VGAI: A Vision-Based Decentralized Controller Learning Framework for Robot Swarms

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Abstract—Despite the popularity of decentralized controller learning, very few successes have been demonstrated on learning to control large robot swarms using raw visual observations. To fill in this gap, we present Vision-based Graph Aggregation and Inference (VGAI), a decentralized learning-to-control framework that directly maps raw visual observations to agent actions, aided by sparse local communication among only neighboring agents. Our framework is implemented by an innovative cascade of convolutional neural networks (CNNs) and one graph neural network (GNN), addressing agent-level visual perception and feature learning, as well as swarm-level local information aggregation and agent action inference, respectively. Using the application example of drone flocking, we show that VGAI yields comparable or more competitive performance with other decentralized controllers, and even the centralized controller that learns from global information. Especially, it shows substantial scalability to learn over large swarms (e.g., 50 agents), thanks to the integration between visual perception and local communication.

I. INTRODUCTION

Large-scale aerial swarms are being increasingly deployed for wireless networking, disaster response, and military situational awareness, among many other applications. A swarm is composed of multiple collaborative agents. Nowadays, most aerial robot swarms rely on the centralized control as a whole, either from a motion capture system (such as IMU sensory measurements) or global navigation satellite system (GNSS) [13, 11, 15, 30, 28, 29]. These systems assume that there is a central manager being able to access to global information at each time step, and the decision of the whole group is made based on the optimal global policy. While centralized control can work decently as long as the swarm scale is moderate, it will become unrealistic when we scale up to a large number of agents. The key drawback lies in the fragility to a single point of failures, as well as the unreliable data links (and in the extreme cases, communication outage). As the number of controlled agents scales up, the probability of unreliable data-links and single point failures will exponentially increase accordingly, putting the swarm autonomy in jeopardy.

The collective motion of animal groups, such as flocks of birds, has profoundly inspired the research of aerial swarm robotics [3]. One of the most attractive characteristics of the collective animal behavior in the wild is that decisions are made based on locally perceived observations. Such decentralized control only involves local data exchanges in-between agents to make the whole collective decisions. Each agent is responsible for its own decision making, based on its own observations as well as purely local interactions with nearby agents. Such a decentralization property has shown superior robustness to single-point failures, strong scalability to large swarms, and saving of communication bandwidth.

While the usage of basic sensor measurements (IMUs, etc.) has been standard in swarm studies [30, 13, 11, 15], in the natural biological swarms, such as flocks of birds, animals often rely most on their visual perception. As the visual cameras are getting cheaper, lighter-weight, and lower in energy consumption, the visual modality has shown the potential to provide an unparalleled information density to maximize the autonomy for robotic systems, which seems to be further enabled by the recent progress in computer vision and deep learning [33, 32]. Visual inputs can capture any change of location or velocity of another drone in its field of view (potentially long-range, and covering more than one-hop neighbors), with no delay caused by network propagation. Using visual information can also lead to extra robustness if the wireless communication channel might turn too noisy or even compromised by adversaries. Those characteristics make the visual sensory specifically desirable for the deployment of an aerial multi-robot system in a decentralized manner.

Nevertheless, developing a decentralized control system based on local visual observations raise unique challenges to overcome. Unlike simple IMU measurements of location or velocity that are clearly related to control actions, visual input is harder to interpret, and might also be more costly to process and/or transmit. Firstly, the semantic gap between
raw visual perception and end decision-making remains under-explored in the research community. Despite that in [23] the authors pioneered the learning of an end-to-end mapping from the raw visual inputs to end actions, their framework was only demonstrated on small-scale swarms (9 agents). The lack of information exchanges between nearby agents make the learned policy challenging to scale up. Secondly, transmitting visual inputs among agents, in the form of either raw visual images or extracted intermediate features, can often cause prohibitive bandwidth load and latency for wireless channels, calling for compact designs of the features to be transmitted.

This work proposes Vision-based Graph Aggregation and Inference (VGAI), a decentralized learning-to-control framework that directly maps raw visual observations to agent actions. As illustrated in Fig. 1, VGAI consists of three stages: (i) visual state estimation; (ii) local graph aggregation; and (iii) action inference. Stages (i) and (iii) are by each agent individually, while Stage (ii) involves local sparse communication. Such a framework is implemented by a cascade of convolutional neural networks (CNNs) and a graph neural network (GNN), addressing Stages (i) and Stage (ii) (iii), respectively. First, each agent has a CNN to process its visual input and map that into a compact, local visual descriptor, such that it can be efficiently transmitted to neighbors. Next, we refer to a recently proposed decentralized learning framework, called Delayed Aggregation Graph Neural Network (DAGNN) [4, 5, 27], where each agent (as a node) will fuse the received visual descriptors with its own, based on which it then predicts the next agent action. The communication here is completely local (it requires, at most, repeated exchanges with the one-hop neighbors only).

To our best knowledge, VGAI represents the first effort considering local data exchange based on visual observations, for decentralized controller learning. Compared to the existing framework [23], VGAI highlights a seamless integration of agent visual perception plus local sparse communication. Thanks to the latter, VGAI is thus able to scale up to medium- and large-sized swarms, e.g., up to 50 agents. We examine the proposed VGAI framework on the application of drone flocking [27]. Extensive experiments demonstrate that our learned controller outperforms other competing decentralized controllers, and achieves comparable performance to the centralized controller that learns from global information.

II. RELATED WORK

We categorize the related work into three main categories. Sec. II-A reviews literature on the decentralized control of a flock of drones. Sec. II-B summarizes recent data-driven advances in general vision-based drone control. Finally, Sec. II-C focuses on discussing existing approaches that are both vision-based and decentralized.

A. Decentralized Flocking with Drones

Centralized controllers are able to access global information to decide on optimal control actions [17, 20], but are not practical for large-scale swarm deployments. On the other hand, the collective motion of animal groups, such as flocks of birds – and that has inspired the research of aerial swarm robotics [11, 5] – operates in a completely decentralized and self-organized manner. That is, each agent is responsible for its own decision making, based on its own observations as well as purely local interactions with nearby agents. Decentralized controllers have shown superior robustness to single-point failures and scalability to larger number of agents. However, it has long been known that finding optimal controllers in these distributed settings is challenging [31], due to the locality restriction of network communication.

Recent efforts on decentralized flocking algorithms have been made on designing local controllers which incorporate local observation from spatial neighbours [26, 17, 9]. Particularly, a recent work [27] presents important progress on developing local controllers based on information exchanges between multi-hop neighbors. Their commonality is the requirement to get access to global navigation satellite system (GNSS) positions through wireless communication among flock members. However, there are many situations in which GNSS positions are too imprecise, particularly in scenarios that require a small inter-drone distance. For example, in urban environments, tall buildings may deflect the GNSS signal causing imprecise position information.

B. Vision-based Single Drone Control

Inspired by natural biological swarms such as flocks of birds, vision emerges as a potential mechanism to provide an unparalleled information density, that can be exploited to maximize the autonomy of robotic systems. In this scenario, imitation learning arises as a common strategy used in vision-based drone control to design meaningful actions. The authors in [20] trained a controller that can avoid trees in the forest by adapting the MAVs heading. Visual features extracted from the corresponding image are mapped to the control input provided by the expert. In the problem of single drone collision avoidance, DroneNet [12] pioneers to predict a steering angle and a collision probability based solely on visual inputs, by formulating angle prediction as a regression problem and using a convolutional neural network (CNN) trained on collected labeled images. The drone is controlled directly by the predicted steering angle, whereas its forward velocity is modulated by the collision probability. Another approach based on reinforcement learning [21] shows that a neural network trained entirely in a simulated environment can generalize to real-world navigation and leads to rare collisions. Other data-driven approaches [7, 6, 25] have also shown generality to fly a robot in real-world environments. However, the aforementioned approaches are for operating and navigating a single drone, and do not extend to coordinating a large multi-agent swarm.

C. Vision-based Decentralized Flocking

A number of prior works try to achieve decentralized vision-based drone control, by mounting special visual markers on the drones [2, 10]. However, these visual markers are often
The proposed VGAI framework is described in this section. As illustrated in Fig. 1, each agent’s visual state estimator firstly map the raw visual observation into compact, local visual descriptors, by a CNN. Next, a DAGNN [5, 27] is executed based on exchanging and aggregating the local visual descriptors, among nearby agents. The novel CNN-GNN cascaded framework conserves both visual interpretation and communication savings. In what follows, VGAI is introduced in more detail.

### A. Problem Setting: Decentralized Flocking

Consider a set of \( N \) agents \( \mathcal{V} = \{1, \ldots, N\} \). At time \( t \in \mathbb{N}_0 \), each agent \( i \in \mathcal{V} \) is described by its position \( \mathbf{r}_i(t) = [r_i^x(t), r_i^y(t)]^T \in \mathbb{R}^2 \), velocity \( \mathbf{v}_i(t) = [v_i^x(t), v_i^y(t)]^T \in \mathbb{R}^2 \) and acceleration \( \mathbf{u}_i(t) = [u_i^x(t), u_i^y(t)]^T \in \mathbb{R}^2 \). We consider \( t \) to be a discrete-time index representing consecutive time sampling instances with interval \( T_s \). The evolution of the system is then given by

\[
\mathbf{r}_i(t + 1) = \mathbf{u}_i(t)T_s^2/2 + \mathbf{v}_i(t)T_s + \mathbf{r}_i(t)
\]

\[
\mathbf{v}_i(t + 1) = \mathbf{u}_i(t)T_s + \mathbf{v}_i(t)
\]

for \( t = 0, 1, 2, \ldots \), which implies that each acceleration \( \mathbf{u}_i(t) \) is held constant for the interval \([tT_s, (t + 1)T_s)\). We further assume that transitions between \( \mathbf{u}_i(t) \) and \( \mathbf{u}_i(t + 1) \) happen instantly.

The objective of flocking is to coordinate the velocities \( \mathbf{v}_i(t) \) of all agents to be the same

\[
\min_{\mathbf{u}_i(t)} \frac{1}{N} \sum_{t \geq 0} \sum_{i = 1}^{N} \left\| \mathbf{v}_i(t) - \frac{1}{N} \sum_{j=1}^{N} \mathbf{v}_j(t) \right\|^2
\]

subject to the constraint enforced by the system dynamics (1). The optimal solution, while avoiding collisions, is given by

\[\text{Note that when conducting experiments using the simulation software, we assume all agents to fly on the same height plane by default, for simplicity but without loss of our method’s generality. That is why we use 2D vectors for the position and velocity.}\]
accelerations $u_i^*(t)$ computed as
\[ u_i^*(t) = -\sum_{j=1}^{N} \left( v_i(t) - v_j(t) \right) - \sum_{j=1}^{N} \nabla r_i(t) U \left( r_i(t), r_j(t) \right) \]
(3)
where
\[ U(r_i(t), r_j(t)) = \begin{cases} 1/\|r_{ij}(t)\|^2 - \log(\|r_{ij}(t)\|^2) & \text{if } \|r_{ij}(t)\| \leq \rho \\ 1/\rho^2 - \log(\rho^2) & \text{otherwise} \end{cases} \]
is a collision avoidance potential, with $r_{ij}(t) = r_i(t) - r_j(t)$ and $\rho$ the value of the minimum distance allowed between agents. It is evident that, in computing the optimal solution (3), each agent $i$ requires knowledge of the velocities of all other agents in the network. Thus, the optimal solution $u_i^*$ is a centralized controller.

Our objective, in contrast, is to obtain a decentralized solution that can be computed only with information perceived by each agent, in combination with information relied by neighboring agents. We determine that agents $i$ and $j$ are able to communicate with each other at time $t$ if $\|r_i(t) - r_j(t)\| \leq R$ for some given communication radius $R$. We describe the communication network by means of a succession of graphs $G(t) = \{V, \mathcal{E}(t)\}$ where $V$ is the set of agents, and $\mathcal{E}(t) \subseteq V \times V$ is the set of edges, i.e., $(i, j) \in \mathcal{E}(t)$ if and only if $\|r_i(t) - r_j(t)\| \leq R$. The communication link $(i, j) \in \mathcal{E}(t)$ allows for exchange of information between nodes $i$ and $j$ at time $t$. Denote by $\mathcal{N}_i(t) = \{j \in V : (j, i) \in \mathcal{E}(t)\}$ the set of all agents that can communicate with node $i$ at time $t$.

A possible heuristic to obtain a decentralized solution is to compute (3) considering only neighboring information, namely
\[ u_i(t) = -\sum_{j \in \mathcal{N}_i(t)} \left( v_i(t) - v_j(t) \right) - \sum_{j \in \mathcal{N}_i(t)} \nabla r_i(t) U \left( r_i(t), r_j(t) \right). \]
(5)
We note that solution (5) relies only on present, one-hop information. In what follows, we propose to learn a decentralized solution that incorporates delayed information from further away neighborhoods. The resulting behavior successfully incorporates past information to improve the performance of the flocking algorithm.

**B. Local Graph Aggregation and Action Inference**

Let $x_i(t) \in \mathbb{R}^F$ be the state of agent $i$ at time $t$, described by an $F$-dimensional vector of features. Denote by $X(t) \in \mathbb{R}^{N \times F}$ the row-wise collection of the state of all agents
\[ X(t) = \begin{bmatrix} x_1^T(t) \\ \vdots \\ x_N^T(t) \end{bmatrix}. \]
(6)
To describe the communication between agents, we define the graph shift operator (GSO) matrix $S(t) \in \mathbb{R}^{N \times N}$ which respects the sparsity of the graph, i.e. $[S(t)]_{ij} = s_{ij}(t)$ is nonzero if and only if $(j, i) \in \mathcal{E}(t)$. Examples of GSO used in the literature are the adjacency matrix $[22]$, the Laplacian matrix $[24]$, or respective normalizations $[13]$. Due to the sparsity of the GSO $S(t)$, right-multiplication of $S(t)$ with $X(t)$ can be computed only by means of local exchanges with neighboring nodes only, yielding
\[ [S(t)X(t)]_i = \sum_{j \in \mathcal{N}_i(t)} s_{ij}(t) x_j(t) \]
(7)
for each feature $f = 1, \ldots, F$. In essence, multiplication (7) updates the state at each agent by means of a linear combination of the states of neighboring agents.

We build the aggregation sequence $[5]$, gathering information from further away neighborhoods by means of $(K - 1)$ repeated exchanges with our one-hop neighbors
\[ Z(t) = \left[ X(t), S(t)X(t-1), S(t)S(t-1)X(t-2), \ldots, S(t) \cdots S(t - (K - 2))X(t - (K - 1)) \right]. \]
(8)
The aggregation sequence $Z(t)$ is a $N \times KF$ matrix, where each $N \times F$ block $Z_k(t)$ represents the delayed aggregation of the state information at the neighbors located at $k$-hops. Denote by $z_i(t) \in \mathbb{R}^{FK}$ the row $i$ of matrix $Z(t)$, which represents the information gathered at node $i$. We note that this information has been obtained by executing $(K - 1)$ communication exchanges with one-hop neighbors, in an entirely local fashion.

Once we have the collected neighboring information at each node, we can proceed to apply a neural network $[8]$ on vector $z_i(t)$ to map the local graph information into an action
\[ z_\ell = \sigma_\ell(\theta_\ell z_{\ell-1}), \quad z_0 = z_i(t), \quad u_i(t) = z_L \]
(9)
where $z_\ell \in \mathbb{R}^{F_\ell}$ represents the output of layer $\ell$, $\sigma_\ell$ is a pointwise nonlinearity (also known as activation function) and $\theta_\ell \in \mathbb{R}^{F_{\ell-1} \times F_\ell}$ are the learnable parameters. The input to the neural network is the aggregated sequence, $z_0 = z_i(t)$, with $F_0 = KF$, and we collect the resulting action as the output of the last layer $u_i(t) = z_L$, so that $F_L = 2$. We compactly describe the neural network as
\[ \hat{u}_i(t) = \text{NN}_\Theta(z_i(t)) \]
(10)
where $\Theta = \{\theta_\ell, \ell = 1, \ldots, L\}$ are the learnable parameters of each layer.

Several important observations are in order. First, the neural network parameters $\Theta$ do not depend on the specific node $i$, nor on the specific time-index $t$. This is a weight sharing scheme that allows for scalability (i.e., once trained, it can be deployed on any number of agents), and prevents overfitting (i.e., it avoids a number of parameters that grows with the data dimension). Second, since the aggregation sequence has already incorporated the graph information [cf. (5)], applying a regular neural network to $z_i(t)$ is already taking into account the underlying graph support, leading to an aggregation neural
network architecture \cite{4,5}. Third, the resulting architecture is entirely local in the sense that, at test time, it can be implemented entirely by means of repeated communication exchanges with one-hop neighboring nodes only.

To train the neural network \cite{10}, we use imitation learning \cite{18}. That is, we assume availability of a training set comprised of trajectories \( \mathcal{T} = \{ (\mathbf{X}(t), \mathbf{U}^*(t)) \}_{t} \) where \( \mathbf{X}(t) \) is the collection of states \cite{6} and \( \mathbf{U}^*(t) \in \mathbb{R}^{N \times 2} \) is the collection of optimal actions for each agent

\[
\mathbf{U}^*(t) = \begin{bmatrix}
\mathbf{u}_i^*(t)^T \\
\vdots \\
\mathbf{u}_N^*(t)^T
\end{bmatrix},
\]

(11)

where \( \mathbf{u}_i^*(t) \in \mathbb{R}^2 \) is the optimal action of agent \( i \) at time \( t \) given by the optimal controller \cite{5}. Then, the optimal parameters can be found as

\[
\Theta^* = \arg\min_\Theta \sum_{t=1}^T \sum_{N} \| \mathbf{\hat{u}}_i(t) - \mathbf{u}_i^*(t) \|
\]

(12)

with \( \mathbf{\hat{u}}_i(t) = \text{NN}_\Theta(\mathbf{z}_i(t)) \) and \( \mathbf{z}_i(t) \) row \( i \) of the aggregation sequence built as in \cite{8}.

In the problem of flocking, the baseline DAGNN method considers an input state given by

\[
\mathbf{x}_i(t) = \left[ \sum_{j \in \mathcal{N}_i(t)} (\mathbf{v}_i(t) - \mathbf{v}_j(t)), \sum_{j \in \mathcal{N}_i(t)} \frac{\mathbf{r}_{ij}(t)}{||\mathbf{r}_{ij}(t)||^4}, \sum_{j \in \mathcal{N}_i(t)} \frac{\mathbf{r}_{ij}(t)}{||\mathbf{r}_{ij}(t)||^2} \right]
\]

(13)

which can be computed locally. In this work, we estimate this state from images taken by each agent by means of a visual state estimator as described next.

C. Visual State Estimator

The objective is to extract compact local visual descriptors from raw photos taken directly from the agents, and use these to estimate \cite{13}, which will then be fed into the DAGNN \cite{10} to decide on an action. Note that we choose the above state estimation vector as the specific regression form, primarily for the desired interpretability in addition to the compactness \cite{27}. Other compact representation forms can be similarly adopted as local visual descriptors here.

The estimate \( \mathbf{\hat{x}}_i(t) \) of state \( \mathbf{x}_i(t) \) [cf. \cite{13}] is obtained by means of a cascade of the CNN-based spatial binning process and a deep neural network. The goal of spatial binning process is to map the images \( \mathbf{H}_i(t) \), the field of view of each agent, into highly compact and interpretable histogram vectors. We firstly obtains a set of bounded boxes of drones by CNN object detector. Then, the binning process is conducted by dividing the input field of view into \( K \) spatial bins, and accumulating the relative portion of drones in each spatial bin according the given bounded boxes, as illustrated in Fig. 3. The obtained histogram vector \( \mathbf{h}_i(t) \in \mathbb{R}^K \) is fed into a deep neural network for imitation learning. Note that the cascade of CNN object detector and deep neural network can be considered as a whole CNN and be further fine-tuned in an end-to-end manner. We denote this processing of mapping \( \mathbf{H}_i(t) \) to \( \mathbf{\hat{x}}_i(t) \) as

\[
\mathbf{\hat{x}}_i(t) = \text{CNN}_\Theta(\mathbf{H}_i(t))
\]

(14)

where \( \Psi \) is the set of learnable parameters (i.e. filter coefficients for the bank of convolutional filters used at each layer). To train this CNN we minimize a loss function \( C \) as follows

\[
\Psi^* = \arg\min_\Psi \{ \mathbf{\hat{x}}_i(t), \mathbf{x}_i(t) \}
\]

(15)

with \( \mathbf{\hat{x}}_i(t) \) depending on \( \Psi \) as determined by \cite{14}. The resultant state estimation, as the compact local visual descriptors, are further integrated into the next stage of graph aggregation and action inference.

D. Implementation Details

For our baseline scenario, we consider a flock of \( N = 50 \) agents with a communication radius of \( R = 1.5m \) and a discretization time period of \( T_s = 0.01s \).

The flock locations were initialized uniformly on the disc with radius \( \sqrt{N} \) to normalize the density of agents for changing flock sizes. Initial agent velocities are controlled by a parameter \( v_{init} = 3.0m/s \). Agent velocities are sampled uniformly from the interval \([-v_{init}, +v_{init}]\) and then a bias for the whole flock is added, also sampled from \([-v_{init}, +v_{init}]\).

To eliminate unsolvable cases, configurations are resampled if any agent fails to have at least two neighbors or if agents begin closer than 0.1m. Finally, acceleration commands are saturated to the range \([-30, 30]m/s^2\) to improve the numerical stability of training.

For the learning process of the VGAI drone detector, we first constructed an image dataset of 1,000 images containing 11,146 highly-confident bounded box annotations. A YOLO-V3 network was thus trained to serve as a reliable agent detector [cf. Fig. 2]. Then, this information is fed into the CNN [cf. \cite{14}] and trained following \cite{15}. The DAGNN is trained under the framework of imitation learning following the optimal trajectory \( \mathbf{u}^*(t) \) [cf. \cite{3}] which is required to be available only at training time.

Finally, we note that to resolve the in-consistent distribution of states between training phase and testing phase, Dataset Aggregation (DAGger) \cite{19} algorithm was employed by following the learner’s policy instead of the expert’s with probability 0.5 when collecting training trajectories. Both the parametrized neural networks for local visual state estimation and aggregated vectors contained 4 fully connected layers of 1024 neurons and ReLU activation functions. The network was trained over a Smooth-L1 loss function, using SGD optimizer with learning rate 0.01.

IV. EXPERIMENTAL RESULTS

We explored, through numerical simulations, the effect of aggregation filter length \( K \), maximum initial velocity \( v_{init} \), and communication radius \( R \) in the ability of VGAI to obtain effective decentralized controllers (Sec.IV-A). Then, we tested the generalization power of the VGAI controller, by testing it on a different number of agents than on what it was originally
Input: Omnidirectional Images

Field of View

Fig. 3. A example of the rendered raw visual input from Microsoft Airsim Simulation environments. The simulation environment allows the user to render four camera-view images, i.e., front-center, front-left, front-right, and back. The complete field of view could be specified by concatenating the four camera images. At each time step, we render complete field of view for the visual state estimation. The resolution of the rendered images are $144 \times 256$ for each camera, which is good enough for state estimation. For the camera configuration, we adjust the quaternion orientation of front-left and front-right cameras to $-0.82$ and $0.82$ in order to maximally increase the visibility of drones. We also set the aptitude of each agent in-between $37$ and $43$ for collision-free random initialization. In real-world deployment, more commercial cameras could be equipped on the drone to increase the information density.

trained on (Sec. IV-B). Finally, we analyzed the the controlled flock behaviour for some specific trajectories (Sec. IV-C).

| Filter Length (K) | Global | Local | DAGNN | VGAI |
|------------------|--------|-------|-------|------|
| 1                | 0.057  | 1.134 | 0.292 | 0.971 |
| 2                | 0.057  | 1.134 | 0.276 | 0.523 |
| 3                | 0.037  | 1.134 | 0.281 | 0.482 |

A. Effect of changing simulation parameters

The experiments are conducted on flocking groups of $N = 50$ agents. The performance is evaluated based on the cost (2). We calculate the median trajectory cost from time index $t = 20$ to $t = 100$ to eliminate the randomness caused by the random initialization of positions and velocities of the flocks. Other hyper-parameters, such as the seeds of random initialization and communication radius, remain identical for the fair comparison.

We conducted the experiments on the Microsoft Airsim Simulation environment. The absolute locations and velocities of the drones are scaled by a factor of 6 before evaluation so that the optimal spacing dictated by the potential function in (4) does not result in collisions. The detail camera configuration could be referred in Fig. 3. The reported cost values are computed by taking the average over 5 random initialized trajectories for each controller. The global (3), local (5), and DAGNN operating directly on the true state (13) are used as benchmarks.

Filter length $K$. Aggregation filter length $K$ determines the depth of temporal information collection. VGAI and DAGNN controllers are allowed to collect information their $(K-1)$-hop neighbours to make localized decisions. Increasing the aggregation filter length potentially broadens the information radius by frequently communicating with one-hop neighbours, but it comes at the expense of communication costs. The goal of this experiment is to test the effect of changing the aggregation filter length on the performance of each controller for flocking behaviours. The experimental results is summarized in Table I.
In general, we observe that the trajectory costs of VGAI controllers are always bounded by the global and DAGNN controllers as upper-bounded baselines, and the local controller as the worst-case baseline, as expected. The trajectory costs of VGAI controllers consistently outperform the local controllers. Besides, the performance of VGAI controller increases significantly when the aggregation filter length is larger than (or equal to) 2. This qualitative performance improvement justifies our conjecture that encouraging more communications in-between multi-hop neighbours could potentially improve flocking behaviors.

### Table II

| Maximum Initial Velocity | Global | Local | DAGNN | VGAI |
|--------------------------|--------|-------|-------|------|
| 2                        | 0.056  | 0.602 | 0.133 | 0.361|
| 3                        | 0.057  | 1.134 | 0.281 | 0.482|
| 4                        | 0.056  | 2.733 | 0.424 | 0.891|

**Maximum Initial Velocity $v_{\text{init}}$.** Increasing maximum initial velocity could potentially enhance the difficulty of the problem since the controlled flocks are required to converge faster to achieve cohesive behaviours, otherwise the flocks will suffer from scattering before they converge to cohesion behaviours (i.e. communications might be lost, and some agents become impossible to be controlled).

In order to evaluate the stability of each solution, we conduct this experiments by varying the maximum initial velocities. For the fair comparisons, we also fix the aggregation filter length $K = 3$ and communication radius $R = 1.5$. The experimental results are summarized in Table II.

In general, we observe that increasing maximum initial velocity makes the flocking task more challenging for all controllers (except the global controller). The trajectory costs of local controllers increase significantly (from 0.602 to 2.733), as the initial velocity changes from $2\text{m/s}^2$ to $4\text{m/s}^2$, while VGAI and DAGNN controllers maintain comparably stable behaviours at the same time by consistently having the costs below 1. We hypothesize that the desired stability of DAGNN and VGAI controllers come from the communications with multi-hop neighbours, where the aggregation features are able to make a cohesion decision before the flock scatters. The experimental results also encourages the sparse local communications for the control flocking behaviours since it increases the radius of information circles.

### Table III

| Comm. Radius | Global | Local | DAGNN | VGAI |
|--------------|--------|-------|-------|------|
| 0.5          | 0.057  | 6.461 | 0.345 | 0.051|
| 1.5          | 0.057  | 1.134 | 0.281 | 0.482|
| 2.5          | 0.057  | 0.996 | 0.279 | 0.488|

**Communication Radius $R$.** Communication radius determines the (multi-hop) neighbouring relationship between agents, i.e., network connectivity patterns. In real-world deployment, rapidly changing networks usually suffer from unstable data linking or unreliable communications. In general, increasing the communication radius could help the localized controllers collect more neighbouring information for individual decision-making, but it usually comes at the higher risk of single-point failures in real-world deployment and at the expense of more power consumption for distant communications. On the other hand, a small communication range could make the sub-flock unable to re-join the flock.

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Fig. 5. An example of the trajectory evolution of the VGAI controlled flock, from time indices 0 to 90.
permanently due to the lack of data exchanges. The objective of this experiment is to test the stability of each controllers with respect to varied communication radius. We summarize the experimental results in Table III.

In general, VGAI controllers consistently outperform local controllers and are bounded by the global and DAGNN controllers (which makes sense, since the DANN has direct access to the true state of each agent). As the radius increases, both localized controllers are benefited from the broad information scale, which justifies that neighboring information exchange is a crucial part for the design of decentralized controller. It is interesting to note that the cost of the VGAI controllers maintain nearly the same trajectory costs as the communication radius varied. At the extreme situation \((R = 0.5)\), VGAI controllers still keep a comparable trajectory cost, while the local controllers allow the flock to scatter. It shows that the flocking problem becomes more challenging as the communication radius decreases.

### TABLE IV
THE SUMMARY OF GENERALITY EVALUATION OF VGAI CONTROLLERS WITH RESPECT TO VARIED NUMBER OF AGENTS.

| #Agents (Training) | #Agents (Testing) | Trajectory Cost |
|--------------------|-------------------|-----------------|
| 35                 | 35                | 0.476           |
| 40                 | 40                | 0.451           |
| 45                 | 45                | 0.551           |
| 50                 | 50                | 0.678           |

#### B. Generality for Changing Agents Number

In the aforementioned experiments, we performed a series of ablation studies to show the stability of learned controller with respect to different hyper-parameter choices. The learned controllers are trained over training data containing 50 agents, and are tested on a group of 50 agents. However, in the real-world deployment, the agent group size can change from the training phase to the test phase. Furthermore, the number of changing agents can happen in real-time, since some of the agents might get disconnected from the group, and rejoin later. The goal of these experiments is to test the generalization power of the VGAI controllers with respect to different number of agents. The tested controller was trained on the data containing 50 agents, and it directly tested on flocks of the number of agents \(N = \{35, 40, 45, 50\}\). The experimental results are summarized in the Table IV.

In general, VGAI controllers maintain cohesive behaviours as the number of agents decreases to 40. When testing on 35 agents, the cost increases. We conjecture that it comes at the unseen visibility of raw input images since the learned controller did not perceive sparse agent visibility in the training trajectories. However, we believe that the issues could be resolved by Dataset Aggregation (DAGger) algorithm, which include learner’s policy during data collection phase to enhance the stability of learned controller.

#### C. Analysis of Flocking Behaviours

Fig. [4] illustrates the trajectory evolution of VGAI controller and local controller. The number of agents, aggregation filter length, communication radius and maximum initial velocity are set to \(N = 50, K = 3, R = 1.5\), and \(v_{\text{init}} = 3\), respectively. Each sub-figure shows the initial agent positions and velocities at time \(t = 0\) and then at \(t = 100\), qualitatively illustrating the stable flocking behaviours of the VGAI controller and failure of the local controller. The VGAI controlled flock converges to cohesive collective behaviours, while the flock controlled by the local controller cannot converge to stable flocking and tend to scatter apart.

Fig. [5] demonstrates the evolutionary behaviours of a VGAI controlled flock. At the beginning, the flock is initialized with chaotic velocities and positions. After 20 time steps, the flock started to demonstrate consensus behaviours. At the time step 90, most of the agents in the flock are behaving the collision-free behaviours, although some of agents seems to drift apart from the main flocking group. That is due to the large collision-free penalty of potential function in \([4]\) that causes “conservative” anti-collision behaviors, which could also be resolved by lowering the collision-free penalty during the imitation learning phase.

#### V. Conclusion

This paper presented a vision-based decentralized controller learning (VGAI) framework for large-scale robot swarms. We demonstrated the utility of CNN-GNN cascaded networks as a tool for automatically learning decentralized controllers. It can operate with large teams of agents based only on local visual observation, with coupled state dynamics and sparse communication links. Experimental results quantitatively confirm the value of local neighborhood information to the stability of controlled flocks. We also show that our learned controller is robust to changes in the range of communication radius, number of agents and maximum initial speed of the flock. In future work, we aim to further improve the cohesion behaviours by exploring an end-to-end visual learning framework, i.e., jointly training the visual estimator with the DAGNN.

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