance. In simulation, targets move in a *random line* mode, in which they move in a straight line most of the time, while change their direction with a small probability of 5% randomly between -45^0 and 45^0. The results are listed in table 1 and Fig 4. The data is the average results of the 100 simulations.

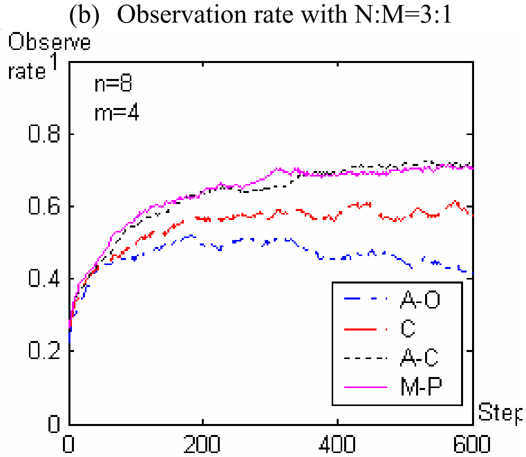
It can be seen from the simulation results: There exists obvious difference among the three algorithms. A-CMOMMT algorithm gained better performance than CMOMMT method while CMOMMT is better than Attract-Only method. This means, the overlap observation is a key problem to prevent the system to reach a higher observation rate. The multiple personalities method does not promise to gain better performance than other methods, but we can see when N:M is 1:1, 2:1, 3:1, the observation rate has the best performance. It is because when the targets are not too many, enlarge the total observation area excessively may not be the best choice. We can come to a conclusion that when multiple personalities exist in the system, it also enable the system to have chance to suit more situations.



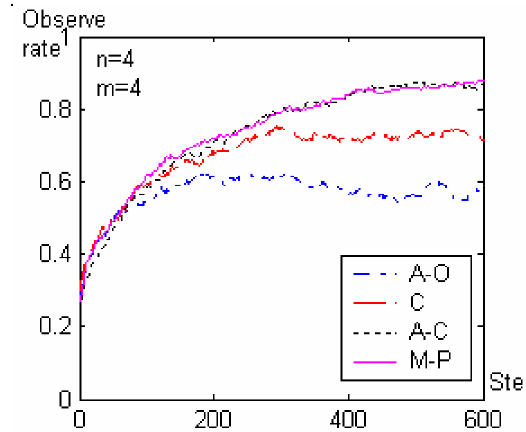
(a) Observation rate with N:M=5:1



(b) Observation rate with N:M=3:1



(c) Observation rate with N:M=2:1



(d) Observation rate with N:M=1:1

Fig4: Observation rate of Attract-only, CMOMMT, A-CMOMMT, Multiple-Personality methods when N:M is 5:1, 3:1, 2:1 and 1:1 respectively.

Table 1: The average observation rate of the four methods

N/M	A-O	C	A- C	M-P
20:4	0.3659	0.4166	0.5308	0.5226
12:4	0.4083	0.4842	0.5767	0.5847
8:4	0.4636	0.5463	0.6310	0.6361
4:4	0.5653	0.6694	0.7332	0.7399

VIII CONCLUSION

The robot personality is introduced into the robot cooperation area. It is used in the COMMT problem. Simulation results shows that personality can produce more cooperation modes and give better performance in some conditions. How to control these modes to get better results is a question needs more researches.

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