Proceedings of the 33rd International Conference on
Information Technologies (InfoTech-2019)
19-20 September 2019, Bulgaria

A SURVEY OF REINFORCEMENT LEARNING FOR FORMATION CONTROL

Full paper

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Abstract: Autonomous agents in moving subspace should move in a particular formation. This article provides a brief overview of current Reinforcement Learning methods for formation control. The approaches to creating the formation and avoiding collisions between individual agents are considered.
Key words: reinforcement learning, formation control, autonomous agents.

1. INTRODUCTION

The idea of formation control is to create a system capable of moving agents into a predetermined spatial pattern. Generally, Formation Control (FC) is a system that allows agents to travel as a group without collision between agents.

In recent years there are many articles devoted to different methods of FC. Moreover, there are several quite extensive surveys [7, 13, 9, 11]. However, the number of studies that are devoted to the implementation of formation control with technical tools of reinforcement learning is relatively small. In 90 years, RL [15] and FC [2] were established as distinctive themes in research into autonomous systems. In the following years, insufficient computing resources were an obstacle to the entry of RL into FC. However, with the increase in computational power, the application of RL in the FC domain is being investigated more and more intensively.

The goal of the paper is to give a brief review of recent papers that are focused on implementing of Formation Control trough Reinforcement Learning (RL).

The paper discusses the recent trends in the application of Reinforcement Learning in area Formation Control. The next section summarizes our work in this

field and some of the most useful methods in the area of Formation Control are presented.

2. REINFORCEMENT LEARNING METHODS FOR FORMATION CONTROL

"There are roughly three main approaches to multiagent coordination reported in the literature, namely leader-following, behavioural, and virtual structures"[3]. Each of these approaches comes with a different set of strengths and weaknesses.

2.1. Formation control

Leader following is based on the division of agent roles into two parts: one that leads and one that follows. Usually, the leader has a different motion programming than his followers. Besides, the leader is the only one who knows where the group is going. The other agents seek to maintain spatial relationships. Then, when the leader moves toward the goal, the other agents move following the leader [3].

The leader-following system has been proven to be able to ensure that a group of decentralized agents stay connected and do not lose track of one and another[10]. Since only the leader knows the direction to the goal, the rest of the robots should receive information from the leader only. Therefore, the connections graph forms a simple spanning directed tree. So, the minimum configuration is needded to achieve the goal. From a technological point of view, this directly affects the simplicity of its implementation. [5]

In recent years in the leader-following system neural networks are becoming popular. There are systems with the primal-dual neural network with parallel capability [19]. Also an adaptive neural network (NN)-based, leader-following consensus approach is proposed [17].

Conduct Based Behaviour FC assigns each agent to set of desired behaviours. For example, behaviour-based FC was used to control DARPA unmanned ground vehicles and maintain several different formations [2].

One way to position a formation is to set the centre of the group as the average position of all agents involved. Another method is to promote a single agent as a group leader. This agent does not attempt to maintain a formation; instead, other agents are responsible for maintaining the formation. This approach is called Leader-reference. Finally, another method of centring a formation is to rely solely on neighbour data, which means Neighbour reference [2].

The main advantage of the behavior-based approach is its ability to combine several competing goals. Also, the behavioral approach is easily implemented in a decentralized system. The main disadvantage of behavior-based formation management is that the group dynamics cannot be defined; instead, the behavior of the group follows from the rules of each agent. It also means that this approach is difficult to analyze mathematically, and the stability of the formation cannot be guaranteed [3].

Virtual structures are another approach for FC. Using virtual structures, the entire group of agents behaves as a single structure. The main advantage of using virtual structures is the simplicity of this approach [16]. Moreover, the feedback with the virtual structures is defined. Yet, since the virtual form requires the group to act as a unit, the flexibility of the system is constrained.

2.2. Reinforcement learning and Multi-Agent Systems

RL is the process of finding a match between situations and actions using a numeric reward signal. As a rule, the agent interacts with the environment, not telling what actions to take or how they will affect the environment. Instead, the agent should examine the behaviour by trial and error [15]. RL can be used for robots to select different behaviours in various situations [21]. It also removes the tedious work of creating a meaningful representation by hand and is able to adapt to different settings in a flexible way. So, applying Deep Q-learning to the problem of FC successfully deals with the large state-spaces environment [1]. The decentralized geometric approach to controlling agents that are implemented by Q-Learning is able to reduce the complexity of team coordination [12].

Several methods that apply the RL algorithm to a leader-follower formation control scenario are proposed [8, 18]. As for the fuzzy logic controller, reinforcement learning could be combined to improve the learning speed of the formation behaviour [20] or estimating the unknown non-linear dynamics [18].

A Multi-Agent System (MAS) consists of several agents whose task is to interact to achieve a specific goal. The form of these agents can be any, from physical robots to virtual components in a software system. Recently the paradigms of deep learning and MAS are combined [6]. Another study used RL to teach agents how to get into formations without using management theory. Multi-agent fuzzy RL algorithm is presented as an extension of fuzzy actor-critic reinforcement learning in a MAS environment [4]. In recent years is developed a consensus-based distributed RL algorithm to design an individual controller of a homogeneous multi-agent system [14].

3. CONCLUSION

The movement of groups of agents into space often requires that certain distances be maintained between individual agents. This is achieved by building a particular formation.

Depending on, how the formations are constructed, the following main approaches are considered: Following the Leader, Conduct Based Behaviour and Virtual Structures. This paper reviews the methods of RL algorithms for formation control.

REFERENCES

[1] Aykin, C., Knopp, M., & Diepold, K. **(2018)**. "Deep Reinforcement Learning for Formation Control." In *2018 27th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)* (pp. 1-5). IEEE.

[2] T. Balch and R. C. Arkin. **(1998)**. "Behavior-based formation control for multirobot teams". *In: IEEE Transactions on Robotics and Automation 14.6* , pp. 926–939.

[3] R. W. Beard, J. Lawton, and F. Y. Hadaegh. **(2001).** "A coordination architecture for spacecraft formation control". I*n: IEEE Transactions on Control Systems Technology 9.6* , pp. 777–790.

[4] Derhami, V., Momeni, Y. **(2016)**. "Applying reinforcement learning in formation control of agents." In *Intelligent Distributed Computing IX* (pp. 297-307). Springer, Cham.

[5] Ge, X., Han, Q. L., & Yang, F. **(2016)**. Event-based set-membership leader-following consensus of networked multi-agent systems subject to limited communication resources and unknown-but-bounded noise. *IEEE Transactions on Industrial Electronics*, *64*(6), 5045-5054.

[6] Gupta, J. K., Egorov, M., Kochenderfer, M. **(2017)**. "Cooperative multi-agent control using deep reinforcement learning". In *International Conference on Autonomous Agents and Multiagent Systems* (pp. 66-83). Springer, Cham.

[7] Kanjanawanishkul, K. **(2016)**. "Formation control of mobile robots: Survey". *วารสาร วิชาการ วิศวกรรมศาสตร์ ม. อบ.*, *4*(1), 50-64.

[8] M. Knopp, C. Aykın, J. Feldmaier, and H. Shen, **(2017)**."Formation control using GQ(λ) reinforcement learning". In *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO- MAN)*, Lisbon, Aug., pp. 1043–1048.

[9] Liu, Y., & Bucknall, R. **(2018)**. "A survey of formation control and motion planning of multiple unmanned vehicles". *Robotica*, *36*(7), 1019-1047.

[10] Loria, A., Dasdemir, J., Jarquin, N. A. **(2015)**. "Leader–follower formation and tracking control of mobile robots along straight paths". *IEEE transactions on control systems* , *24*(2), 727-732.

[11 Oh, K. K., Park, M. C., & Ahn, H. S. **(2015)**. "A survey of multi-agent formation control". *Automatica*, *53*, 424-440.

[12] Prasad, B. S., Manjunath, A. G., & Ramasangu, H. **(2017)**. "Multi-agent Polygon Formation using Reinforcement Learning". In *ICAART (1)* (pp. 159-165).]

[13] Ren, W., Beard, R. W., & Atkins, E. M. **(2005)**. "A survey of consensus problems in multi-agent coordination". In *Proceedings of the 2005, American Control Conference, 2005*. (pp. 1859-1864).

[14] Shinde, C., Das, K., Kumar, S., & Behera, L. **(2018)**. "Distributed Reinforcement Learning Based Optimal Controller For Mobile Robot Formation". In *2018 European Control Conference (ECC)* (pp. 2800-2805). IEEE.]

[15] Sutton R. S. Barto A. G **(1998)**. "Introduction to Reinforcement Learning". Cambridge, MA, USA: MIT Press, 1998. ISBN: 0262193981.

[16] Tan, K. H., & Lewis, M. A. **(1996)**. "Virtual structures for high-precision cooperative mobile robotic control". In *Proceedings of IEEE/RSJ International Conference on Intelligent Robots and Systems. IROS'96* (Vol. 1, pp. 132-139). IEEE.

[17] Wen, G. X., Chen, C. P., Liu, Y. J., & Liu, Z. **(2015)**. "Neural-network-based adaptive leader-following consensus control for second-order non-linear multi-agent systems". *IET Control Theory & Applications*, *9*(13), 1927-1934.

[18] G. Wen, C. L. P. Chen, J. Feng, and N. Zhou, **(2018)**. "Optimized multi-agent formation control based on an identifier-actor-critic reinforcement learning algorithm," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 5, pp. 2719–2731, Oct.

[19] Xiao, H., Li, Z., & Chen, C. P. **(2016)**. Formation control of leader–follower mobile robots' systems using model predictive control based on neural-dynamic optimization. *IEEE Transactions on Industrial Electronics*, *63*(9), 5752-5762.

[20] Zhang R, Y. Shi, **(2004)**. "Research on intelligent robot formation based on Q-learning". In *Proceedings of International Conference on Machine Learning*, vol. 3, Shanghai, pp. 1936–194

[21], G., Han, J., & Han, G. **(2010)**. "Multi-robot formation control using reinforcement learning method". In *International Conference in Swarm Intelligence* (pp. 667-674). Springer, Berlin, Heidelberg.