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Occlusion-Based Coordination Protocol Design for Autonomous Robotic Shepherd Tasks

Junyan Hu, Ali Emre Turgut, Tomáš Krajník, Barry Lennox and Farshad Arvin

Abstract—The robotic shepherding problem has earned significant research interest over the last few decades due to its potential application in precision agriculture. In this paper, we first modeled the sheep flocking behavior using adaptive protocols and artificial potential field methods. Then we designed a coordination algorithm for the robotic dogs. An occlusion-based motion control strategy was proposed to herd the sheep to the desired location. Compared to formation based techniques, the proposed control strategy provides more flexibility and efficiency when herding a large number of sheep. Simulation and lab-based experiments, using real robots and global vision-based tracking system, were carried out to validate the effectiveness of the proposed approach.

Index Terms—Autonomous robots, bio-inspired swarm intelligence, shepherding, multi-robot coordination, mobile robotics.

I. INTRODUCTION

Collective motion of autonomous agents has attracted significant interest from biologists, physicists, mathematicians and engineers in the last few decades. Inspired by behaviors in nature, such as schools of fish, flock of birds and bee colonies, algorithms have been developed to coordinate large-scale robotic swarm systems [1]. For example, shape formation [2]–[4], pheromone-based aggregation [5], collision detection and avoidance [6], and self-organized flocking in swarm robotics [7] are bio-inspired mechanisms which have been explored for potential applications in real-world scenarios. One of the interesting real-world applications of swarm robotics is the robotic shepherding problem (as shown in Fig. 1), where a flock of sheep (or robotic agents that behave with herd dynamics) is navigated to a goal location by ‘robotic dogs’. The main motivation for robotising shepherding tasks is to address the challenges imposed by ageing farmer populations and lamb demand growth [8]. Hence, developing an autonomous shepherding platform that provides a daily exercise, e.g. regular outdoor herding of sheep using specific trajectories, can potentially improve the health condition and productivity of sheep and other animals in farms.

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Fig. 1. Autonomous shepherding scenario using three UAV robotic dogs.

The shepherding problem in robotics raises two major questions: i) how to model the flocking behavior of sheep? and ii) how to design the control strategies for the robotic dogs? To answer these two questions, many attempts have been made to obtain a better understanding of how a single agent can interact with a group of other agents and how groups of herds can be maneuvered to their desired location. Single-agent indirect herding problems with uncertain dynamics has been solved in [9], where the target agents can be regulated to some desired formation. However, in this work it is assumed that there is no interaction between the target agents. The articles [10]–[12] have laid significant contribution in investigating how to influence a flock using a set of influencing agents. Following ad hoc teamwork methodology, the flock’s trajectory, such as obstacle avoidance behavior, can be altered indirectly by the proposed methods. Using an Unmanned Aerial Vehicle (UAV) to herd a flock of birds away from a designated volume of space was shown in the work of [13], an m -waypoint algorithm was developed based on Reynolds’ rules. In [14], a self-propelled model of local attraction-repulsion behavior was proposed that used one shepherd to herd a group of interacting agents. In [15], shepherding behaviors using a single shepherd was also simulated. In this approach, a variety of behaviors such as herding, covering, patrolling and collecting were analyzed by determining the trajectory of the shepherd. However, only one shepherd or dog was considered in the studies [13]–[15], which may be viewed as a limitation in a real-world application with a large size flock and multiple shepherds available.

Unfortunately, when multiple shepherds exist, the problem becomes more challenging as the cooperation between the shepherds needs to be considered. A distributed game theoretic approach was developed in [16] to solve the problem of defense-intrusion interaction and intruder herding, but the

number of herds in this work was limited to one. In [17], two shepherd formations, namely, line formation and arc formation were proposed for multiple shepherds, to steer a flock to the milestone. However, a greedy method was applied to the shepherds, which meant that each shepherd would choose the closest steering point without considering others, meaning some shepherds travelled farther than necessary. Another study on the shepherding problem [18] proposed a controller that used no arithmetic computation or memory, to manoeuvre mobile e-puck robots in simulation. In [19], sheepdog style navigation was analyzed for cases in which the goal position was invisible. A biologically-inspired control law for a shepherding task was also proposed in [20] to achieve an arc formation to control the flock effectively. In the article [21], a circular formation based approach was proposed to control non-cooperative herds with robotic herds. The desired position for each dog was specified on a circle around the flock of sheep. A similar caging based herding approach was investigated in [22], where a group of mobile robots formed a cage around all the herds such that they could not escape. However, such containment-type methods can be conservative as it may require more dogs to complete the task than necessary.

Recently, with the development of distributed cooperative control techniques, interactions among agents are modeled using graph theory and the agents can be coordinated effectively via a reliable control architecture [23]–[25]. Different from [13]–[15] where only one dog was considered in the control strategy, in most of the real applications, multiple robotic dogs may be required to complete the large-scale shepherding tasks. The cooperation among the dogs must be designed properly to avoid conflicts and save more energy. Even though multiple shepherds were analyzed in [16]–[22], some approaches may fail to provide an efficient solution to coordinate all the shepherds considering the total travel distance and the minimum number of dogs required in the tasks. Motivated by the limitations of existing techniques, in this paper, we firstly develop a model of sheep flocking, with the motion of each sheep controlled by feedback consensus algorithms and artificial potential fields to simulate its real behavior. All the robotic dogs are then controlled by an occlusion-based motion strategy to steer the sheep to the desired location. The advantage of using the proposed coordination protocol is that it requires fewer dogs to complete the task compared to formation based approaches and it offers more efficiency and robustness to deal with large flock sizes. The contributions of this paper are summarized as follows:

- The model of sheep flocking was developed based on distributed consensus algorithms and artificial potential fields, which provides greater realism than single herds or a group of cooperative herds.
- A novel occlusion-based motion strategy was applied to steer the sheep to the desired goal location. The performance of the proposed coordination protocol is guaranteed by Lyapunov stability theory.
- Real-robot experiments were implemented to validate the effectiveness of the proposed coordination algorithms.

The rest of the paper proceeds as follow. Section II covers the background and also discusses the problem statement. In Section III, the model of sheep flocking is developed and a two-layer coordination algorithm is proposed. A simulation case study is given in Section IV to highlight the feasibility of the proposed scheme. Experimental validation using small-scale mobile robots is shown in Section V. Section VI concludes the paper.

II. PROBLEM FORMULATION

Consider M herd members (or 'sheep') with position $s_i \in \mathbb{R}^2$ where $i \in \{1, 2, \dots, M\}$ and N shepherds (or 'dogs') with positions $d_i \in \mathbb{R}^2$ where $i \in \{1, 2, \dots, N\}$. The dogs can be UAVs or mobile robots which are under our control and the herd members can be robots or animals. The goal of the dogs is to relocate the sheep from their arbitrary initial positions to the desired location in the environment.

A. Assumptions

For each dog, we have the following three assumptions:

- 1) Each dog knows the target position that the sheep must be herded to.
- 2) Each dog can detect its relative distance to the flock's center of mass (COM).
- 3) Each dog can communicate with its neighboring dogs.

B. Communication Networks

Consider a weighted and directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ with a non-empty set of nodes $\mathcal{V} = \{1, 2, \dots, N\}$, a set of edges $\mathcal{E} \subset \mathcal{V} \times \mathcal{V}$, and the associated adjacency matrix $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N \times N}$. An edge rooted at the i^{th} node and ended at the j^{th} node is denoted by (i, j) , which means information can flow from node i to node j . a_{ij} is the weight of edge (j, i) and $a_{ij} = 1$ if $(j, i) \in \mathcal{E}$. Node j is called a neighbour of node i if $(j, i) \in \mathcal{E}$. In-degree matrix associated with $\mathcal{G}$ is defined as $D = \text{diag}\{d_i\} \in \mathbb{R}^{N \times N}$ with $d_i = \sum_{j=1}^N a_{ij}$ and the Laplacian matrix $L \in \mathbb{R}^{N \times N}$ of $\mathcal{G}$ is given by $L = D - \mathcal{A}$. If the i^{th} node for any $i \in \{1, 2, \dots, N\}$ is attached to the root (labelled as 'node 0'), then the node is called a 'pinned' node and an edge $(0, i)$ is said to exist between them having the weight $g_i > 0$. We denote the pinning matrix as $G = \text{diag}\{g_i\} \in \mathbb{R}_{\geq 0}^{N \times N}$.

The following two lemmas provide the necessary mathematical foundation to develop the main idea of this paper.

Lemma 1 ([26]): Consider a non-singular M -matrix U . Then, there exists a positive definite matrix $\Xi = \text{diag}\{\psi_1, \dots, \psi_N\}$ such that $\Xi U + U^T \Xi > 0$.

By using this Ξ matrix, we can find a suitable Lyapunov function candidate to analyze the performance of the attractive force in the flock.

Lemma 2: [27] Suppose $a \in \mathbb{R}_{\geq 0}$, $b \in \mathbb{R}_{\geq 0}$, $p \in \mathbb{R}_{> 0}$ and $q \in \mathbb{R}_{> 0}$ such that $\frac{1}{p} + \frac{1}{q} = 1$, then $ab \leq \frac{a^p}{p} + \frac{b^q}{q}$. Moreover, $ab = \frac{a^p}{p} + \frac{b^q}{q}$ if and only if $a^p = b^q$.

This property can be used to simplify the proof condition, such that the stability of the flock can be guaranteed via Lyapunov theory.

Fig. 2. Interaction rules for the sheep. In this example, the green circle with a radius of d_v shows the view range of the sheep s_i . There are five neighboring sheep represented by red circles in this range. The COM is marked by the black star.

C. Problem Description

Let $\mathcal{S} = \{1, 2, \dots, M\}$ and $\mathcal{D} = \{1, 2, \dots, N\}$ be the sets of the flocks, sheep and dogs respectively. We assume that both sheep and dogs have single integrator dynamics

$$\dot{s}_i = v_i \quad i \in \mathcal{S}, \quad (1)$$

$$\dot{d}_i = u_i \quad i \in \mathcal{D}, \quad (2)$$

where v_i and u_i are the control inputs to be specified.

In this work, we first build the dynamic model of the sheep flocking behavior using an adaptive consensus protocol and artificial potential field method. Then, we design a coordination algorithm for the dogs to drive the herds to the desired location.

III. COORDINATION PROTOCOL DESIGN

A. Model of the Sheep Flocking

Each sheep has a view distance of d_v . The features of the sheep flocking behavior can be summarized as follows [14]:

- 1) The sheep are attracted to the COM of their neighbors.
- 2) The sheep are repelled from other sheep within a distance of d_s .
- 3) The sheep are repelled from the dog if it is within their viewing range d_v .

According to the aforementioned three principles, the movement of the sheep is a linear combination of three different components as

$$\dot{s}_i = v_{a,i} + v_{b,i} + v_{c,i} \quad (3)$$

for all $i \in \mathcal{S}$.

Motivated by [28], the first component $v_{a,i}$ is defined as

$$\begin{cases} v_{a,i} = -c_i \rho_i(\xi_i^T \sqrt{Q} \xi_i) \sqrt{Q} \xi_i, \\ \dot{c}_i = \xi_i^T Q \xi_i, \end{cases} \quad i \in \mathcal{S} \quad (4)$$

where $\xi_i = \sum_{j \in \mathcal{N}_i} a_{ij}(s_i - s_j)$, $\mathcal{N}_i$ is the neighborhood set of the i^{th} sheep, $c_i(t)$ is a time-varying coupling weight associated with the i^{th} sheep with $c_i(0) > 1$, $Q > 0$ is a positive scalar to be designed, and $\rho_i = (1 + \xi_i^T \sqrt{Q} \xi_i)^3$ is the smooth and monotonically increasing function. The coupling gain $c_i(t)$ used in the adaptive protocol plays an important

role in adjusting the attractive force between each sheep. This will help the flock to recover from unexpected disturbances such as dogs and obstacles. Similar design and analysis have been discussed in [29].

Now we would like to show that, without considering the effects of the second component $v_{b,i}$ and the third component $v_{c,i}$, all the sheep will rendezvous to the COM. As shown in Fig. 2, each sheep can detect the positions of other sheep (represented by red circle) within the sensing distance of d_v .

The stability analysis of the sheep flocking behavior is given by the following Theorem.

Theorem 1: Suppose all the sheep in the flock are connected by a communication network. The positions of the sheep can be coordinated to the COM by using the adaptive control protocol (4).

Proof: The position of the COM is given by $\bar{s} = \frac{\sum_{j=1}^M s_j}{M}$. Define the global consensus tracking error as $\xi = [\xi_1^T, \dots, \xi_M^T]^T$, then we have

$$\xi = ((L + G) \otimes I_2) \begin{bmatrix} s_1 - \bar{s} \\ \vdots \\ s_M - \bar{s} \end{bmatrix}. \quad (5)$$

We can then obtain the following expressions for $\dot{\xi}$ and $\dot{c}_i$

$$\begin{cases} \dot{\xi} = -(L + G)C\rho \otimes \sqrt{Q}I_2 \\ \dot{c}_i = \xi_i^T Q \xi_i, \end{cases} \quad (6)$$

where $C = \text{diag}\{c_1, \dots, c_M\}$ and $\rho = \text{diag}\{\rho_1, \dots, \rho_M\}$.

We consider the following Lyapunov function candidate:

$$V = \sum_{i=1}^M \frac{c_i \varphi_i}{2} \int_0^{\xi_i^T \sqrt{Q} \xi_i} \rho_i(s) ds + \frac{\lambda_0}{24} \sum_{i=1}^M \tilde{c}_i^2 \quad (7)$$

where $\tilde{c}_i = c_i - \alpha$, and α is a positive scalar to be determined later. $\Xi = \text{diag}\{\varphi_1, \dots, \varphi_M\}$ is a positive definite matrix with $\varphi_i \in \mathbb{R}_{>0} \forall i \in \mathcal{S}$ such that $\Xi = \text{diag}\{\varphi_1, \dots, \varphi_M\} > 0$, and λ_0 is the smallest eigenvalue of $\Xi(L + G) + (L + G)^T \Xi$. Since $c_i(0) > 1$, it follows the second equation in (4) that $c_i(t) \geq 0$ for all $t > 0$. Besides, the smooth and monotonically increasing function ρ_i satisfies $\rho_i(s) \geq 1$ for $s > 0$, it can be easily obtained that V is positive definite with respect to ξ_i and $\tilde{c}$ for all $i \in \mathcal{S}$.

Now, the time derivative of V along any trajectory of (6) is given by

$$\begin{aligned} \dot{V} &= \sum_{i=1}^M c_i \varphi_i \rho_i \xi_i^T \sqrt{Q} \dot{\xi}_i + \frac{\lambda_0}{12} \sum_{i=1}^M (c_i - \alpha) \xi_i^T Q \xi_i \\ &\quad + \sum_{i=1}^M \frac{\dot{c}_i \varphi_i}{2} \int_0^{\xi_i^T \sqrt{Q} \xi_i} \rho_i(s) ds. \end{aligned} \quad (8)$$

Note that

$$\begin{aligned} \sum_{i=1}^M c_i \varphi_i \rho_i \xi_i^T \sqrt{Q} \dot{\xi}_i &= \xi^T (C\rho \Xi \sqrt{Q}) \dot{\xi} \\ &= -\frac{1}{2} \xi^T (C\rho(\Xi(L + G) + (L + G)^T \Xi)C\rho Q) \xi \\ &\leq -\frac{1}{2} \xi^T (\lambda_0 C^2 \rho^2 Q) \xi, \end{aligned} \quad (9)$$

where the property $\Xi(L+G)+(L+G)^T\Xi \geq \lambda_0 I_M$ is exploited to obtain the first inequality.

Considering that ρ_i is monotonically increasing and $\rho_i(s) \geq 1$ for $s > 0$, the following relation can be obtained by using Lemma 2

$$\begin{aligned} \sum_{i=1}^M \dot{c}_i \varphi_i \int_0^{\xi_i^T \sqrt{Q} \xi_i} \rho_i(s) ds &\leq \sum_{i=1}^M \dot{c}_i \varphi_i \rho_i \xi_i^T \sqrt{Q} \xi_i \\ &\leq \sum_{i=1}^M \frac{\dot{c}_i \varphi_i^3}{3\lambda_0^2} + \sum_{i=1}^M \frac{2}{3} \lambda_0 \dot{c}_i \rho_i^{\frac{3}{2}} (\xi_i^T \sqrt{Q} \xi_i)^{\frac{3}{2}} \\ &\leq \sum_{i=1}^M \frac{\dot{c}_i \varphi_i^3}{3\lambda_0^2} + \sum_{i=1}^M \frac{2}{3} \lambda_0 \dot{c}_i \rho_i^{\frac{3}{2}} (1 + \xi_i^T \sqrt{Q} \xi_i)^{\frac{3}{2}} \\ &\leq \sum_{i=1}^M \left(\frac{\varphi_i^3}{3\lambda_0^2} + \frac{2}{3} \lambda_0 \rho_i^2 \right) \xi_i^T Q \xi_i. \end{aligned} \quad (10)$$

Substituting (9) and (10) into (8), we get

$$\dot{V} \leq - \sum_{i=1}^M \left(\lambda_0 \left(\frac{1}{2} c_i^2 \rho_i^2 - \frac{1}{12} c_i - \frac{1}{3} \rho_i^2 \right) + \frac{1}{12} (\lambda_0 \alpha - \frac{2\varphi_i^3}{\lambda^2}) \right) \xi_i^T Q \xi_i.$$

Select $\alpha \geq \beta + \max_{i \in \mathcal{S}} (\frac{2\varphi_i^3}{\lambda^2})$, where $\beta > \frac{1}{\lambda_0^2}$ is a positive scalar. Since $\rho_i \geq 1$ and $c_i \geq 1$, we can get the following relation

$$\begin{aligned} \dot{V} &\leq - \frac{\lambda_0}{12} \sum_{i=1}^M (c_i^2 \rho_i^2 + \beta) \xi_i^T Q \xi_i \\ &\leq - \frac{1}{6} \xi^T (\sqrt{\beta} \lambda_0 C \rho Q) \xi \\ &\leq - \frac{1}{6} \xi^T (C \rho Q) \xi. \end{aligned} \quad (11)$$

Applying the change of variable $\zeta = \sqrt{C \rho} \xi$ into (11), the expression of $\dot{V}$ becomes

$$\dot{V} \leq -\zeta^T Q \zeta, \quad (12)$$

which implies $\dot{V} \leq 0$ and $\dot{V} = 0$ only when $\zeta = 0$. This implies asymptotic stability of (6) invoking LaSalle's invariance principle [30]. Hence, all the sheep will move to the COM after implementing the adaptive protocol (4). ■

Remark 1: The tuning parameter Q in the adaptive protocol (4) plays an important role in adjusting the cohesion of the flock. A larger Q will result in a stronger attractive force and a faster rendezvous speed, but it will also increase the control effort to be applied to the sheep (e.g., the energy used for movement). Hence, the value of Q should be properly selected to simulate the dynamics of the real sheep. □

Now we need to consider the second and the third components, where repulsive forces should be applied to each sheep in order to keep a distance from the neighbors and the dogs. The repulsive force can be modelled using artificial potential fields. Motivated by [31], we include the following protocol for each sheep to avoid other sheep and the dog:

$$v_{b,i} = \sum_{j \in \mathcal{N}_j} \theta_s \tau_{ij} \left(\frac{1}{\|s_i - s_j\|} - \frac{1}{d_s} \right) \frac{s_i - s_j}{\|s_i - s_j\|^2}, \quad (13)$$

$$v_{c,i} = \sum_{k=1}^N \theta_d \phi_{ik} \left(\frac{1}{\|s_i - d_k\|} - \frac{1}{d_v} \right) \frac{s_i - d_k}{\|s_i - d_k\|^2}, \quad (14)$$

where θ_s and θ_d are positive constants, which determine the magnitude of the repulsive force generated to repel a sheep from another sheep or a dog. The factors τ_{ij} and ϕ_{ik} are defined as follow:

$$\tau_{ij} = \begin{cases} 1, & \|s_i - s_j\| \leq d_s, \\ 0, & \text{otherwise} \end{cases} \quad (15)$$

$$\phi_{ik} = \begin{cases} 1, & \|s_i - d_k\| \leq d_v, \\ 0, & \text{otherwise.} \end{cases} \quad (16)$$

The following theorem shows the avoidance behavior of the sheep in the presence of other sheep or dogs in the view distance.

Theorem 2: Artificial potential field based protocols (13) and (14) ensure each sheep to keep a certain distance d_s with its neighbours and push it away from the dogs.

Proof: Define $\psi_{ij} = \|s_i - s_j\|$, $\psi_{ik} = \|s_i - d_k\|$, $\varsigma_{ij} = s_i - s_j$ and $\varsigma_{ik} = s_i - d_k$. Following similar derivation as shown in [31], the proof contains two different cases.

Case I: When other sheep and dogs are not in the repulsive region, i.e., $\psi_{ij} \geq d_s$, $\psi_{ik} \geq d_v$, $\forall i, j \in \mathcal{S}$, $\forall k \in \mathcal{D}$, we have $\tau_{ij} = 0$ and $\phi_{ik} = 0$. Thus the avoidance protocols $v_{b,i}$ and $v_{c,i}$ are eliminated and the behaviors of the sheep are guaranteed by the rendezvous protocol (4) as shown in Theorem 1.

Case II: Firstly, consider that the j^{th} sheep moves into the repulsive region, i.e., $\psi_{ij} \leq d_s$. then we can obtain that

$$\begin{aligned} \frac{1}{2} \dot{\varsigma}_{ij}^2 &= (s_i - s_j)(v_{a,i} + v_{b,i} + v_{c,i}) \\ &= (s_i - s_j)v_{a,i} + (s_i - s_j)v_{b,i} + (s_i - s_j)v_{c,i}. \end{aligned} \quad (17)$$

From Theorem 1, it can be obtained that $(s_i - s_j)v_{a,i}$ is bounded. Define $\varsigma_{ij}^* = (s_i - s_j)v_{b,i}$ and substitute (13) into ς_{ij}^* , we get

$$\varsigma_{ij}^* = \sum_{j \in \mathcal{N}_j} \theta_s \tau_{ij} \left(\frac{1}{\psi_{ij}} - \frac{1}{d_s} \right) \frac{\varsigma_{ij}^2}{\psi_{ij}^2}. \quad (18)$$

Since s_j moves into the repulsive distance d_s , there exist a region ε_j such that $\|s_i - s_j\| \leq \varepsilon_j \leq d_s$. Hence we obtain $\frac{1}{2} \dot{\varsigma}_{ij}^* > 0$ and $\varsigma_{ij} \rightarrow \infty$. Moreover, if $\tau_{ij} \gg 0$, $\varepsilon_j \rightarrow d_s$. This implies that s_i will not equal to s_j by implementing avoidance protocol (13).

Similarly, if the k^{th} dog moves into the view distance d_v , i.e., $\psi_{ik} \leq d_k$. then the following relation can be obtained

$$\begin{aligned} \frac{1}{2} \dot{\varsigma}_{ik}^2 &= (s_i - d_k)(v_{a,i} + v_{b,i} + v_{c,i}) \\ &= (s_i - d_k)v_{a,i} + (s_i - d_k)v_{b,i} + (s_i - d_k)v_{c,i}. \end{aligned} \quad (19)$$

Since $(s_i - d_k)v_{a,i}$ is bounded. Define $\varsigma_{ik}^* = (s_i - d_k)v_{c,i}$ and substitute (14) into ς_{ik}^* , we get

$$\varsigma_{ik}^* = \sum_{j \in \mathcal{N}_j} \theta_d \phi_{ik} \left(\frac{1}{\psi_{ik}} - \frac{1}{d_v} \right) \frac{\varsigma_{ik}^2}{\psi_{ik}^2}. \quad (20)$$

Fig. 3. Occlusion based motion control strategy. In this example, a flock of sheep with radius of R_s and three dogs (quadrotor UAV) are considered. An artificial potential field is generated for the dogs (the yellow area) to avoid pushing the sheep away from the goal. The occlusion area is marked with the blue color. Based on the designed feedback tracking controller and artificial potential field, all the dogs will reach this blue occlusion area and push the sheep towards the goal autonomously. $\bar{s}$ represents the COM of the flock.

Because d_k is in the view distance d_v , there exist a region ε_k such that $\|s_i - d_k\| \leq \varepsilon_k \leq d_v$. Hence we obtain $\frac{1}{2}\zeta_{ik}^* > 0$ and $\zeta_{ik} \rightarrow \infty$. Furthermore, if $\phi_{ik} \gg 0$, $\varepsilon_k \rightarrow d_v$. This implies that s_i will also not equal to d_k by implementing avoidance protocol (14). ■

Remark 2: In order to produce sufficiently strong repulsive force to repel the i^{th} sheep from all the adjacent sheep and the dogs, θ_s and θ_d must be set appropriately to make $v_{b,i}$ and $v_{c,i}$ stronger than the first component $v_{a,i}$. □

B. Coordination Algorithm of the Dogs

In this subsection, an occlusion-based coordination strategy is adopted for the dogs to relocate the sheep to the desired position.

Motivated by [32], the dogs will first move to the place where the goal location is occluded by sheep and then start pushing the flock of sheep to the goal location. Note that the desired occlusion area is computed based on the locations of the flock and the goal only, it is a virtual area that can not be measured by the robots' onboard sensors directly.

In order to let the dogs find the appropriate place that occludes its view of the goal, a potential field approach is implemented. As shown in Fig. 3, a repulsive field is centered at the COM to avoid pushing the sheep backwards when the dogs are in front of the sheep. The control inputs are given as:

$$u_{a,i} = \theta_d \mu_i \left(\frac{1}{\|d_i - \bar{s}\|} - \frac{1}{R_s + d_v} \right) \frac{d_i - \bar{s}}{\|d_i - \bar{s}\|^2}, \quad i \in \mathcal{D} \quad (21)$$

where θ_d is a positive constant which determines the magnitude of the repulsive force generated to repel a dog from the goal while avoiding pushing the sheep backwards, $\bar{s}$ is the position of the COM, and the factor μ_i is defined as follows:

$$\mu_i = \begin{cases} 1, & \|d_i - \bar{s}\| \leq R_s + d_v \wedge \\ & \left(\frac{|\det([g - d_i, \bar{s} - d_i])|}{\|g - d_i\|} \geq R_s \vee \right. \\ & \left. \|d_i - g\| \leq \|\bar{s} - g\| \right), \\ 0, & \text{otherwise.} \end{cases} \quad (22)$$

An attractive force is also applied to the dog so that the dog will reach the occluded area and start pushing sheep towards the goal. An adaptive tracking controller is designed for this purpose as:

$$\begin{cases} u_{b,i} = -\hat{c}_i \hat{\rho}_i (\hat{\xi}_i^T \sqrt{\omega} \hat{\xi}_i) \sqrt{\omega} \hat{\xi}_i, \\ \dot{\hat{c}}_i = \hat{\xi}_i^T \omega \hat{\xi}_i, \end{cases} \quad i \in \mathcal{D} \quad (23)$$

where $\hat{\xi}_i = d_i - \bar{s}$ and $\hat{c}_i(t)$ is a time-varying coupling weight associated with the i^{th} dog with $\hat{c}_i(0) > 1$, $\omega > 0$ is a positive scalar to be designed, and $\hat{\rho}_i = (1 + \hat{\xi}_i^T \sqrt{\omega} \hat{\xi}_i)^3$ is the smooth and monotonically increasing function.

In order to achieve cooperative herding, a desired spacing S_d is set between each dog such that they can distribute themselves around the sheep. To achieve this operation, a repulsive force is generated when the distance between two neighboring dogs is less than the desired spacing S_d :

$$u_{c,i} = \sum_{k=1}^N \theta_a \kappa_{ik} \left(\frac{1}{\|d_i - d_k\|} - \frac{1}{S_d} \right) \frac{d_i - d_k}{\|d_i - d_k\|^2}, \quad (24)$$

where θ_a is a positive constant and

$$\kappa_{ik} = \begin{cases} 1, & \|d_i - d_k\| \leq S_d, \\ 0, & \text{otherwise.} \end{cases} \quad (25)$$

As a result, the control input for each dog is a combination of the three components, the dynamics of the dog can be described by

$$\dot{d}_i = u_{a,i} + u_{b,i} + u_{c,i}. \quad (26)$$

Theorem 3: Suppose all the assumptions listed in the Section II.A are satisfied. The occlusion-based cooperative shepherding task can be achieved by the dogs using coordination protocols (21), (23) and (24).

Proof: The proof follows similar derivation shown in the previous section, thus it is omitted here. ■

Remark 3: Even though obstacle avoidance is not considered in our coordination algorithm, it can be achieved via human-robot interaction. For example, we can add some additional waypoints to the dogs manually before pushing the flock to the goal directly, these waypoints must be set at a certain distance from the obstacles as analyzed in [15], [32]. □

Remark 4: When the dogs have reached the occlusion area and start pushing the sheep, their speed should be set smaller than the maximum speed of the sheep in order not to destroy the flock, that is, $\|u_i\| \leq \sigma$, where σ is a positive constant determined by the sheep to be steered. This constraint can be predefined in the robotic system or supervised by a human operator as shown in [33]. In [14], there is no such speed limit for the dogs, which is more realistic considering the behavior of real dogs. However, the proposed strategy aims to minimize the travel distance of the dog using a simple guideline from an application perspective (e.g., save more battery energy when using UAVs to perform shepherding tasks in a real farm). Due to the technical differences between these two methods, the speed limit used in this work is essential. If the speed limit is not applied, no matter how strong cohesion the flock has, it

Fig. 4. Position of the dog (red square) and sheep (blue circle) over time. The goal is represented by red star. At the beginning, all the dogs are randomly placed around the goal. Based on the clustering algorithm [35], three dogs are coordinated to handle the larger flock and two dogs steer the smaller one. According to the occlusion-based motion control strategy, it can be seen from 8 s to 16 s that they first go behind the flock and then start pushing the sheep. From 25 s to 40 s, all the sheep are steered toward the goal. One flock reaches the goal after 40 s and the corresponding dogs start helping the other team. At 50 s, two flock of sheep are merged into one big flock and the shepherding task is accomplished.

may still be easily separated by the dogs due to the design of the proposed strategy. $\square$

Remark 5: Different from the object transportation task using a swarm of robots as in [34], the shape of the sheep flocking in this paper is time-varying, which brings more challenges to the controller design. Besides, in [34], the controller is centralized and the movement of the robot is controlled manually. However, in this work, we use distributed mechanism to reduce the communication costs, which provides more reliability when herding a large-scale swarm system. $\square$

IV. SIMULATION RESULTS

In this section, an in-depth simulation case study conducted in the Matlab/Simulink environment is discussed.

A. Case 1: Control Performance

In this simulation, we have two flocks of sheep consisting of 30 sheep and 20 sheep, respectively, and 5 UAVs with linearized single-integrator dynamics working as robotic dogs. The sheep model developed in Section III.A was applied to each sheep and the coordination algorithm proposed in Section III.B was implemented on each UAV. The view distance of the sheep d_v was set to 1.5 m, the minimum distance between sheep was set to 0.5 m and the desired distance between two UAVs S_d was set as 0.8 m. The maximum speed of each sheep was limited to 0.05 m/s, the maximum linear speed of the UAV was 0.1 m/s, once the UAVs reach the occlusion area and start pushing the flock, we set a speed constraint of 0.03 m/s to the UAV in order to avoid separating the herds.

Fig. 4 illustrates the trajectories of the sheep and dogs in the simulation at different time instants. At the beginning of the simulation, a flock of 30 sheep and a flock of 20 sheep are placed on the left and right hand sides of the arena respectively. Five robotic dogs are placed randomly in the center of the arena and the goal coordinate is given by $[0 \ 1]^T$. Firstly, we design the following utility function for the i^{th} dog as

$$\Psi_{ik} = \varepsilon^R \frac{R_k}{|\mathcal{V}_k \cup \{i\}|} - \varepsilon^d d_{ik}, \quad \forall k \in \{1, 2\}, \quad (27)$$

for all $i \in \{1, 2, \dots, 5\}$ where R_k represents the radius of the k^{th} flock; d_{ik} denotes the distance between the i^{th} dog and the center of the k^{th} flock; $\mathcal{V}_k$ represents the set containing dogs assigned to the k^{th} flock; ε^R and ε^d are the positive weights used to scale the factors R_k and d_{ik} . In this task, we choose $\varepsilon^R = 3$ and $\varepsilon^d = 1$. This utility function makes a dog less attracted by flocks with other dogs. By using the clustering algorithm [35], the dogs are divided into two teams autonomously, three of them herd the bigger flock and the remaining two dogs are assigned to the smaller flock after achieving Nash equilibrium. From $t = 8$ s, all the dogs are moving to the back of the flock and start pushing the flock to the goal location (represented by a red star). Note that once a flock of sheep has arrived at the goal (in this case study, we set a threshold distance of 1 m between the COM and the goal to judge whether the goal is reached), the corresponding dogs will start helping the other team as the flock would reach a steady state as discussed in Theorem 1. The shepherding task is accomplished within 50 seconds as shown in Fig. 4. The relative distance between each sheep and the goal location is

Fig. 5. Time variation of the relative distance between the sheep and the goal location. The red line indicates the median and shaded area represents the minimum and maximum of the data.

illustrated in Fig. 5, where it can be seen that the relative distance is effectively reduced due to the implementation of our shepherding algorithm. Note that all the sheep cannot reach the goal simultaneously (which is unrealistic), so the relative distance to goal can only converge to a small positive constant depending on the size of the flock.

B. Case 2: Result Analysis

A second set of simulations has been conducted to evaluate the performance of the proposed coordination protocol. In this case, we only consider one flock of sheep and we test the effect of the number of sheep on dogs. The initial position of the sheep is randomly set around a fixed COM and the range of number of sheep in the flock is increased from 10 to 50.

For each case, 50 iterations were run and the average completion time for each case was calculated. As can be seen from Fig. 6, for a single dog, the maximum number of sheep it can handle is 30, if the size of the flock is larger than that, the shepherding task cannot be achieved using the proposed algorithm. Similar situation happens when two dogs try to shepherd flocks with more than 40 sheep. The reason for this limitation is that when the size of the flock is larger than a certain threshold, it becomes more difficult for dogs to steer all the sheep without separating the flock. This is because when the size of the flock becomes too large, small number of dogs cannot produce enough repulsive force to steer the flock efficiently. The flock may deviate from the desired trajectory, thus causing more time for dogs to adjust the direction of the movement of the flock. However, the proposed coordination still shows its efficiency and feasibility when compared to the formation-based shepherding methods.

V. EXPERIMENTAL VALIDATION

In order to investigate feasibility of the proposed coordinated protocol, real-robot experiments involving miniature size mobile robots, acting as sheep and dogs were performed. The video is available in the Supplementary Material and <https://youtu.be/DPTGvIqqtGg>.

Fig. 6. Performance for different number of dogs. 50 trials have been tested for each case, and we compare the average complete time of the task using different number of dogs with different size of the flock.

Fig. 7. The Mona robot [36] used in the experimental validation.

A. Experimental Setup

1) *Robotic Platform*: Mona robots [36] were used in the real-robot experiments. Fig. 7 shows a Mona robot and its various components. It is a small-sized (with diameter of 8 cm) mobile robot which was developed at the University of Manchester as an open-source, swarm robotic platform.

The robot has two gear head DC motors as its actuator. These motors are controlled independently by two pulse-width modulation (PWM) channels of the main micro-controller, which generates control signals for the left and right motors simultaneously. The motors actuate Mona with relatively slow speed in the range from 0 to 8 cm/s.

There are three communication channels (I2C, RS232, and SPI) which are used to communicate with the base-station and other robots. Serial Peripheral Interface (SPI) is used to communicate with the RF (radio frequency) module.

2) *Experimental Platform*: Fig. 8 shows the experimental platform which includes a digital camera connected to a host PC which runs tracking software, an arena (i.e., the frame with its dimension being 160cm $\times$ 140cm) and walls made of aluminium strut profile and the wooden floor. The position tracking system used in this experiment is based on an extension of an open-source fiducial localization method described in [37]. The system can track the positions and orientations of the robots by identifying the unique circular tags attached to the top of the robots. These positions are transmitted as an array of floating point numbers to the controller via the ROS communication framework similarly as in the ROS branch of

Fig. 8. Arena configuration including a PC which tracks the position of robots using digital camera and sends motion commands to the robots using RF communication.

the COS Φ system [38]. The global tracking system can be removed if each robot can detect the relative positions of its neighbors using on-board range & bearing sensors, which will be implemented and tested in future work.

B. Robot Model

Each mobile robot has the same mechanical structure and they are described by the following dynamic equations in terms of the global coordinates

$$\begin{aligned}\dot{p}_{xi} &= v_i \cos \theta_i, \\ \dot{p}_{yi} &= v_i \sin \theta_i, \\ \dot{\theta}_i &= \omega_i,\end{aligned}\quad (28)$$

where (p_{xi}, p_{yi}) is the position of the i^{th} robot and θ_i is the orientation. v_i and ω_i are linear and angular velocities of the i^{th} robot respectively.

Consider the nonholonomic kinematic constraint, we define the head position $d_i = [\tilde{p}_{xi}, \tilde{p}_{yi}]^T$ and

$$\begin{aligned}\tilde{p}_{xi} &= p_{xi} + l \cos \theta_i, \\ \tilde{p}_{yi} &= p_{yi} + l \sin \theta_i,\end{aligned}\quad (29)$$

where l is the distance between the head position and the inertial position.

By letting $u_i = [u_{xi}, u_{yi}]^T$ and

$$\begin{aligned}u_{xi} &= v_i \cos \theta_i - l\omega_i \sin \theta_i, \\ u_{yi} &= v_i \sin \theta_i + l\omega_i \cos \theta_i,\end{aligned}\quad (30)$$

the feedback linearized kinematic model of the robot can be described by

$$\dot{d}_i = \begin{bmatrix} \dot{\tilde{p}_{xi}} \\ \dot{\tilde{p}_{yi}} \end{bmatrix} = \begin{bmatrix} \cos \theta_i & -l \sin \theta_i \\ \sin \theta_i & l \cos \theta_i \end{bmatrix} \begin{bmatrix} v \\ \omega \end{bmatrix} = u_i, \quad (31)$$

which is same as (2) and hence enables all the previous theoretical developments to be applied.

In this experiment, the maximum speed of the sheep is set as $\sigma = 3$ cm/s, so we have a speed constraint $\max(u_i) = 5$ cm/s when the dog is not in the occlusion area and $\max(u_i) = 1$ cm/s when it starts pushing the flock towards the goal to avoid separating it.

C. Experimental Results

In the experiment, a swarm of ten Mona robots which contains three robotic dogs (the green color tags) and seven robotic sheep (the white color tags) is placed in a two dimensional arena. Fig. 9(a) shows the initial positions of the robotic sheep (marked by the blue circle) and the robotic dog (marked by the red square) on the arena. At the beginning, two flocks of sheep are placed at the left bottom corner and right top corner respectively. The COM of the flock is marked by the black star. Three dogs are placed randomly. The goal is set in the middle of the arena (represented by a red star). Fig. 9(b) shows that the dogs were automatically divided into two groups and started to circle behind the corresponding flock. The trajectories of the sheep and the dogs are represented by solid lines. Fig. 9(c) depicts that the dogs began to drive the flock towards the goal. Fig. 9(d) shows that all the sheep were led to the target position within 80 s. From all these figures, the feasibility of the proposed control protocol is verified and the robotic shepherd task is accomplished.

D. Discussions

In this experiment, a simplified scenario was tested and the mobile robot (Mona) was used as an affordable robotic platform. It can be inferred that although the feasibility of the proposed coordination algorithm was validated through small-scale mobile robots in a laboratory environment, it can also be applied to real-world scenarios. In that case, the low-level feedback linearization controller implemented in the robotic platform will be different, such that the dynamics of the robot can still be reduced to (2). Based on the linearized dynamics, the proposed shepherding algorithm will remain the same.

In contrast to [18], [22] where only simulations are given, the proposed coordination has been examined via real robot experiments, where it shows certain robustness against time-delays and noises appeared in the actuators. In [15], only the target points are assigned to the shepherd without considering the dynamics of the robot. However, in this work, both high-level coordination and low-level control are considered in a unified framework, which provides more feasibility in real implementation. Different from [17] where steering points around each flock are assigned to shepherds via a centralized control scheme, the dogs in this work are controlled via a distributed manner and they only need to communicate with their neighboring dogs during cooperation. Besides, each dog does not need to track a specific steering point, which gives more efficiency and freedom for the dogs to complete the desired shepherding task. In [21], [22], formation based approaches are investigated for the shepherding task. By using such containment-type methods, all the dogs must first enclose the flock before relocate them to the goal, which may be conservative as a large number dogs are required in order to form the desired circular formation around a big flock of sheep. However, by using the proposed occlusion based shepherding algorithm, only a small number of dogs may be used to achieve a similar performance.

In reality, sheep may not strictly follow the principle proposed in Section III.A (e.g., random walk). Besides, position

Fig. 9. Experimental validation of the proposed ordination protocol. (a) Initial positions of the sheep and dogs; (b) Dogs go behind the corresponding flock at $t=20$ s. (c) Once the dogs have reached the occlusion area, they start pushing the sheep towards to goal at $t=60$ s (d) All the sheep are steered to the goal and the shepherding task is accomplished at $t=80$ s.

tracking error and communication delays may also affect the performance of the robots when conducting the experiments in the outdoor farm. In the future, more challenging situations and realistic sheep behaviors could be considered by improving the proposed coordination protocol using machine learning techniques.

VI. CONCLUSIONS

In this paper, we modeled the sheep flocking properties based on their collective behavior observed in nature. A novel coordination algorithm for the robotic dogs was developed using occlusion-based motion control strategy. The proposed protocol was investigated using both simulations and real-robot experiments. In the experiments, global tracking and communication systems were used to validate the proposed shepherding strategy, but it may also be removed in the future if the robots can be equipped with onboard position and proximity sensors. The results demonstrated the efficiency and feasibility that could be obtained by combining distributed consensus algorithms and artificial penitential fields. The proposed coordination protocol lays the foundation for more complex and realistic tasks. In the future work, we will test our algorithm in real-world experiments with small and medium sizes animal populations in outdoor environments. Besides, more factors should be considered in the protocol design, for example, merge split flocks and allow higher pushing speed.

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