A General Auxiliary Controller for Multi-agent Flocking

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Abstract—We aim to improve the performance of multi-agent flocking behavior by quantifying the structural significance of each agent. We designed a confidence score (ConfScore) to measure the spatial significance of each agent. The score will be used by an auxiliary controller to refine the velocity of agents. The agents will be enforced to follow the motion of the leader agents whose ConfScores are high. We demonstrate the efficacy of the auxiliary controller by applying it to several existing algorithms including learning-based and non-learning-based methods. Furthermore, we examined how the auxiliary controller can help improve the performance under different settings of communication radius, number of agents and maximum initial velocity.

I. INTRODUCTION

Multiple collaborative agents can form large scale swarms which have wide application in various fields including assisting public safety communications [11], environment mapping and exploration [13, 2], and cooperative hunting [3]. A centralized controller is capable of handling these problems when the scale of the swarm is moderate, while it fails as the scale becomes much larger. Thus, a decentralized method is an appropriate solution to deal with this situation. In a decentralized system, each agent makes its own decision based on the local information it collects by itself and the information shared by its neighbours.

Flocking is a task to coordinate the motion of several autonomous agents which is closely related to the natural animal behaviours [25, 10]. The early research in ecology and biology [1, 26, 12] has inspired the multi-agent flocking research. A computer animation program [14] mimicking the animal aggregation behaviour was proposed and paved the path for several following work leading to the creation of a new research area called artificial life in computer graphics [20]. Flocking is also an important problem in control and robotics [22], and has many practical applications especially in the control of UAVs [23, 17, 5].

Some previous work uses machine learning methods like imitation learning [9, 15, 16] and reinforcement learning [7], which require a lot of time to train the controller. While other methods like [18, 14, 6, 19] require no training but will be very difficult to find an optimal controller in a distributed setting.

As proposed in [21], graph neural networks [4, 27, 8] are suited for the decentralized control system where communication is limited and agents can only share information with their nearby peers. Aggregation graph neural networks are useful when dealing with information sharing, but it aggregates information only depending on the adjacency relationship and ignores the significance of it. Veličković et al. [24] combined attention mechanism with graph neural networks but they only considered point-to-point attention and did not use the information provided by neighbours to measure each agent’s structural significance in a point-to-group manner. Moreover, such proposed attention can only be used in a learning-based method, which means that it needs extra time to train the network.

In order to address these issues, we introduce the ConfScore to comprehensively measure the quality of each agent’s position and the consistency of its motion with neighbours. We also propose an auxiliary controller based on the ConfScore for better coordination. We examine the dynamic structural importance of each agent and enforce the agents to follow those opinion leaders in a swarm. It proves to be beneficial to a wide variety of algorithms and requires no extra training. The whole procedure is illustrated as in Fig. 1.

II. CONTROL OF MULTI-AGENT SWARM

We consider there are N agents in a swarm involved in some dynamic process which requires to be controlled. The process can be characterized by some state value \(\mathbf{x}_i(t) \in \mathbb{R}^p\) which demonstrates the states including position, velocity and acceleration of each agent in time \(t\). Also, some control action \(\mathbf{u}_i(t) \in \mathbb{R}^p\) is also needed so as to illustrate the action that agents take so as to realize the goal of controlling the whole system. We denote matrix \(\mathbf{x}(t) = [\mathbf{x}_1^T(t); \ldots; \mathbf{x}_N^T(t)] \in \mathbb{R}^{N \times p}\) as a collection of the states of all the agents in a swarm and the matrix \(\mathbf{u}(t) = [\mathbf{u}_1^T(t); \ldots; \mathbf{u}_N^T(t)] \in \mathbb{R}^{N \times q}\) as a collection of the control action of the system in time \(t\).

The evolution of the dynamic process can be formulated as a differential equation: \(\dot{\mathbf{x}}(t) = f(\mathbf{x}(t), \mathbf{u}(t))\).

Our controller operates in discrete time with a sampling time \(T_s\) and the index \(n\). During one sampling time, the control action \(\mathbf{u}(n)\) is kept the same from time \(nT_s\) until \((n + 1)T_s\). As the state value matrix \(\mathbf{x}_n = \mathbf{x}(nT_s)\), we can accumulate \(\dot{\mathbf{x}}(t)\) from time \(nT_s\) to \((n + 1)T_s\) and give a formulation of the discrete dynamic system as:
Based on different tasks we are dealing with, we have different cost function \( l(x(t), u(t)) \). So at each time step \( nT_s \), we have an immediate cost \( l_n = l(x(n), u(n)) \). The objective of the control policy is to minimize the accumulative cost \( \sum_{n=0}^{\infty} l_n \).

We use a graph \( G \) to denote an agent network and use \( n \) to represent the collection of all the agents. We define a communication radius \( R \). If the distance between two agents \( n_i \) and \( n_j \) are within \( R \), then we add an edge \( (i, j) \in E_n \) to the graph and \( n_i \) and \( n_j \) are treated as neighbours. Thus we can define the neighbourhood of \( n_i \) at time \( n \) as \( \mathcal{N}_{ij} = \{ j : (i, j) \in E_n \} \).

III. CONFSCORE-BASED AUXILIARY CONTROLLER

As different agents take different positions in a swarm, they intrinsically have different structural significance. We first propose a ConfScore to comprehensively measure the structural importance as well as the motion quality of an agent in the swarm. We evaluate it based on two criteria (1) the number of the neighbours and (2) to which extent its velocity is in accordance with its neighbours. Criterion (1) measures the goodness of an agent’s position and criterion (2) is used to decide an agent’s motion quality. Thus we propose a ConfScore \( C_i \) to measure the extent to which one agent should be confident about its current motion.

\[
C_i = \sum_{j \in \mathcal{N}_i} \frac{v_i \cdot v_j}{||v_i|| \cdot ||v_j||} \quad (2)
\]

One agent would have higher score if it has more neighbours sharing similar velocity with it and vice versa.

After the computation of the ConfScores, every agent is assigned with one score. The score can be interpreted as how confident an agent should stick to its current motion or change its velocity in order to follow other agents who are more likely to be on the right track. Then we utilize ConfScores to compute assistant acceleration as in Algorithm 1.

\[
x_{n+1} = \int_{nT_s}^{(n+1)T_s} f(x(t), u(t)) \, dt + x_n \quad (1)
\]

\begin{algorithm}
\caption{Computation of Assistant Acceleration Based on ConfScore}
\textbf{Require:} \( n \): collection of agents; \( \mathcal{N} \): collection of neighbourhood of all agents; \( \mathbf{v} \): collection of velocity of all agents; \( \lambda \): a heuristic magnitude coefficient

\textbf{Ensure:} \( \mathbf{c} \): collection of ConfScores of all agents \( \mathbf{\bar{u}} \): collection of assistant acceleration of all agents

1: Initialize \( \mathbf{c}, \mathbf{u} \) to be 0
2: for each agent \( n_i \) in \( n \) do
3: \quad for each neighbour \( n_j \) in \( n_i \)'s neighbourhood \( \mathcal{N}_i \) do
4: \quad \quad \( c_{n_j} = c_{n_i} + \frac{\mathbf{v}_{n_j} \cdot \mathbf{v}_{n_j}}{||\mathbf{v}_{n_i}|| \cdot ||\mathbf{v}_{n_j}||} \)
5: \quad end for
6: end for
7: for each agent \( n_i \) in \( n \) do
8: \quad counter = 0
9: \quad for each neighbour \( n_j \) in \( n_i \)'s neighbourhood \( \mathcal{N}_i \) do
10: \quad \quad if \( c_{n_j} > c_{n_i} \) and \( n_j \) is among \( n_i \)'s top-\( k \) neighbours with regard to \( \mathbf{c} \) then
11: \quad \quad \quad \( \mathbf{u}_{n_i} = \mathbf{u}_{n_i} + \lambda (C_m - C_i)(\mathbf{v}_{n_j} - \mathbf{v}_{n_i}) \)
12: \quad \quad \quad counter++ = 1
13: \quad \quad end if
14: \quad end for
15: \quad \( \mathbf{\bar{u}}_{n_i} = \frac{\mathbf{u}_{n_i}}{\text{counter}} \)
16: end for
17: return \( \mathbf{c}, \mathbf{\bar{u}} \)
\end{algorithm}

\( \lambda \) is a coefficient used to determine the extent to which we wish the agent to follow its leaders. It is set heuristically to be number of agents \( \frac{30}{N} \) for a non-learning-based algorithm and \( \frac{15}{N} \) for a learning-based algorithm.

The scalar difference \( (C_m - C_i) \) shows the extent to which the agent is enforced to follow the motion of its neighbours. If both agents are similarly confident, their neighbours’ motion will not have much influence while as the difference gets larger, the impact of the neighbours will be stronger.
The vector difference \((v_m - v_i)\) is used to adjust the velocity. Note that only when the two vectors \(v_m\) and \(v_i\) is completely same both in direction and magnitude will it take no effect, in other words, even if two agents move in same direction, still, the auxiliary controller will force them to be at the same speed.

We can generalize flocking algorithms using some policy \(\Phi\) to be

\[
u = \Phi(x)
\]

So it will be convenient to modify the final control action by an assistant control action \(\bar{u}\) using policy \(\bar{\Phi}\) as

\[
u = \Phi(x) + \bar{\Phi}(x) = u + \bar{u}
\]

Our ConfScore gives a good measurement to the agents and the auxiliary controller can push the agent to follow at least one best neighbour, which prevents agents losing communication with other agent.

**IV. EXPERIMENT**

We apply the auxiliary controller to flocking controller proposed in [19, 21] which cover centralized, decentralized, learning-based and non-learning-based methods to see how the auxiliary controller can improve the performance of different kinds of methods. We examine the performance under different settings of number of agents \(N\), communication radius \(R\) and maximum initial velocity \(V\). ConfScore-based auxiliary controller is denoted as SA for simplicity. We use the variance in velocities

\[
L = \frac{1}{N} \sum_{n=1}^{N} \sum_{j=1}^{T} \|v_{j,n} - \frac{1}{N} \sum_{i=1}^{N} v_{i,n}\|^2
\]

as our cost function.

**A. Applying to Non-learning-based Method**

\(u_{local}\) proposed in [19] can be used as a local controller to make the control action. Its centralized version

\[
u^* = -\sum_{j \in n} (v_i - v_j) - \sum_{j \in n} \nabla v_i U_{ij}
\]

is a more powerful controller yet needs access to the global information. Both \(u_{local}\) and \(u^*\) have no learnable parameters. We apply the auxiliary controller to both of the controllers and examine the performance based on different settings. For a local controller, the controller should enforce the agents not to disperse sparsely at early stage otherwise the drastic loss of neighbours will quickly occur. The performance of a local controller depends highly on the number of the neighbours each agent have because it relies only on local information to decide its control action. Once an agent completely loses communication with its peers, it will simply keep moving in its original velocity unless it comes into its peers again, which rarely happens.

The auxiliary controller helps improve the robustness of the controller in regard with the maximum initial velocity. As Fig. 2 shows, the main reason for the local controller to behave poorly as the maximum initial velocity increases is that high velocity will cause the agents to quickly scatter at the very beginning, and it will result in a random motion behaviour. However, the auxiliary controller can help alleviate this situation in that the magnitude of the auxiliary controller is in proportion to the velocity of the agents and the ConfScore can selectively amplify or shrink the magnitude. So the swarm can keep cohesive even if it is driven by a high velocity. In Fig. 2(a), the swarm is driven by the fast initial speed and get scattered. But in Fig. 2(b), the agents are still cohesive. We fix the \(N\) to be 100 and \(R\) to be 1m. From Fig. 2(b) we can see that the performance of a local controller with auxiliary controller is far more stable than a vanilla one.

The number of neighbours will increase as the communication radius increases, thus each agent can sample more neighbours’ speed so as to choose a better leader. As is shown in Fig. 3 when the swarm is first initialized, due to the randomness of velocity, the distribution of the ConfScores is largely dependent on the position of the agents. Generally, an agent’s ConfScore is higher if it is located near the center of the swarm, as it will have more neighbours, and lower if it is closed to the margin. This can cause an phenomenon that the outer agents tend to follow the motion of the inner ones which can help prevent the agents from scattering. As
the process proceeds, the distribution of the ConfScores will be attributed to the communication radius $R$. As in Fig. 3(b), a small $R = 1.5m$ will result in that the agents with high scores scatter over the entire swarm while in Fig. 3(d) a large $R = 4m$ will then make the confident agents gather in the center of the swarm. In consequence, the entire swarm tends to split up if the communication radius is too small while much more robust as the radius increases.

We also examine different $k$ values. As $k$ increases from 1, instead of only focusing on the leader of the highest score, each agent pays more attention to other neighbours. However, different to simple averaging over the velocity of an agent’s neighbours, the assistant acceleration actually only focuses on those neighbours whose scores are higher ignoring those with scores lower than the agent itself, even if they are among its top-k neighbours. Increase in $k$ can enhance the robustness of the acceleration since it is intuitive that the weighted average over the top-k neighbours can avoid the situation where a fake leader, whose motion may be in consistency with its neighbours while different from the whole swarm, may be too confident about itself and just split the original swarm leading some agents to move in a wrong way with it.

We also test on the global controller $u^*$ to see how it works. As we can see from Fig. 3(b), 3(d), 3(e) the auxiliary controller can help a global controller to achieve better performance, although as the communication radius varies, the controller will sometimes become unstable. In general, still, it is of much benefit.

**B. Applying to Learning-based Method**

As is illustrated, the auxiliary controller can be conducive to non-learning methods, likewise, it can be readily applied to a learning-based method.

DAGNN proposed by [21] uses imitation learning to train an aggregation graph neural network as a local controller. It imitates the behavior of a global expert algorithm by utilizing local observation shared by multi-hop information exchange.

The auxiliary controller is compatible with an imitation learning algorithm in that it doesn’t cause the failure of convergence. We conduct experiments on different stages when we apply the auxiliary controller to DAGNN, namely we (1) train a DAGNN with auxiliary controller and (2) apply the controller to the output of a pre-trained DAGNN model. It can be seen from Fig. 3(b), 3(d), 3(e) the auxiliary controller can largely help the improvement of the DAGNN model in both ways.

Use of the auxiliary controller helps the local DAGNN controller to excel the performance of a global control. The
drawback of a local controller mainly lies in the lost of communication caused by scattering and since the auxiliary controller can largely help alleviate the scattering problem, it is of much benefit to the existent local controllers. Further, As the communication radius expands, the performance of a vanilla DAGNN plateaus, the application of auxiliary controller helps the model break through the bottleneck to achieve better performance as shown in Fig.4(f).

V. CONCLUSION

We have demonstrated that the utility of auxiliary controller is convenient and compatible to various kinds of existing flocking algorithms. We test it under different settings of the scale, communication radius and maximum initial velocity of swarms. We show that the auxiliary controller is adaptive to the scale of the swarm and can improve other algorithms’ robustness. It was also discussed that how the distribution of ConfScore varies due to different communication radius and how it takes affect to keep the agents cohesive. We propose the ConfScore to be a proper measurement of an agent’s motion quality and the auxiliary controller to be a general tool to improve the performance of the flocking task.
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