Decentralized Multi-agent Formation Control via Deep Reinforcement Learning

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Abstract: Multi-agent formation control has been a much-researched topic and while several methods from control theory exist, they require astute expertise to tune properly which is highly resource-intensive and often fails to adapt properly to slight changes in the environment. This paper presents an end-to-end decentralized approach towards multi-agent formation control with the information available from onboard sensors by using a Deep Reinforcement learning framework. The proposed method directly utilizes the raw sensor readings to calculate the agent's movement velocity using a Deep Neural Network. The approach utilizes Policy gradient methods to generalize efficiently on various simulation scenarios and is trained over a large number of agents. We validate the performance of the learned policy using numerous simulated scenarios and a comprehensive evaluation. Finally, the performance of the learned policy is demonstrated in new scenarios with non-cooperative agents that were not introduced during the training process.

1 INTRODUCTION

Multi-agent systems are rapidly gaining momentum due to their several real-world applications in disaster relief scenarios, rescue operations, military operations, warehouse management, agriculture and many more. All these tasks require the teams of robots to cooperate autonomously to produce the desired results as displayed by many animals and insects in nature which emulate swarming behaviour.

One of the major challenges for multi-agent systems is autonomous navigation while adhering to the three rules of Reynolds (Reynolds and Craig, 1987). Modern control theory presents numerous solutions, supported with rigorous proofs, to this problem and demonstrates the feasibility of multi-agent formation control and obstacle avoidance. (Marko and Stiepan, 2012), (Anuj et al., 2020), (Egerestedt, 2007) present an artificial potential field approach and have demonstrated stable autonomous navigation of a swarm of unmanned aerial vehicles (UAVs). While this approach does the work, it neglects the non-linearities in the system dynamics and thus fails to demonstrate optimal behaviour in conjunction with the vehicle dynamics. Further, these approaches require extensive tuning to provide desired performance.

Further, in (Hung and Givigi, 2017), a Q-learning based controller is presented for flocking of a swarm of UAVs in unknown environments using a leader-follower approach. This approach does not yield an optimal solution as state space and action space is discretized to limit the size of the Q-table. As the number of states increases, computing the Q-table becomes increasingly inefficient. Another disadvantage of this approach is the single point of failure offered by the leader agent.

In (Johns and Rasmus, 2018), Reinforcement learning is utilized to improve the performance of a behaviour-based control algorithm which serves as both a baseline from which the RL algorithm compares with and a base from which the RL algorithm starts training. This approach produces significant results but is not an end to end solution which can be directly applied to any kind of system. Appropriate tuning of the behaviour-based control algorithm is still required for the efficient performance of the complete controller.

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The contribution of this paper is to propose a decentralized, end-to-end framework that is scalable, adaptive, and fault-tolerant which directly maps the sensor data to optimal steering commands. To overcome the problems offered by discrete state space and discrete action space controllers, we propose a policy gradient-based controller, which utilizes a Deep neural network map the continuous state space directly to a continuous action space. The effectiveness of policy learned from the proposed method is demonstrated through a series of simulation experiments where it is able to find the optimal trajectories in complex environments.

The rest of the paper is organised as follows: Section II gives a short introduction to Policy Gradient methods and leads on for the mathematical formulation of our problem statement in the context of RL. Section III introduces the proposed algorithm and the underlying structure of the complete controller for decentralized implementation. Subsequently, section IV describes the simulation environment, the computational complexity of our approach and presents the quantitative results obtained. Further, it also provides the experimental results in unknown environments to demonstrate the generalization capability of the learned policy. Finally, Section V concludes the paper with recommendations for future work.

2 PRELIMINARIES

2.1 Markov Decision Process

A Markov decision process (Bellman and Richard, 1957) is a finite transition graph which satisfies the markov property. For a single agent MDP can be represented by a tuple $Z = (S, A, R)$ where $S = \{s_1, \dots, s_T\}$ is the set of states, $A = \{a_1, \dots, a_{T-1}\}$ is the set of actions and $R = \{r_1, \dots, r_{T-1}\}$ is the set of rewards obtained by through transition between states (s_T represents the terminal state). The objective is to find the solution of this MDP to maximize the expected sum of rewards by finding the optimal policy, value function or action-value function.

2.2 Deep Q-learning

Deep Q-learning (Mnih et al., 2015) is one of the well-known methods in Deep RL and has been shown to provide extremely efficient results. It uses deep neural networks for estimating the action-value function for a given problem to identify the optimal action in any state. The estimator function can be described as:

$$Q^{\pi}(s,a) = E_{s'\sim P}\left[r(s,a) + \gamma \max_{a'} Q^{\pi}(s',a')\right] \quad (1)$$

where, E is the denotes the expectation operator. Therefore, if the neural network representing the Q function is given by parameters φ, the loss function can be given by:

$$L(\varphi, D) = E_{(s,a,r,s')\sim P}[(Q^{\pi}(s,a) - y)^2] \quad (2)$$

$y = (r + \gamma(1-d)\max_{a'} Q^{\pi'}(s',a')$ is called the temporal difference and is calculated using target network Q^π' which is updated with the same parameters as main Q-function periodically. This method stores the set of experiences generated over time into the Replay buffer which is used to randomly sample data for training the loss function given above.

2.3 Policy Gradient Algorithms

Policy gradient algorithms explicitly denote the policy as $\pi_{\theta}(a|s)$ represented by a deep neural network with parameter θ. These parameters can be trained by maximizing the objective function $J(\pi_{\theta}) = E_{s'\sim P, a\sim\pi_{\theta}}(R)$, where R is the reward function. Thus, to update the policy parameters, gradient ascent can be used by calculating the gradient of the objective function.

$$\theta_{k+1} = \theta_k + \alpha \nabla_{\theta} J(\pi_{\theta})|_{\theta_k} \quad (3)$$

Where,

$$\nabla_{\theta} J(\pi_{\theta}) = E_{s\sim P, a\sim\pi_{\theta}}\left[\sum_{t=0}^{T} \nabla_{\theta} \log \pi_{\theta}(a_t|s_t) R\right]$$

These methods can be used for both stochastic as well as deterministic policies and thus are suitable for problems with continuous action spaces.

2.4 Algebraic Graph Theory

A complete multi-agent system can be mathematically represented by a weighted undirected graph $G = (V, E)$ where $V = \{1,2, \dots, N\}$ is the set of agents and $E = \{(i,j): i,j \in V, i \neq j\}$ is the edge set. The adjacency matrix of graph G represented by $A(G)$ is a standard matrix in graph theory which represents the weights of the edges. This matrix can be used to represent the relationship between agents.

3 PROBLEM FORMULATION

In this paper, the task of formation flocking is defined in the context of holonomic agents moving on the Euclidean plane. The position vector for each agent can be denoted by $p_i^t = [x_i, y_i]^T$ and the velocity vector by $v_i^t = [\dot{x}_i, \dot{y}_i]^T$, for the UAV i (i = 1, 2, …, N) at time t, where N is the number of UAVs. The goal of the agents is to attain the desired formation using the adjacency matric A_{FM} of the formation matrix graph G_{FM} (where the weight of each edge (i, j) of the graph corresponds to the desired distance between the agents i and j) and navigate to the goal position $p_g^t = [x_g, y_g]^T$ while avoiding inter-agent collisions. To maintain the formation at the goal position, another adjacency matrix A_{GFM} of graph G_{GFM} (where the weight of each edge (i, p_g) of the graph corresponds to the desired distance between the agent i and goal position p_g.

Thus, the problem statement can be modelled as a sequential MDP defined by a tuple $Z = (S, A, R, O)$ where, $S = \{S_1, \dots S_N\}, A = \{A_1, \dots, A_N\}$, $R = \{R_1, \dots, R_N\}$, $O = \{O_1, \dots, O_N\}$ is the set of sets of states, actions, rewards and observations of all agents.

At time step t, agent i is present in state s and has access to an observation o, which is used to calculate action a. As a consequence of this action, the agent reaches a new state s', receives a reward r and has access to new observation o'. The goal of the agent is to learn the optimal policy $\pi_\theta^*(a|s)$ where θ denotes the policy parameters which maximizes the sum of obtained rewards. This process continues until all the agents reach the goal position where the episode terminates.

The sequence of the tuple (o, a, r, o') made by the robot i can be considered as a trajectory denoted by τ. The set of these trajectories collected by all the agents is denoted by D and is stored in memory as the Replay buffer. B denotes the minibatch of experiences randomly samples from D for training the model.

4 APPROACH

4.1 Environmental Setup

To solve the sequential MDP defined in Section III, an environmental model with appropriately defined observation space, action space and reward function is required.

4.1.1 Observation Space

The observation space o consists of the planar position of each agent given by p_i^t along with the goal position p_g^t. These values are flattened and passed to a fully connected input layer of the policy network to calculate the action values. Thus, the size of input layer varies with the number of agents which also increases the training time for the policy network.

4.1.2 Action Space

The holonomic agents considered for the problem statement have an action space that consists of a set of permissible velocities in the continuous space. The output action is the two-dimensional velocity vector $v_i^t = [\dot{x}_i, \dot{y}_i]^T$. The output layer is constrained by the hyperbolic tangent ($tanh$) activation function which limits the output value in the range of (-1,1). This output value is then multiplied by v_{max} parameter to limit the action value, which is then directly passed to the navigation controller of the agent.

4.1.3 Reward Function

To achieve the target of formation control and navigation in the minimum time possible, the reward function is designed as follows:

$$r_i^t = (r_G)_i^t + (r_F)_i^t + (r_C)_i^t \tag{4}$$

where, the total reward r_i^t is the sum of goal reward (r_G), formation reward (r_F) and inter-agent collision penalty (r_C) of an agent i at timestep t.

The goal reward $(r_G)_i^t$ is awarded for the agent i for reaching the goal position as:

$$d_g = \|p_g^t - p_i^t\|$$

$$(r_G)_i^t = \begin{cases} r_{goal} & , \left|d_g - A_{GFM}^{i,p_g}\right| < d_{wp} \\ \frac{C_g}{N}\left(\left|d_g - A_{GFM}^{i,p_g}\right|\right), otherwise \end{cases} \tag{5}$$

To maintain the desired formation as governed by the formation graph G_{FM}, the agents are penalized for deviating from their desired relative position with other agents as:

$$(r_F)_i^t = \frac{C_f}{N} \sum_{j=1, j\neq i}^{N} \left| \|p_i^t - p_j^t\| - A_{FM}^{i,j} \right| \tag{6}$$

Finally, to avoid inter-agent collisions, the agents are penalized as follows:

$$(r_C)_i^t = \sum_{j=1, j\neq i}^{N} \begin{cases} r_{collision}, \|p_i^t - p_j^t\| < d_{safe} \\ 0, otherwise \end{cases} \tag{7}$$

Algorithm 1: Multi-agent TD3.

Initialize policy network with parameters θ, Q-functions with parameters φ_1, φ_2. Empty the replay buffer D

Set target network parameters equal to main parameters

$$\theta_{target} \leftarrow \theta, \varphi_{target,1} \leftarrow \varphi_1, \varphi_{target,2} \leftarrow \varphi_2$$

for number of episodes **do**

  for robot $i = 1,2, \dots N$ **do**

    Take observation o^t select action

$$a = clip\left(\mu_{\theta_{target}}(s') + \varepsilon, a_{Low}, a_{High}\right)$$

    Execute action a in the environment

    Observe next state o', reward r and done signal d to indicate whether o′ is terminal.

    Store (o, a, r, o', d) in replay buffer D

    If o' is terminal, reset environment state.

  end for

  if memory can provide minibatch **then**

    Randomly sample a batch of transitions,

$$B = \{(o, a, r, o', d)\} \text{ from } D$$

    Compute target actions

$$a'(o') = clip\left(\mu_{\theta_{target}}(o') + q, a_{Low}, a_{High}\right)$$

$$q = clip(\varepsilon, -c, c)$$

    Compute Bellman target

$$y(r, o', d) = r + \gamma(1 - d) \min_{k=1,2} Q_{\varphi_{target,k}}(o', a'(o'))$$

    Update Q-functions by one step of gradient descent using lr_ϕ

$$\nabla_{\varphi_k} \frac{1}{|B|} \sum_{(o,a,o',d) \in B} \left(Q_{\varphi_k}(o, a) - y(r, o', d)\right)^2 \quad k = 1,2$$

    if time to update policy **then**

      Update policy by one step of gradient ascent using lr_θ

$$\nabla_\theta \frac{1}{|B|} \sum_{o \in B} Q_{\varphi_1}(o, \pi_\theta(o))$$

      Update target networks with

$$\theta_{target} \leftarrow \rho\theta_{target} + (1 - \rho)\theta$$

$$\varphi_{target,k} \leftarrow \rho\varphi_{target,k} + (1 - \rho)\varphi_k \quad k = 1,2$$

    end if

  end if

end for

4.2 Algorithm Design

The algorithm used in this paper is an extended version of the state-of-the-art Twin Delayed Deterministic Policy Gradient algorithm (Fujimoto et al., 2018), (Lillicrap et al., 2015)) commonly known as TD3. TD3 concurrently learns two Q-functions and a policy and uses the smaller out of the two Q-values to calculate the loss function. We use the paradigm of centralized training with decentralized execution, which means that the data collected by all the agents is used for training the policy network $\pi_\theta(a|s)$, but each agent takes action in a decentralized fashion by using this policy.

During each episode of the training process, there are two major steps. First, all the agents exploit the same policy to calculate their actions and record their new observations which are then stored in the replay buffer. Second, random batches of experiences are sampled from the replay buffer to calculate the Bellman target which is used to calculate the loss function as given in eq.2. This loss is optimized using Adam optimizer (Kingma et al., 2014). Further, for policy training, the problem statement requires a deterministic policy $\pi_\theta(a|s)$ which gives the action that maximizes the Q-function. Therefore, the objective function can be modified as

$$J(\pi_\theta) = \max_\theta E_{o \sim B}\left[Q_\varphi(o, \pi_\theta)\right] \quad (8)$$

and therefore, the policy gradient can be calculated as

$$\nabla_\theta J(\pi_\theta) = \nabla_\theta \frac{1}{|B|} \sum_{o \in B} Q_{\varphi_1}(o, \pi_\theta(o)) \quad (9)$$

The target networks in the algorithm are updated periodically using the Polyak averaging method as follows:

$$\theta_{target} \leftarrow \rho\theta_{target} + (1 - \rho)\theta \quad (10)$$

$$\varphi_{target,k} \leftarrow \rho\varphi_{target,k} + (1 - \rho)\varphi_k \quad ; k = 1,2 \quad (11)$$

where $\rho \ll 1$.

4.3 Network Architecture

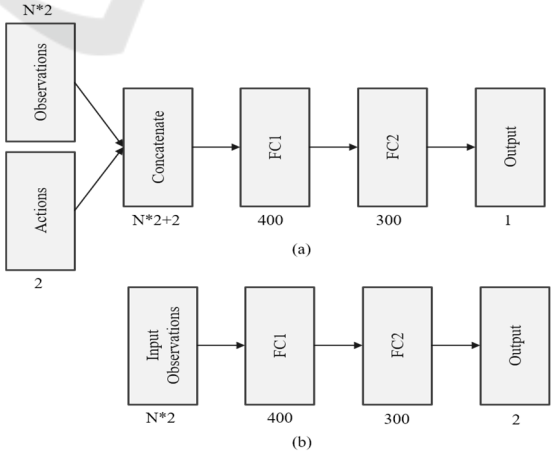


Figure 1: Network architecture of the (a) critic and (b) actor neural networks.

TD3 algorithm utilizes six neural networks in total, three main and three target networks. The target networks are employed to stabilize the training process. The observation o with dimensions $(N * 2 * 1)$ directly acts as the input for the policy network and outputs the action value. While for the Q-network, observation o and action a are concatenated to form the input layer and the output is a single Q-value which gives the quality of that action. The network architecture for both policy network and the Q-network is given in Figure.1. RELU activation function is used for the hidden layers while the output layer utilizes a 'tan h' activation function to limit the output velocity by a maximum limit.

5 SIMULATION AND TESTING

In this section, first the method of simulation is explained. Then, the computational complexity of the algorithm and training resources utilized is described. Lastly, the quantitative results of various simulations in varying environments are demonstrated.

5.1 Simulation Environment

The simulation environment is a custom developed GUI using Matplotlib library in python. The blue circles represent the agents, the red circle is the goal and the black circles are the obstacles.

The start position of the agents, goal position and all the obstacles are randomly generated after each episode is over. This approach was found to prevent the policy from exploiting the errors in the Q-function and thus improved the performance of the algorithm substantially.

5.2 Training Configuration

The complete implementation was carried out using TensorFlow 2 on a computer with a Nvidia GTX 1060 GPU and an Intel i7-8750 CPU with the set of hyper-parameters as mentioned in Table 1. The complete training process took about 22 hours for the learned policy to achieve robust performance in a complete simulation of 10 agents.

During the execution, since only the actor network is required, the computational resources required are minimal and thus the same architecture can be used on single-board computers like the Nvidia Jetson nano and Raspberry Pi.

Table 1: Hyperparameters used for simulation.

Hyperparameter	Value	Hyperparameter	Value
B	1000	ε	0.1
γ	0.99	c	0.5
lr_θ	0.0001	r_{goal}	10
lr_ϕ	0.001	$r_{collision}$	-50
ρ	0.995	d_{wap}	0.5
D	1000000	d_{safe}	1
a_{Low}	-2	C_f	-0.1
a_{High}	2	C_g	-0.1

5.3 Experiments and Results

Since, the observation space consists of the planar positions of all the agents and the goal position, the training time increases rapidly as the number of agents scale up. Figure 3 shows the training time required for training the policy on three, five, seven and ten agents respectively.

Further, Figure 3 shows the average reward received as training progresses. Figure 4-6 shows the performance of the learned policy on a varying number of agents for different formations.

To test the generalization capabilities of the learned policy, we introduced non-cooperative agents [agents travelling directly towards the goal position in a straight line with constant velocity] which were not used during the entire training process. But the learned policy was able to generalize well with these agents as demonstrated in Figure 7. (Non-cooperative agents are shown by square boxes)

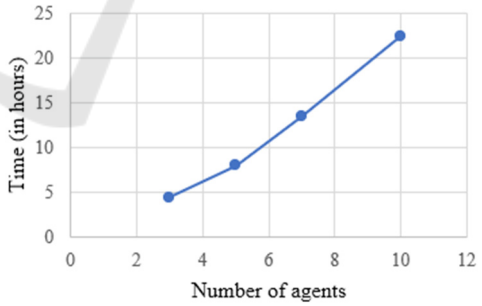


Figure 2: Increase in training time with increment in number of agents.

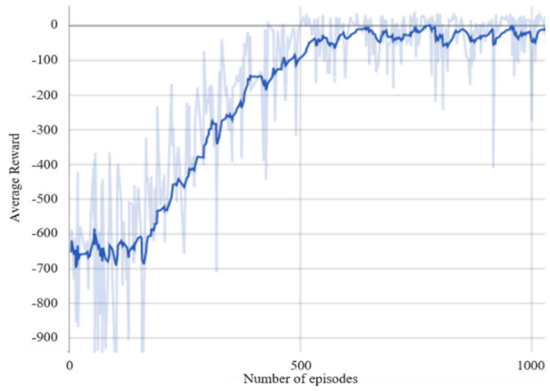
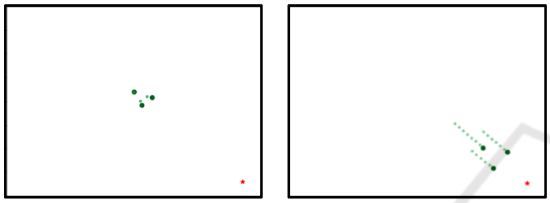


Figure 3: Average rewards progression with increasing episodes during training process.

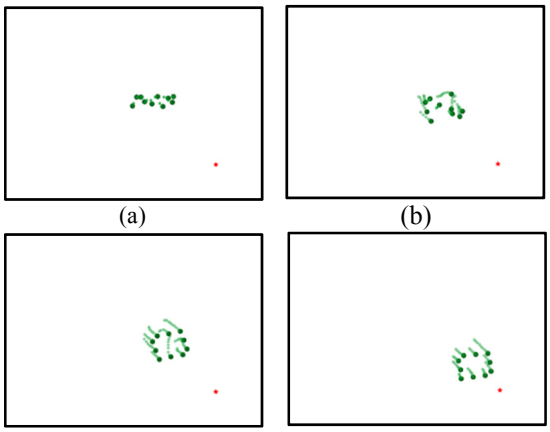


(a) (b)

Figure 4: V-formation using 3 agents.

(a) (b)

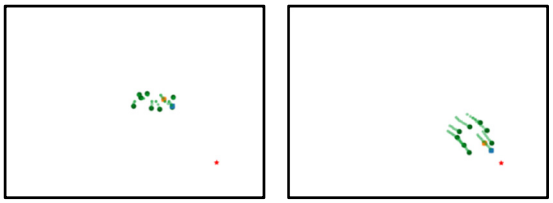
Figure 5: X-formation using 5 agents.



(a) (b)

(c) (d)

Figure 6: Diamond-formation using 10 agents.



(a) (b)

Figure 7: Diamond-formation using 8 cooperative and 2 non-cooperative agents.

6 CONCLUSIONS

In this paper, we addressed the problem of Multi-agent formation control and navigation in unknown environments by using an end-to-end Deep Reinforcement Learning framework. The learned policy demonstrates several advantages over the existing methods in terms of maintaining the desired formation, collision avoidance performance, adaptability to the environments and generalized performance.

Multi-agent systems are the future of the robotics industry and as they become more prevalent, these systems will require adaptive controllers which can execute the tasks effectively in unfamiliar situations. Thus, integration of Reinforcement Learning with multi-agent systems is a step towards developing truly intelligent systems which can perform efficiently in real-world. We hope that our work can serve as the starting step in developing swarming systems for future applications.

Our future work in this area will be aimed towards following two goals:

1. Developing an efficient approach to solve the problem of extended training time with increase in number of agents.
2. Applying DRL to mission-specific problems such as target search and area coverage and to apply better exploration techniques to improve the learning time of the policy.

REFERENCES

Reynolds, Craig, 1987. Flocks, herds and schools: A distributed behavioural model. SIGGRAPH '87: Proceedings of the 14th Annual Conference on Computer Graphics and Interactive Techniques. Association for Computing Machinery. pp. 25–34.

Marko Bunic, Stjepan Bogdan, 2012. Potential Function Based Multi-Agent Formation Control in 3D Space, IFAC Proceedings Volumes, Volume 45, Issue 22, Pages 682-689.

Anuj Agrawal, Aniket Gupta, Joyraj Bhowmick, Anurag Singh, Raghava Nallanthighal, 2020. “A Novel Controller of Multi-Agent System Navigation and Obstacle Avoidance”, Procedia Computer Science, Volume 171, Pages 1221-1230.

M. Egerestedt, 2007. “Graph-theoretic methods for multi-agent coordination” in ROBOMAT.

S. Hung and S. N. Givigi, 2017. "A Q-Learning Approach to Flocking with UAVs in a Stochastic Environment," in IEEE Transactions on Cybernetics, vol. 47, no. 1, pp. 186-197.

Johns, Rasmus, 2018. “Intelligent Formation Control using Deep Reinforcement Learning.”.

Mnih, V., Kavukcuoglu, K., Silver, D. et al, 2015. Human-level control through deep reinforcement learning. Nature 518, 529–533.

Fujimoto, Scott & Hoof, Herke & Meger, Dave, 2018. Addressing Function Approximation Error in Actor-Critic Methods.

Lillicrap, Timothy & Hunt, Jonathan & Pritzel, Alexander & Heess, Nicolas & Erez, Tom & Tassa, Yuval & Silver, David & Wierstra, Daan, 2015. Continuous control with deep reinforcement learning. CoRR.

Kingma, Diederik and Ba, Jimmy, 2014. “Adam: A method for Stochastic Optimization.”

Bellman, Richard, 1957. “A Markovian Decision Process.” *Journal of Mathematics and Mechanics*, vol. 6, no. 5, pp. 679–684., www.jstor.org/stable/24900506.