A Multi-Robot Cooperative Hunting Approach Based on Dynamic Prediction of Target Motion

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Abstract—**Multi-robot hunting receives much attention due to its natural antagonism. In this paper, a hunting approach based on dynamic prediction of target motion is proposed where the prediction step is optimized according to current environment. Based on the predicted target positions, encirclement points corresponding to different prediction steps are obtained. Then, an optimized prediction step is determined according to the variance of the distances between the robots and their respective desired encirclement points. Finally, the robots shrink to capture the target. The validity of the proposed approach is verified by simulations.**

Keywords—Multi-robot hunting; dynamic prediction of target motion; desired encirclement points; optimized prediction step.

I. Introduction

Inspired by group intelligence from biological societies, multi-robot systems have received much attention [1][2]. The typical multi-robot scenarios have been extended from collision avoidance, foraging to formation control, hunting, etc. Among them, multi-robot hunting has been specifically researched due to its characteristics of antagonism in unknown environments.

For multi-robot hunting, a few researches on target detection concern the implementation by external aids. Vidal *et al.* proposed a probabilistic approach for a team of unmanned ground vehicles pursuing the evader [3], and the position of the evader is provided by unmanned aerial vehicle. It is because of the unmanned aerial vehicle that the target is detected in a large scale. The majority of multi-robot hunting focuses on the coordination of ground robots. Cao *et al.* proposed a distributed local interaction approach under the framework of local coordinate systems [4], and the proposed approach can cope with accumulative errors of wheels and imperfect communication networks. Li *et al.* applied game theory to the hunting task where a coordinated hunting model is established based on the angles and distances among the robot, its companions, and the target [5]. In [6], a bioinspired neural network was proposed for real-time cooperative hunting by the multirobot team, without prior knowledge of the dynamic environment, and without learning procedures. Shen *et al.* formulated the relative dynamics according to the kinematics relationship between the target and hunting robots, and a Lyapunov based cooperative controller is then designed [7]. In [8], the besieging circle shrinking with leader adjusting (BCSLA) algorithm is proposed to solve the drag problem where the group shape is destroyed after the long chase in dynamic environments. The process of hunting include four states: dispersion-random-search, surround, catch, and prediction. Muro *et al.* produced the computational simulations of multi-agent systems in which wolf agents chase the prey agents, and the results suggest that wolf-pack hunting is considered as an emergent collective behavior [9]. It is worth noting that the prediction of target motion is a crucial step to improve the hunting performance [10]-[11]. Hu and Zhu predicted the next *m*-step position of the target by using a polynomial fitting method, and *m* is chosen empirically [10]. On this basis, the robots are allocated appropriate desire hunting points by negotiation. Li conducted the research on short-time position prediction of the evader for the problem of multiple cooperative defenders preventing an evader from escaping a circular region [11]. If the prediction step is selected adaptively based on current environment, a more superior hunting performance will be achieved.

In this paper, we propose an optimization solution of prediction step by minimizing the variance of distances between the robots and their respective desired encirclement points. Notice that the variance is related to the predication step. The rest of paper is organized as follows. Section II presents the proposed cooperative hunting approach in detail. Section III demonstrates the simulations and Section IV concludes the paper.

II. Cooperative Hunting Approach

In this paper, we label the pursuit robots and the target to be pursued as R_T^j (j=1,2,…,N) and R_T^G, respectively, where T refers to time. In order to perceive the environment for collision avoidance, a range sensor model S_{range} is adopted. Moreover, the robots are assumed to recognize each other, and each robot can identify the target. Compared with the robot's radius, its maximum sensing range is much greater.

In order to achieve the hunting task in unknown environments, we design an approach based on dynamic prediction of target motion, which firstly forms a larger ring of

This work was supported in part by the National High Technology Research and Development Program of China (863 Program) under Grant 2015AA042201, and in part by the National Natural Science Foundation of China under Grants 61633020, 61633017, and in part by the basic research program under Grant B132011××, and in part by the Key Research and Development Program of Shandong Province under Grant 2017CXGC0925.
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encirclement and then shrinks to catch the target by multiple robots. Specifically, the desired prediction step is introduced to acquire the best encirclement points suitable for current circumstance. For a robot R_T^j whose position is expressed by P_T^j, it first uses the latest K sampled data to predict the positions of mobile target. We denote the prediction step with ξ. Clearly, the larger ξ is, the less accurate the prediction for the target is. Therefore, ξ should be confined to a small interval, for example, $\xi \in [0, 6]$. $\xi=0$ means that there is no prediction of the target, which is corresponding to the case without target prediction. According to the cubic spline interpolation, we acquire the predicted position $(x_{T+\xi}^G, y_{T+\xi}^G)$ of target $R_{T+\xi}^G$ at next ξ step. And then, encirclement points $E_q(\xi)$ (q=1,2,…,N) corresponding to ξ are acquired according to the estimated location of mobile target. Next, an optimal algorithm for desired prediction step is designed. Based on the variance of the distances between pursuit robots and their respective encirclement points, the optimized prediction step is selected, and a set of optimal encirclement points are then determined. Each robot moves toward respective encirclement point for the formation of the ring of encirclement. After the conditions to catch the target is satisfied, the pursuit robots shrink to capture the target.

In the following, the proposed hunting approach is described by the three parts: the determination of encirclement points for pursuit robots, the selection of the desired prediction step, and a shrinking algorithm.

A. Determination the Encirclement Points for Pursuit Robots

A reference vector corresponding to the target is introduced by $\overrightarrow{P_T^G P_T^{far}} = (x_T^{far}, y_T^{far}) - (x_T^G, y_T^G)$, where P_T^{far} is the position of the robot that is farthest to the target. On this basis, the positions $P_q^E(\xi)(x_q^E, y_q^E)$ of encirclement points $E_q(\xi)$ (q=1,2,…,N) for the pursuit robots are determined by rotating $\overrightarrow{P_T^G P_T^{far}}$ clockwise with an angle of $\theta = \frac{360°}{N}$.

$$(P_q^E)^{\mathrm{T}} = \begin{pmatrix} x_{T+\xi}^G \\ y_{T+\xi}^G \end{pmatrix} + \rho \begin{pmatrix} \cos((q-1)\times\theta) & -\sin((q-1)\times\theta) \\ \sin((q-1)\times\theta) & \cos((q-1)\times\theta) \end{pmatrix} \frac{\overrightarrow{P_T^G P_T^{far}}}{|\overrightarrow{P_T^G P_T^{far}}|}^{\mathrm{T}} \quad (1)$$

where ρ is the radius of the ring of encirclement, which is given empirically. Notice that the ring of encirclement shall become invalid for the hunting execution if ρ is too large, while ρ with a too small value will easily result in the interferences among the robots.

With N encirclement points, the pursuit robots need an effective non-overlapping selection with the combination of their current positions. The purpose of this selection is to minimize average distances of the robots to encirclement points, which can shorten the execution time of hunting task. For the case with N encirclement points and N pursuit robots, there exists a permutation with A_N^N. The detailed selection algorithm $S_a(R_T^j, E_q, \xi)$ of the encirclement point $E_{q*}^j(\xi)$ for a robot R_T^j is shown in Algorithm 1, where j=1,2,…,N, q=1,2,…,N.

Algorithm 1. Selection algorithm $S_a(R_T^j, E_q^j, \xi)$ of the encirclement point $E_{q*}^j(\xi)$ for a robot R_T^j

Input: the positions P_T^j, the positions P_q^E $(q = 1,2,\dots,N)$ of all encirclement points E_q, and ξ.

Output: the encirclement point $E_{q*}^j(\xi)$ of R_T^j.

```
for q=1, 2,…, N
    d_{E_q}^{R_T^j} = |P_T^j P_q^E|; //the distance between P_T^j and P_q^E.
end for
for n=1,…, N
  if n≠j then
    for q=1,…, N
      d_{E_q}^{R_T^n} = |P_T^n P_q^E|;
    end for
  end if
end for
Min_length=∑_{n=1}^{N} d_{E_n}^{R_T^n};
Q=j;
for k=1,…, N
   Initialize Ψ={1,…,N};
   Ψ.delete(k);
   do
      Sum_length=d_{E_k}^{R_T^j}+∑_{n=1,n≠j}^{N} d_{E_ψ}^{R_T^n};
      if Sum_length<Min_length then
         Min_length=Sum_length;
         Q=k;
      end if
   while (permutation(Ψ));
end for
E_{q*}^j(ξ)=E_Q;
Return E_{q*}^j(ξ).
```

B. Selection of the Desired Prediction Step

For each robot R_T^j(j=1,2,…,N), an encirclement point $E_{q*}^j(\xi)$ has been determined by Algorithm 1, and its position is labelled as $P_{q*}^{E,j}(\xi)$. It shall be noted that this encirclement point is related to the prediction step ξ. Next, an optimized selection of ξ shall be given. An intuitional solution for the selection of ξ to minimize the sum of distances between the robots and their respective encirclement points.

As illustrated in Fig. 1, the sum of distances at ξ=0 and $\xi=\zeta$ are $\sum_{j=1}^{N}|P_T^j P_{q*}^{E,j}(0)|$ and $\sum_{j=1}^{N}|P_T^j P_{q*}^{E,j}(\zeta)|$, respectively, and $\sum_{j=1}^{N}|P_T^j P_{q*}^{E,j}(0)| < \sum_{j=1}^{N}|P_T^j P_{q*}^{E,j}(\zeta)|$. Actually, the case with ξ=0 shall result in a lengthy execution time of the robot R_T^2 due to $|P_T^2 P_{q*}^{E,2}(0)| > |P_T^2 P_{q*}^{E,2}(\zeta)|$; furthermore, it also leads to a waste of other robots' resources as $|P_T^2 P_{q*}^{E,2}(0)|$ is too long compared with $|P_T^1 P_{q*}^{E,1}(0)|$ and $|P_T^3 P_{q*}^{E,3}(0)|$. To solve this problem, the variance $V(\xi)$ to better characterize the distances

$$\xi^* = \underset{\xi\in[0,6]}{\operatorname{argmin}} V(\xi) = \underset{\xi\in[0,6]}{\operatorname{argmin}} \frac{f(\xi)}{N} \left(\sum_{j=1}^{N} \left(\left|P_T^j P_{q*}^{E,j}(\xi)\right| - \frac{1}{N}\sum_{j=1}^{N}\left|P_T^j P_{q*}^{E,j}(\xi)\right|\right)^2\right)$$

$$s.t.\ E_{q*}^j(\xi) = \underset{\substack{q\in[1,N],\psi\in E_\psi \\ E_\psi \subsetneq \text{permutation}(\Psi) \\ \Psi=\{1,\ldots q-1,q+1,N\}}}{\operatorname{argmin}} \left(\left|P_T^j P_q^E(\xi)\right| + \sum_{n=1,n\neq j}^{N}\left|P_T^n P_\psi^E(\xi)\right|\right) \quad (3)$$

between the robots and their respective desired encirclement points is introduced, which is given in equation (2).

$$V(\xi) = \frac{1}{N}\left(\sum_{j=1}^{N}\left(\left|P_T^j P_{q*}^{E,j}(\xi)\right| - \frac{1}{N}\sum_{j=1}^{N}\left|P_T^j P_{q*}^{E,j}(\xi)\right|\right)^2\right) \quad (2)$$

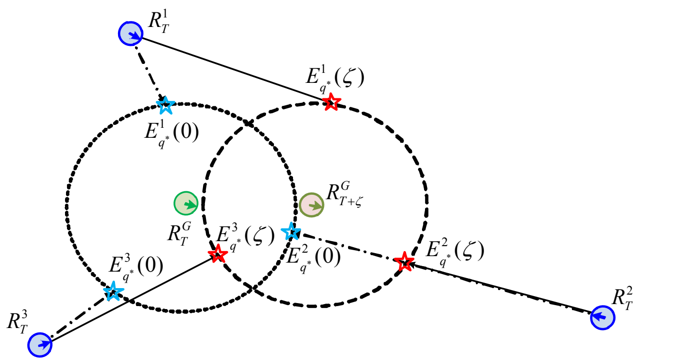

Fig. 1. The illustration of encirclement points corresponding to different ξ in a three-robot scenario.

Take $V(\xi)$ as the selection criteria, the optimal ξ^* can be solved by the equation (3), where $f(\xi)= e^{k\xi}$ is a deviation weighting function related to the prediction step ξ with f(0)=1,where k=0.05. $f(\xi)$ is used to reflect the inaccuracy of target prediction, and it increases as ξ becomes larger.

C. Shrinking Algorithm

When the distances of each pursuit robot with the target $\left|P_T^j P_T^G\right|$(j=1,2,…,N) are no more than $k_1\rho$, it means that each robot has arrived at the vicinity of the target. For each robot R_T^j, based on the line from this robot to the target, we divided other robots into two sets: Ω_l^j and Ω_r^j, which correspond to the left and right sides of the robot R_T^j, respectively. According to angles formed by $\overrightarrow{P_T^G P_T^j}$ and the direction from the target to the robots in Ω_l^j, we obtain the minimal and maximum left angles $\left|\theta_{min}^l\right|$ and $\left|\theta_{max}^l\right|$.

$$\begin{cases} \theta_{\min}^l = \min\limits_{R_T^l\in\Omega_l^j} \arctan\left(\dfrac{\overrightarrow{P_T^G P_T^j} \times \overrightarrow{P_T^G P_T^l}}{\overrightarrow{P_T^G P_T^j} \cdot \overrightarrow{P_T^G P_T^l}}\right) \\ \theta_{\max}^l = \max\limits_{R_T^l\in\Omega_l^j} \arctan\left(\dfrac{\overrightarrow{P_T^G P_T^j} \times \overrightarrow{P_T^G P_T^l}}{\overrightarrow{P_T^G P_T^j} \cdot \overrightarrow{P_T^G P_T^l}}\right) \end{cases} \quad (4)$$

Similarly, the minimal and maximum right angles $|\theta_{min}^r|$ and $|\theta_{max}^r|$ formed by R_T^j, R_T^G, and the robots in Ω_r^j are also acquired, which are given as follows.

$$\begin{cases} \theta_{\min}^r = \min\limits_{R_T^r\in\Omega_r^j} \arctan\left(\dfrac{\overrightarrow{P_T^G P_T^j} \times \overrightarrow{P_T^G P_T^r}}{\overrightarrow{P_T^G P_T^j} \cdot \overrightarrow{P_T^G P_T^r}}\right) \\ \theta_{\max}^r = \max\limits_{R_T^r\in\Omega_r^j} \arctan\left(\dfrac{\overrightarrow{P_T^G P_T^j} \times \overrightarrow{P_T^G P_T^r}}{\overrightarrow{P_T^G P_T^j} \cdot \overrightarrow{P_T^G P_T^r}}\right) \end{cases} \quad (5)$$

If the condition $|\theta_{max}^r| + |\theta_{max}^l| \geq \theta_{th}$, where θ_{th} is a given threshold by experience. In this case, the robot R_T^j will shrink to capture the target. Intuitively, the pursuit robots may move towards the target directly, however, this solution may make the target to escape the ring of encirclement easily due to a larger encirclement. On the basis of the direction from the robot to the target, a reasonable deviation is required. Fig. 2 illustrates the shrinking strategy. It is seen that based on θ_{min}^r and θ_{min}^l, a better idea for the robot R_T^j is to deviate to the right. From the smoothness improvement of the robot motion perspective, an allowance interval for angle adjustment $\hat{\boldsymbol{\theta}} = [\hat{\theta}_{min}, \hat{\theta}_{max}] = [\frac{360^\circ}{N} - w, \frac{360^\circ}{N} + w]$ is defined, where w is given empirically. To better pursue the target for the whole robotic system and prevent the target from escaping the ring of encirclement, when the larger the minimal left and right angles formed by R_T^j, R_T^G, and other robots deviate the interval $\hat{\boldsymbol{\theta}}$, the more adjustment the robot requires.

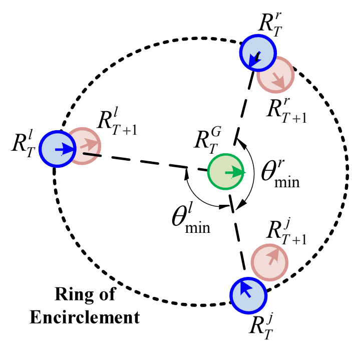

Fig. 2. The shrinking strategy.

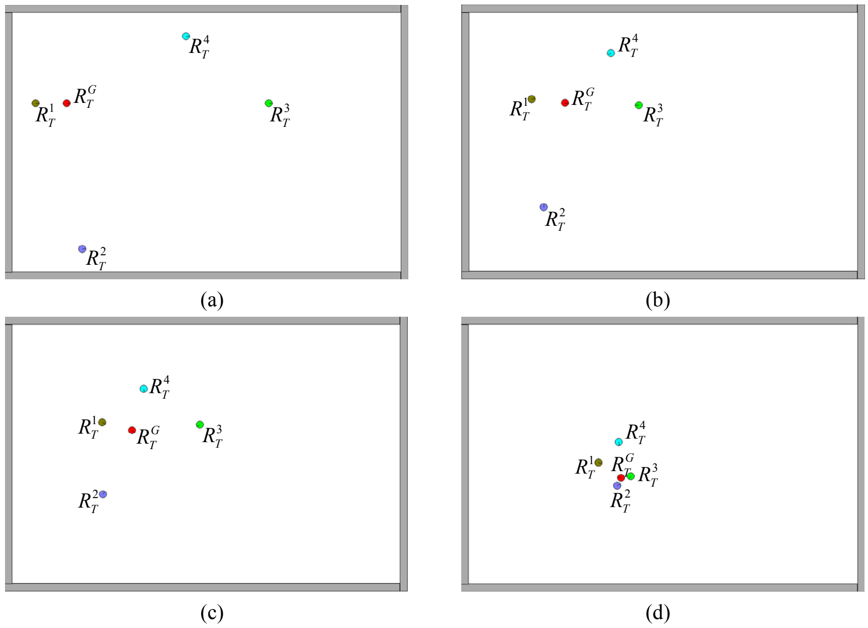

Fig. 3. The snapshots of simulation 1.

We denote with the deviation angle β. The sign of β is decided based on the influences from other robots in the sets Ω_l^j and Ω_r^j, and it has a negative sign when the left robots have a larger influence than the right robots. Its magnitude is calculated as follows, where k_2 is a given constant.

$$|\beta| = \begin{cases} k_2\left(\max(|\theta_{min}^r|,|\theta_{min}^l|) - \hat{\theta}_{max}\right) & \begin{array}{c}\left(\max(|\theta_{min}^r|,|\theta_{min}^l|) > \hat{\theta}_{max}\right) \\ \cap\left(\min(|\theta_{min}^r|,|\theta_{min}^l|) < \hat{\theta}_{max}\right)\end{array} \\ k_2\left(\hat{\theta}_{min} - \min(|\theta_{min}^r|,|\theta_{min}^l|)\right) & \begin{array}{c}\left(\min(|\theta_{min}^r|,|\theta_{min}^l|) < \hat{\theta}_{min}\right) \\ \cap\left(\max(|\theta_{min}^r|,|\theta_{min}^l|) \in \hat{\boldsymbol{\theta}}\right)\end{array} \\ 0 & others \end{cases} \tag{6}$$

Thus, the next moving direction of the robot R_T^j is given by

$$V_{direction} = \begin{pmatrix} \cos\beta & -\sin\beta \\ \sin\beta & \cos\beta \end{pmatrix} \cdot \frac{\overrightarrow{P_T^j P_T^G}}{|\overrightarrow{P_T^j P_T^G}|}^{\mathrm{T}} \tag{7}$$

III. Simulation

A team of pursuit robots with the proposed approach are required to hunt an intelligent mobile target. They have the same physical parameters, and the radius, maximum sensing range, and maximum step size are 0.5, 6, 0.3, respectively. The parameters of the proposed approach are ρ=4, k_1=1.5, k_2=2, and D_{stop}=1.3.

Simulation 1 adopts four robots R_T^j (j=1,2,…,N) to pursue the target R_T^G. The motion snapshots of robots are shown in Fig. 3. Initially, only the robot R_T^1 can detect the target. The target tries to escape toward the right before it detects the robot R_T^3, which is shown in Fig. 3(b). After it finds this robot, it intelligently changes its moving direction (see Fig. 3(c)). Finally, after the efforts of all robots, the target is smoothly captured, as shown in Fig. 3(d).

Simulation 2 considers a three-robot hunting scenario in an obstacles environment. The trajectories of all robots and the target are shown in Fig. 4, where their initial positions are expressed by S_1-S_3, and S_T, respectively. The simulation result demonstrates that the proposed approach can achieve effective coordination among the pursuit robots by reasonable arrangement of encirclement points around the target.

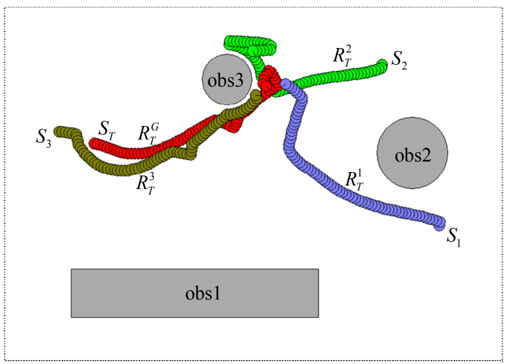

Fig. 4. The result of simulation 2.

Simulation 3 is used to testify the anti-disturbance capability of the proposed approach. The Fig. 5 depicts the simulation results under the same conditions of simulation 1. It is seen that when the target arrives at the position shown in Fig. 5(b), a sudden interference is exerted on the target, and it is moved manually to a new position (see Fig. 5(c)). In this case, the robots make timely adjustment to cope with this emergency. Finally, the target is captured, as illustrated in Fig. 5(d).

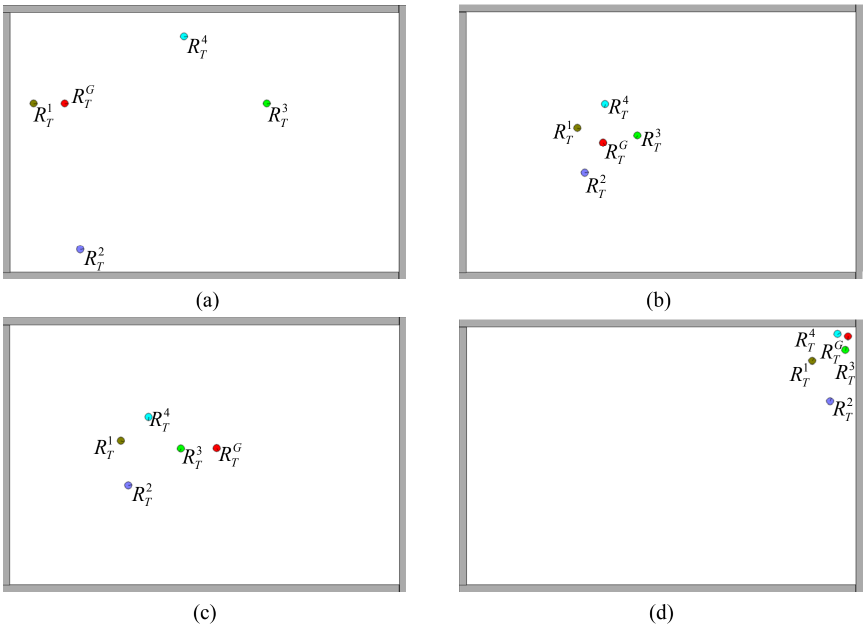

Fig. 5. The snapshots of simulation 3 where the target is moved manually to a new position.

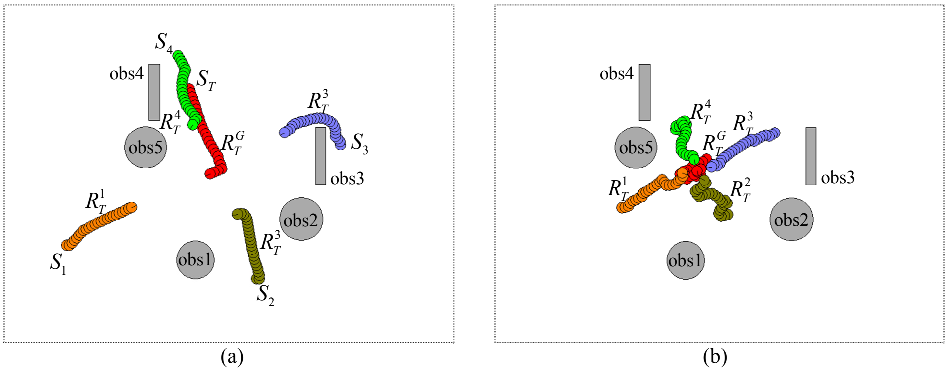

Fig. 6. The simulation 4 with a faster target.

Simulation 4 is conducted with a faster target, and its maximum step size is 30 percent higher than that of robots. The trajectories of the robots and the target are depicted in Figs. 6(a) and 6(b), and the task is completed smoothly. Clearly, the higher the target speed is, the larger the possibility of the target being out of the encirclement is. However, it may be compensated to some extent by the coordination of the robots.

As mentioned above, Existing approaches based on current position of the target [4][6][7][8] face the problem with an increased possibility of the target being out of the robots encirclement, while the approaches with target prediction [10][11] are lack of adaptability. Simulation 5 is conducted under the environment of simulation 1, where the robot R_T^3 took different initial positions by adjusting their x-coordinates. Fig. 7 gives the comparisons of the proposed approach with the hunting approaches with ξ=0, 1, 3. The approach with ξ=0 is based on current position of the target, while the approach with ξ=1 and ξ=3 correspond to target prediction with fixed next 1-step and next 3-step, respectively. Both these four approaches fulfill the task, and the proposed approach(ξ=ξ*) achieves a shorter task execution time. From all the simulations we have conducted, the proposed approach is considered as effective.

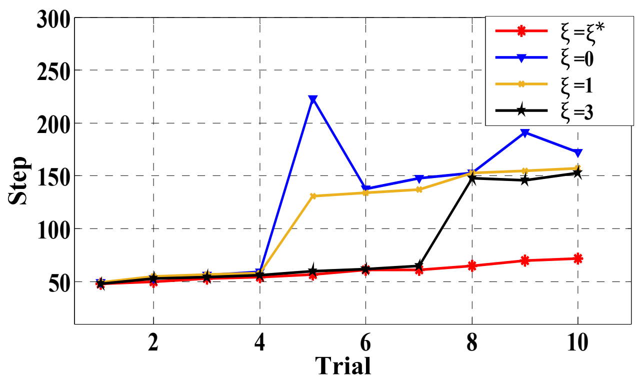

Fig. 7. The comparisons of different proposed approaches.

IV. Conclusion

This paper proposes a cooperative multi-robot hunting approach based on adaptive optimization of target prediction step where a set of optimal encirclement points for pursuit robots are generated, which guarantees that the task is fulfilled effectively. Simulation results show the effectiveness of the proposed approach.

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