Pursuing a Faster Evader Based on an Agent Team with Unstable Speeds

(Extended Abstract)

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ABSTRACT

Previous studies of multiagent pursuit-evasion problem usually assume that the pursuers can move at stable speeds. However, in many real cases, the pursuers' speeds may be unstable. In this paper, we study multiagent pursuit-evasion problem based on pursuers with unstable speeds in a continuous open world. We present a feasible pursuing strategy, and the experimental results show that our strategy can generally lead to higher capture success ratios than previous strategies in the situations where the pursuers' speeds are unstable.

Keywords

Multiagent Pursuit-Evasion Problem, Unstable Speeds, Pursuing Strategy

1. INTRODUCTION

The multiagent pursuit-evasion problem has been widely investigated in related areas [13, 8, 9, 1, 4, 16, 15, 6, 3, 14, 19, 5, 12, 2, 17, 7]. Previous studies usually assume that the pursuers can move at stable speeds [13, 8, 9, 1, 4, 16, 15, 6, 3, 14, 19, 5, 12, 2, 17, 7]. However, in some real cases, agent cannot always move at stable speed, and the actual speed may fluctuate uncontrollably in pursuit-evasion process. For instance, a quadruped robot's speed is influenced by touchdown angle so that the speed may fluctuate because of the undulations of the ground [11].

In this paper, we discuss the multiagent pursuit-evasion problem where the pursuers move at unstable speeds. The instability of the pursuers' speeds brings challenges for team collaboration. Therefore, the capture success ratio based on previous stable-speed pursuers-oriented strategies will decrease because of the instability of pursuers' speeds.

In order to increase the capture success ratio, we present a more feasible pursuing strategy. It can be known based on experimental data that, our strategy can generally lead to higher capture success ratios than previous strategies in the situations where the pursuers move at unstable speeds. The more unstable the pursuers' speeds are, the more obvious the advantage of our strategy is.

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2. PROBLEM FORMULATION

In this paper, we study the multiagent pursuit-evasion problem in a continuous open world [14, 5]. Let there be n pursuers and one single evader. The evader and pursuers are set as circles, and the diameters of them are all set as one unit distance. Both the evader and pursuers have enough visual ranges. Initially, the pursuers are randomly located surrounding the evader. The distance between the evader and each pursuer is randomly set in [0, d_0].

The evader's speed and the pursuers' maximum speed are known. Let v_e denote the evader's speed. Besides, let v_p denote the pursuers' maximum speed. We have $v_e > v_p$. The pursuers' actual speeds are initially v_p but will fluctuate between the maximum speed v_p and a lower bound v_p' every one unit time. Moreover, the pursuers do not known the values of v_p', such as that the robot cannot predict the interference of the undulations of the ground.

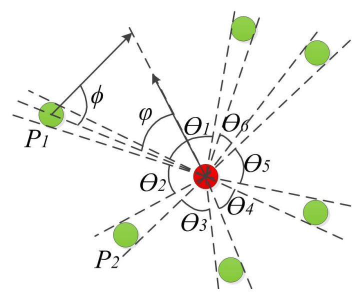

Figure 1: A case of pursuit-evasion game.

The evader's escape strategy is presented in [14], such as shown in Figure 1:

- The evader will initially compare the angles θ_1, θ_2... θ_n and select the maximum one. Then, the evader moves along the angular bisector of the maximum angle.
- If the maximum angle changes in pursuit-evasion process, the direction of the evader will also change.

If the distance between the evader and a pursuer is small enough, the evader is captured [14, 5]. In this paper, the pursuers must touch the evader to capture it. On the other hand, if the evader is out of the encircled formation consisting of pursuers, it is considered escaping successfully [14].

Overall, the problem is to find a suitable pursuing strategy to maximize the capture success ratio which is the ratio of successful captures in repeated pursuit-evasion games with various initial states [7].

3. PURSUING STRATEGY

As the pursuers' speeds are unstable, it is hard for pursuers to predict which moving direction is better. In this case, we can refer to the idea of reinforcement learning [18, 10]. It is worth noting that the learning algorithm cannot be directly used in this problem. The reason is that reinforcement learning is usually based on discrete Markov decision process while the problem in this paper is continuous [18, 10]. Therefore, we need to combine the idea of reinforcement learning with our analyses to design our own algorithm. In detail, we set ten states and ten actions. The state is based on the angle φ, and the action is represented by the value of ϕ. The reward function is based on the two angles between a pursuer and its two neighboring pursuers. It is assumed that $\theta_1(t)$ and $\theta_2(t)$ are the two angles between a pursuer and its two neighboring pursuers at time t. Then,

$$r = \lambda_1[\theta_1(t-\Delta t) - \theta_1(t)] + \lambda_2[\theta_2(t-\Delta t) - \theta_2(t)]. \quad (1)$$

Here, if $\theta_1(t-\Delta t) > \theta_2(t-\Delta t)$, $\lambda_1 = 2$ and $\lambda_2 = 1$; if $\theta_1(t-\Delta t) < \theta_2(t-\Delta t)$, $\lambda_1 = 1$ and $\lambda_2 = 2$; if $\theta_1(t-\Delta t) = \theta_2(t-\Delta t)$, $\lambda_1 = \lambda_2 = 1$. Besides, Δt represents the minimum interval between the time points at which the agents make decisions. Then, the pursuing strategy is shown in Algorithm 1. The value of ϕ is the output.

Algorithm 1 The Pursuing Algorithm

Input the angle φ, time t, speed v_p and v_e.
Initialize $Q_1(s,a)$ and $Q_2(s,a)$ randomly if $t = 0$.
if $\varphi \geq \pi/2$ **then**
  if $k\pi/20 + \pi/2 < \varphi < (k+1)\pi/20 + \pi/2$ **then**
    $s(t) \leftarrow k$
  if $t > 0$ **then**
    Calculate r based on Equations (1)
    $Q_1(s(t-\Delta t), a) \leftarrow (1-\alpha)Q_1(s(t-\Delta t), a) + \alpha[r + \gamma argmax_{a'} Q_1(s(t), a')]$
  $a^* \leftarrow argmax_{a'} Q_1(s(t), a'), a \leftarrow \varepsilon - greedy(a^*)$
  $\phi \leftarrow a(\pi - \varphi)/9$
else
  if the largest angle among θ_1, θ_2... θ_n is larger than $2arcsin(v_p/v_e)$ **then**
    $\phi \leftarrow \pi/2$
  else
    if $k\pi/20 < \varphi < (k+1)\pi/20$ **then**
      $s(t) \leftarrow k$
    if $t > 0$ **then**
      Calculate r based on Equations (1)
      $Q_2(s(t-\Delta t), a) \leftarrow (1-\alpha)Q_2(s(t-\Delta t), a) + \alpha[r + \gamma argmax_{a'} Q_2(s(t), a')]$
    $a^* \leftarrow argmax_{a'} Q_2(s(t), a'), a \leftarrow \varepsilon - greedy(a^*)$
    $\phi \leftarrow \pi/2 - a\varphi/9$

4. EXPERIMENTS

In this section, we test our strategy based on simulation experiments. Simulating continuous time, the evader and the pursuers can make decisions and change their directions per 0.1 unit time ($\Delta t = 0.1$). Each experiment is performed with 5000 replications, and the ratio of the replications where the pursuers capture the evader successfully is shown as capture success ratio. In each replication, the locations of pursuers are reset randomly.

We test our strategy and three other strategies in the experiments:

- Strategy 1: The pursuers adopt our strategy that is shown in Algorithm 1 with the parameters $\varepsilon = 0.5$, $\alpha = 0.5$ and $\gamma = 0.5$.
- Strategy 2: If $\varphi < \pi/2$, $\phi = \pi/2$. If $\varphi \geq \pi/2$, the pursuers move towards the current location of the evader.
- Strategy 3: If $\varphi < \pi/2$, $\phi = \pi/2$. If $\varphi \geq \pi/2$, the pursuers move in the same direction with the evader.
- Strategy 4: The pursuers adopt the strategy presented in [5]. Strategy 4 is a modification of Strategy 2 [5].

In Table 1, $d_0 = 50$, $n = 15$, $v_p = 1.5$ and $v_e = 2$. As v_p' is the lower bound of the pursuers' speeds, the pursuers move at stable speeds if $v_p' = v_p$. Therefore, if v_p' is larger, the pursuers' speeds are more stable. Conversely, if v_p' is smaller, the pursuers' speeds are more unstable.

Table 1

v_p'	Strategy 1	Strategy 2	Strategy 3	Strategy 4
0.1	**0.2214**	0.1826	0.1386	0.1852
0.3	**0.2832**	0.2382	0.2054	0.2486
0.5	**0.3754**	0.3226	0.2868	0.333
0.7	**0.455**	0.4238	0.3796	0.4232
0.9	**0.5684**	0.5492	0.5234	0.5516
1.1	0.6562	0.6656	0.637	**0.6678**
1.3	0.7392	0.7752	0.737	**0.776**
1.5	0.8242	**0.8754**	0.8388	**0.8754**

As shown in Table 1, our strategy is the best when $v_p' \leq 0.9$. It means that our strategy can generally lead to higher capture success ratios than previous strategies when the pursuers move at unstable speeds. When v_p' is large enough, Strategy 2, 3 and 4 are better than our strategy. The reason is that, when speeds are stable, the pursuers can directly seek the optimal decisions. As there is no uncertainty, learning process becomes insignificant. Besides, the random decision in learning process decreases the capture success ratio. Therefore, previous classical strategies becomes better than our strategy if the pursuers' speeds become stable.

Overall, our strategy is more feasible when the pursuers' speeds are unstable, but our strategy cannot exceed previous classical strategies when the pursuers' speeds are stable. Especially, the more unstable the pursuers' speeds are, the more obvious the advantage of our strategy is.

5. CONCLUSIONS

In this paper, we study multiagent pursuit-evasion game based on pursuers with unstable speeds and present a feasible pursuing strategy. The experiments show that our strategy can generally lead to higher capture success ratios than previous strategies in the situations where the pursuers' speeds are unstable.

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REFERENCES

[1] A. Alexopoulos, T. Schmidt, and E. Badreddin. Cooperative pursue in pursuit-evasion games with unmanned aerial vehicles. In *Proceedings of the 27th IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 4538–4543. IEEE, September - October 2015.

[2] M. D. Awheda and H. M. Schwartz. Decentralized learning in pursuit-evasion differential games with multi-pursuer and single-superior evader. In *Proceedings of the 4th Annual IEEE Systems Conference (SysCon)*, pages 1–8. IEEE, June 2016.

[3] S. Barrett, P. Stone, and S. Kraus. Empirical evaluation of ad hoc teamwork in the pursuit domain. In *Proceedings of the 10th International Conference on Autonomous Agents and Multiagent Systems-Volume 2 (AAMAS)*, pages 567–574. International Foundation for Autonomous Agents and Multiagent Systems, May 2011.

[4] S. Bhattacharya, T. Başar, and M. Falcone. Numerical approximation for a visibility based pursuit-evasion game. In *Proceedings of the 26th IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 68–75. IEEE, September 2014.

[5] J. Chen, W. Zha, Z. Peng, and D. Gu. Multi-player pursuit–evasion games with one superior evader. *Automatica*, 71:24–32, September 2016.

[6] T. H. Chung, G. A. Hollinger, and V. Isler. Search and pursuit-evasion in mobile robotics. *Autonomous robots*, 31(4):299–316, November 2011.

[7] B.-F. Fang, Q.-S. Pan, B.-R. Hong, L. Ding, Q.-B. Zhong, and Z. Zhang. Research on high speed evader vs. multi lower speed pursuers in multi pursuit-evasion games. *Information Technology Journal*, 11(8):989, 2012.

[8] X. Huang, P. Maupin, and R. Van Der Meyden. Model checking knowledge in pursuit evasion games. In *Proceedings of the 22nd International Joint Conference on Artificial Intelligence (IJCAI)*, volume 22, page 240, July 2011.

[9] X. Huang and R. Van Der Meyden. Synthesizing strategies for epistemic goals by epistemic model checking: An application to pursuit evasion games. In *Proceedings of the 26th AAAI Conference on Artificial Intelligence (AAAI)*, July 2012.

[10] L. P. Kaelbling, M. L. Littman, and A. W. Moore. Reinforcement learning: A survey. *Journal of artificial intelligence research*, 4:237–285, 1996.

[11] K. Y. Kim, O. Kwon, J. S. Yeon, and J. H. Park. Elliptic trajectory generation for galloping quadruped robots. In *Proceedings of the 3rd IEEE International Conference on Robotics and Biomimetics (ROBIO)*, pages 103–108. IEEE, December 2006.

[12] J. Y. Kuo, H.-F. Yu, K. F.-R. Liu, and F.-W. Lee. Multiagent cooperative learning strategies for pursuit-evasion games. *Mathematical Problems in Engineering*, 2015.

[13] E. Raboin, U. Kuter, and D. Nau. Generating strategies for multi-agent pursuit-evasion games in partially observable euclidean space. In *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems-Volume 3 (AAMAS)*, pages 1201–1202. International Foundation for Autonomous Agents and Multiagent Systems, June 2012.

[14] M. Ramana and M. Kothari. A cooperative pursuit-evasion game of a high speed evader. In *Proceedings of the 54th IEEE Conference on Decision and Control (CDC)*, pages 2969–2974. IEEE, December 2015.

[15] T. Shima. Optimal cooperative pursuit and evasion strategies against a homing missile. *Journal of Guidance, Control, and Dynamics*, 34(2):414–425, March 2011.

[16] V. Turetsky and J. Shinar. Missile guidance laws based on pursuit–evasion game formulations. *Automatica*, 39(4):607–618, April 2003.

[17] H. Wang, Q. Yue, and J. Liu. Research on pursuit-evasion games with multiple heterogeneous pursuers and a high speed evader. In *Proceedings of the 27th Chinese Control and Decision Conference (CCDC)*, pages 4366–4370. IEEE, May 2015.

[18] C. J. Watkins and P. Dayan. Q-learning. *Machine learning*, 8(3-4):279–292, 1992.

[19] T. Yasuda, K. Ohkura, T. Nomura, and Y. Matsumura. Evolutionary swarm robotics approach to a pursuit problem. In *Proceedings of the 4th IEEE Symposium on Robotic Intelligence In Informationally Structured Space (RiiSS)*, pages 1–6. IEEE, December 2014.