Bearing-only formation control with auxiliary distance measurements, leaders, and collision avoidance

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Bearing-only formation control with auxiliary distance measurements, leaders, and collision avoidance

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Abstract—We address the controller synthesis problem for distributed formation control. Our solution requires only relative bearing measurements (as opposed to full translations), and is based on the exact gradient of a Lyapunov function with only global minimizers (independently from the formation topology). These properties allow a simple proof of global asymptotic convergence, and extensions for including distance measurements, leaders and collision avoidance. We validate our approach through simulations and comparison with other state-of-the-art algorithms.

I. INTRODUCTION

The goal of formation control is to move a group of agents in order to achieve and maintain a set of desired relative positions. This task has applications in many fields such as surveillance, exploration, and transportation [2], [16], [19], [25], [29], [35]. Formations also allow the control of a large number of agents by a single human operator, and provide robustness to the failure of single agents.

The formation control problem dates back to early work on multi-robot control [4], [12]. Since then, there has been extensive work considering different control strategies (e.g., with [13], [17] or without leader nodes [2]), inter-agent sensing methodologies (positions [7], [22], distances [2], or, as reviewed below, relative directions), types of sensing or constraint graph (e.g., with limits on the number of agents [2], [8], or on the graph topology [14], [37]), strategies for connectivity control [36], models for the agents (simple integrators, non-holonomic [13], [17], second order integrators [30]), and collision avoidance mechanisms [10], [20].

In the last decade, there has been an increasing interest in vision-based solutions, where each agent is equipped with an onboard camera (early examples are [11], [21], [28]). In this setting, relative direction measurements (i.e., bearing measurements) are often more reliable than the corresponding distance measurements. Therefore, there has been a recent emphasis on minimizing the use of distance measurements.

Review of prior work. Given the extent of the literature, we focus only on works based on bearing-based formations. With a goal similar to ours, [7], [9] and [6] propose a distributed control law for pure bearing or mixed bearing and distance formations. However, in order to be implemented, the law also requires the distance measurements corresponding to each bearing measurement. The control strategy proposed by [14] requires only one or no distance measurements, and the control law, under ideal conditions, produces linear trajectories. In turn, however, they rely on special graph structures (where all agents can communicate and measure their relative bearings with respect to two leader agents) or on the use of distributed estimators (which “virtually” realize the unavailable measurements but are not formally considered in the stability analysis). The paper most similar to our work is [38], which proposes a bearing-only control law based on projection operators. The control law is based on a modified gradient where the (unknown) distances are removed. The stability analysis, however, does not use this fact, and crucially relies on the state of the entire network evolving on a sphere.

In most of the work above, it is assumed that the agents share or can agree on a common rotational frame (i.e., a common sense of “direction”). This can be fulfilled with a rotation localization algorithm [26], [28], [34]. The paper [38] is the only one to include a formal analysis of the effects of such localization algorithms on bearing-only formation control. On the other hand, [8] and [37] do not require a common rotational frame, but their approaches are limited to, respectively, triangular and 2-D formations with graphs containing a single cycle.

Regarding collision avoidance, this topic also has a long history [3]. Optimal solutions have been proposed [31], but they do not scale well to multiple agents and distributed settings. A more common approach is to employ local mechanisms based on either a modified potential function [18], [24], compositions of vector fields [15], [23], or constraints on the computed control laws [5], [10], [20]. All these methods, however, assume full relative state information between obstacles and agents, and are hence incompatible with bearing-only formulations.

Paper contributions. We present a formation control solution that can work with bearing measurements alone, or can be augmented with corresponding distances. As in the majority of the literature, we assume that (a) each agent can be modeled as a single integrator; (b) each agent is equipped with omnidirectional sensors (no field of view constraints); (c) the agents can agree on a common rotational frame. With respect to existing work (and in particular [14], [38]), our key contribution is to propose a control law based on the exact gradient of a Lyapunov function with global convergence guarantees (Theorem 1). While unknown distances and the full formation graph appear in the cost, the resulting control
We define a vector of derivatives. Equivalent if they produce the same measurements; that is, \( \beta_{ij}(x_{g,i}, x_{g,j}) = \beta_{ij} \) for all \( (i, j) \in E_b \) and \( d_{ij}(x_{g,i}, x_{g,j}) = d_{ij} \) for all \( (i, j) \in E_d \).

Identical if they have the same configuration, \( x = x' \).

Congruent if they have the same shape and scale, that is, \( x' \) and \( x \) are related by a translation \( t \in \mathbb{R}^n \) (i.e., \( x'_i = x_i + t \)).

Similar if they have the same shape, that is, \( x' \) and \( x \) are related by a translation and dilatation \( \alpha > 0 \) \( (x'_i = \alpha x_i + t) \).

Note that similar and congruent configurations are always equivalent, but the converse might not be true. We then say that a formation is rigid if all formations equivalent to it are also similar (for the case of pure bearing formations) or congruent (for the case of bearing+distance formations).

In practice, one can check whether a formation is rigid by checking the rank of the so called rigidity matrix (see [7], [27], [38] for details).
In this section, we formulate the problem of formation control for a network of kinematic agents and propose our gradient-based solution. For the moment, we consider only leaderless formations (that is, all agents follow the same strategy). Leader-based formations are considered in Section VI. The main feature of our method is the global asymptotic convergence of the closed loop system to a configuration equivalent to the desired $x_{0}$. Rigidity, although not specifically required in the proofs, will then imply rigid equivalence.

We assume that each agent $i \in V$ follows the model $\dot{x}_{i}(t) = u_{i}$, where $u_{i}$ is a control input. In vector notation, we have $\dot{x}(t) = u$ where $u = \text{stack}(\{u_{i}\}_{i \in V})$. Given desired measurements $\beta_{g},d_{g}$, which are consistent with a desired rigid formation $(\mathcal{F},x_{0})$, our goal is to design inputs $u$ that drive the agents into a configuration equivalent to $x_{0}$. Our control law is the negative gradient of a cost function $\varphi(x)$, $u = -\nabla\varphi(x)$. By carefully defining the structure of $\varphi$, this law can be directly computed from the available measurements (as mentioned before, this is in contrast to previous work where additional information such as distance measurements is generally required).

### A. The cost function

The cost function we propose is of the following form:

$$\varphi(x) = \alpha_{b} \sum_{(i,j) \in E_{b}} \varphi^{b}_{ij}(x_{i},x_{j}) + \alpha_{d} \sum_{(i,j) \in E_{d}} \varphi^{d}_{ij}(x_{i},x_{j}),$$

(6)

$$\varphi^{b}_{ij}(x_{i},x_{j}) = d_{ij}f_{b}(c_{ij}), \quad \varphi^{d}_{ij}(x_{i},x_{j}) = f_{d}(q_{ij}).$$

(7, 8)

We now proceed to explain the various parts of this equation (the reader is invited to refer back to (6) as we proceed). At a high level, $\varphi$ is composed of a summation, weighted by $\alpha_{b}, \alpha_{d} > 0$, over the edges $E_{b}$ and $E_{d}$. Each term in the summation is a function of one of the two following “similarity measures” between the current measurements $\beta(x),d(x)$ and the desired ones, $\beta_{g},d_{g}$:

$$\begin{align*}
c_{ij}(x_{i},x_{j}) &= \beta^{T}_{g,ij}\beta_{ij} = \cos(\angle(\beta_{g,ij},\beta_{ij})), \quad (i,j) \in E_{b} \\
q_{ij}(x_{i},x_{j}) &= \beta^{T}_{g,ij}(x_{j} - x_{i} - (x_{g,j} - x_{g,i})) \\
&= \beta^{T}_{g,ij}(d_{ij}\beta_{ij} - d_{g,ij}\beta_{g,ij}) \\
&= d_{ij}c_{ij} - d_{g,ij}, \quad (i,j) \in E_{d}.
\end{align*}$$

(9, 10)

Eq. (9) is the cosine of the angle between the measured and desired bearings ($c_{ij} = 1$ when the bearings coincide), while (10) quantifies the discrepancy between the measured and desired relative position of the agents projected on the line given by $\beta_{g,ij}$ ($q_{ij} = 0$ when bearing and distances coincide, see Figure 1 for an illustration). We use $q_{ij}$ instead of a simple difference of the distances because $q_{ij}$ is actually linear in the configuration $x$ (see first line of (10)). Each of these similarities is weighted by a reshaping function $f_{b}$ (for the $c_{ij}$’s) or $f_{d}$ (for the $q_{ij}$’s). In this paper, we use $f_{b}(c) = 1 - c$ and $f_{d}(q) = \frac{1}{2}q^{2}$, but the choice of other $C^{2}$ (i.e., twice differentiable) functions is also possible, as explained in Section V.

### B. The gradient and control law

Using the chain rule, the gradient of each term (7) and (8) can be computed as (see [32] for detailed derivations):

$$\begin{align*}
g^{b}_{ij} &= \nabla_{x} \varphi^{b}_{ij}(x_{i},x_{j}) = -f_{b}(c_{ij})(I_{n} - \beta_{ij}\beta^{T}_{ij})\beta_{g,ij}, \\
g^{d}_{ij} &= \nabla_{x} \varphi^{d}_{ij}(x_{i},x_{j}) = -f_{d}(d_{ij}c_{ij} - d_{g,ij})\beta_{g,ij}.
\end{align*}$$

(11, 12)

The gradient of (6) with respect to the $i$-th agent is then:

$$g_{i} = \nabla_{x} \varphi(x) = \alpha_{b} \sum_{j:(i,j) \in E_{b}} g^{b}_{ij} + \alpha_{d} \sum_{j:(i,j) \in E_{d}} g^{d}_{ij}.$$  

(13)

Note that, while the cost function depends on the range $d_{ij}$, the gradient information for $\varphi^{b}_{ij}$ depends only on local bearing information and no range information is necessary (this is because $d_{ij}$ in (7) cancels out when taking the gradient).

### IV. Properties of the control law

Before giving a detailed analysis of the convergence of the algorithm, we elaborate on a few of its properties.

**Choice of local reference frame.** The proposed control law can be computed in any local reference frame, in the sense that if $\beta_{ij}$ and $\beta_{g,ij}$ are provided in either the local frame $\mathcal{R}_{i}$ or the global frame $\mathcal{R}_{0}$, then $g_{i}$ will represent the control action in that same frame. Practically, this means that we can avoid unnecessary coordinate transformations during the implementation on a real platform.

This property is a direct consequence of the following proposition, which shows that the measurements, the similarity measures, and the terms for the cost function behave “as one would expect” under coordinate transformations.

**Proposition 1:** Let $g_{ij} = (R_{ij},t_{ij})$ represent a common rigid transformation acting on $x_{i},x_{j}$ and their counterparts $x_{g,i},x_{g,j}$. Then, the bearing vectors $\beta_{ij}(x_{i},x_{j})$ are invariant to the action of $t_{ij}$, follow the common rotation $R_{ij}$, and are skew-symmetric with respect to a permutation of the indexes.
\[ \beta_{ij}(R_{ij}x_i + t_{ij}, R_{ij}x_j + t_{ij}) = R_{ij}\beta_{ij}(x_i, x_j) \]  
\[ \beta_{ij}(x_i, x_j) = -\beta_{ij}(x_j, x_i). \]  
(14)  
(15)

Additionally, the quantities \( d_{ij}, c_{ij}, q_{ij}, \varphi_{ij}^b, \varphi_{ij}^d \) are all invariant to \( R_{ij}, t_{ij} \) and permutation of the indexes:

\[ d_{ij}(R_{ij}x_i + t_{ij}, R_{ij}x_j + t_{ij}) = d_{ij}(x_i, x_j) \]  
\[ d_{ij}(x_i, x_j) = d_{ij}(x_j, x_i). \]  
(16)  
(17)

with similar expressions for the other quantities.

**Proof:** Eqs. (14)–(17) directly follow from the definitions of \( d_{ij}, \beta_{ij} \). These can then be used to prove the invariance properties for \( c_{ij}, q_{ij} \). Since \( \varphi_{ij}^b \) and \( \varphi_{ij}^d \) are functions of \( c_{ij} \) and \( q_{ij} \), their properties follow as well.

We used the notation \( g_{ij} \) to underline the fact that, in principle, we can have different a different rotation and translation pair for each edge. This is needed in the convergence proof of Section V. Nevertheless, we stress the fact that these do not represent physical transformations, but only convenient analytical tools.

**Correspondence-less control.** For \( f_b(c) = 1 - c \) and pure bearing formations, we have \( f_b'(c) = -1 \). Recalling that \( c_{ij} = \beta_{ij}^0 \beta_{g,ij} \), the gradient (11) becomes: \( y_{ij}^b = \beta_{g,ij} - \beta_{ij} \). Then, our control law simplifies to:

\[ u_i = \alpha_b \sum_{j:(i,j)\in E} \beta_{g,ij} - \alpha_b \sum_{j:(i,j)\in E} \beta_{ij}, \]

(18)

which contains two (unordered) sums. Each sum can be computed independently without explicitly associating each \( \beta_{g,ij} \) with its corresponding \( \beta_{ij} \) (in fact, the first sum could be precomputed offline). As a result, we say that the law is correspondence-less.

**Centroid invariance.** Since the gradient follows the structure of a symmetric network, we have the following:

**Proposition 2:** The centroid \( \bar{x} = \frac{1}{|V|} \sum_{i \in V} x_i \) is invariant with respect to the trajectories of the closed loop system (i.e., \( \bar{x} = 0 \)).

**Proof:** Proposition 1 applied in (11) and (12) implies the following anti-symmetry of the gradients: \( g_{ij}^b = -g_{ji}^b \), \( g_{ij}^d = -g_{ji}^d \). The evolution of \( \bar{x} \) is given by:

\[ \dot{\bar{x}} = \frac{1}{N} \sum_{i \in V} (\alpha_b \sum_{j:(i,j)\in E_b} g_{ij}^b + \alpha_d \sum_{j:(i,j)\in E_d} g_{ij}^d) \]

\[ = \frac{\alpha_b}{N} \sum_{j:(i,j)\in E_b} (g_{ij}^b + g_{ji}^b) + \frac{\alpha_d}{N} \sum_{j:(i,j)\in E_d} (g_{ij}^d + g_{ji}^d) = 0, \]

(19)

that is, the centroid is invariant under the trajectories of our proposed controller.

Proposition 2 has two practical implications. First, the final centroid of the configuration will be identical to the initial one (i.e., the average of the positions of the agents remains constant without any drift). Second, since the relation between the centroid and the configuration is linear, we could leverage the superposition principle to control the position of the centroid of the formation by adding the exogenous control of a “virtual leader” to one of the agents.

**V. Stability analysis**

In this section, we prove convergence of our control law to the desired formation from any initial condition. We split the analysis into two steps. In the first step, we show that the set of global minimizers of \( \varphi \) corresponds exactly with the set of configurations \( x \) equivalent to \( x_g \). We also show that these are the only critical points of \( \varphi \) (i.e., points where \( \text{grad} \varphi(x) = 0 \)). In the second step, we add technical results showing that the trajectories of the closed-loop system do not diverge, thus showing global asymptotic stability.

For our analysis, we will leverage some of the ideas from [32], but with significant extensions due to the fact that here we consider a multi-agent problem, while [32] focuses on a single-agent problem (visual homing).

**A. Global minimizers and critical points**

In order for the results in this section to hold, the functions \( f_b \) and \( f_d \) introduced in Section III-A must adhere to the following definitions.

**Definition 1:** The function \( f_b : [-1, 1] \to \mathbb{R} \) is \( C^2 \) and:

\[ f_b(c) \geq 0, \text{ with equality iff } c = 1, \]

(20)

\[ f_b'(c) \]

(21)

\[ f_b(c) \begin{cases} \leq 0 & \text{for } c = 1, \\ < 0 & \text{otherwise,} \end{cases} \]

(22)

\[ f_b(c) + (1 - c)f_b'(c) \leq 0. \]

(23)

**Definition 2:** The function \( f_d : \mathbb{R} \to \mathbb{R} \) is \( C^2 \) and:

\[ f_d(q) \geq 0, \text{ with equality iff } q = 0, \]

(24)

\[ \text{sign}(f_d'(q)) = \text{sign}(q), \]

(25)

\[ f_d''(0) > 0. \]

(26)

Properties (20), (22), (24)–(26) are general statements to ensure that these functions can be used as similarity measures (i.e., lower values correspond to measurements closer to the desired ones) and that \( f_d \) is locally quadratic near the origin. Eq. (23) is a technical property which required later.

With these definitions, we can state our first result on the global minimizers of the cost function. The proof is based on the non-negativity of each term in \( \varphi \).

**Lemma 1:** A configuration \( x \) is a global minimizer of \( \varphi \) if and only if it is equivalent to \( x_g \).

**Proof:** From the fact that \( d_{ij} > 0 \) and from the properties of \( f_b \) (respectively, \( f_d \)), each term \( \varphi_{ij}^b \) (resp., \( \varphi_{ij}^d \)) is non-negative, and it is zero if and only if \( c_{ij} = 1 \) and \( \beta_{ij}(x_i, x_j) = \beta_{g,ij} \) (and, respectively, \( q_{ij} = 0 \) and \( d_{ij}(x_i, x_j) = d_{g,ij} \)). By definition, \( x \) is then equivalent to \( x_g \).

Now, we need to show that there are no other critical points of \( \varphi \). Since \( \varphi \) is non-convex, we analyze the function by considering radial lines in \( \mathbb{R}^{n|V|} \) starting from a global minimizer (a configuration equivalent to \( x_g \) and going in any arbitrary direction. By showing that the cost along these lines is always increasing, and using (1), it follows that \( \varphi \) does not have any other critical point. We start by considering each individual term in \( \varphi \) using radial lines in \( \mathbb{R}^{2n} \).
Lemma 2: Define the line \((\tilde{x}_i(t), \tilde{x}_j(t)) = (x_{i0} + tv_i, x_{j0} + tv_j)\), where \(v_i, v_j \in \mathbb{R}^n\) are arbitrary and where \((x_{i0}, x_{j0})\) are such that \(\beta_{ij}(x_{i0}, x_{j0}) = \beta_{g,ij}\). Define \(v = v_j - v_i\). Under the conditions in Definition 1, the derivative of the function

\[
\dot{\varphi}_{ij}^b(t) = \varphi_{ij}^d(\tilde{x}_i(t), \tilde{x}_j(t))
\]

satisfies the following. If \(t = 0\) or \(v = 0\), then \(\dot{\varphi}_{ij}^b = 0\). Otherwise, for \(v \neq 0\) and for all \(t > 0\), \(\dot{\varphi}_{ij}^b > 0\), except when:

- If \(v = a\beta_{g,ij}, a < 0\), for which \(\dot{\varphi}_{ij}^b \equiv 0\).
- If \(v = a\beta_{g,ij}, a > 0\), for which

\[
\begin{align*}
\dot{\varphi}_{ij}^b & \equiv 0 & \text{for } t \in \left[0, \frac{1}{\|v\|} \right], \\
& > 0 & \text{for } t > \frac{1}{\|v\|}.
\end{align*}
\]

Proof: The proof extends and relies on [32, Lemma 3.6]. Define the following change of variables: \(\tilde{x}_i'(t) = \tilde{x}_i(t) - \tilde{x}_i(t), x_i' = \tilde{x}_i(0), x_i' = \beta_{ij}(x_{i0}, x_{j0}), y_i' = \beta_{ij}(x_{i0}, x_{j0})\). Note \(\tilde{x}_i'(t) = v\). From the invariance of \(\varphi_{ij}\) given by Proposition 1, we have

\[
\dot{\varphi}_{ij}^b(\tilde{x}_i(t), \tilde{x}_j(t)) = \varphi_{ij}^d(0, \tilde{x}_j(t) - \tilde{x}_i(t))
\]

\[
= d_{ij}(x_i', x_j) f_0(y_i', T y'_i),
\]

which is of the same form as \(\varphi_i\) in [32, Lemma 3.6]. The claim is then simply a restatement of that lemma with our choice of variables. □

Lemma 3: Define the line \((\tilde{x}_i(t), \tilde{x}_j(t)) = (x_{i0} + tv_i, x_{j0} + tv_j)\), where \(v_i, v_j \in \mathbb{R}^n\) are arbitrary and where \((x_{i0}, x_{j0})\) are such that \(x_{j0} - x_{i0} = d_{g,ij}\beta_{g,ij}, \) i.e., \(x_{j0}\) and \(x_{i0}\) are consistent with both \(d_{g,ij}\) and \(\beta_{g,ij}\). Under the conditions on \(f_d\) of Definition 1, the derivative of the function

\[
\dot{\varphi}_{ij}^d(t) = \varphi_{ij}^d(\tilde{x}_i(t), \tilde{x}_j(t))
\]

does not have the property

\[
\dot{\varphi}_{ij}^d(t) \geq 0, \text{ with equality iff } t = 0, \text{ when } v^T \beta_{g,ij} \neq 0,
\]

\[
\equiv 0, \text{ when } v^T \beta_{g,ij} = 0.
\]

Proof: Define \(v = v_j - v_i\) and note that (8) can be rewritten as

\[
\dot{\varphi}_{ij}^d = \varphi_{ij}^d(\tilde{x}_i, \tilde{x}_j) = f_d(\beta_{g,ij}(\tilde{x}_i - \tilde{x}_j) - (x_{g,i} - x_{g,j}))
\]

\[
= f_d(\beta_{g,ij}(d_{g,ij}x_{g,ij} + tv - d_{g,ij}x_{g,ij})) = f_d(t\beta_{g,ij}^T v).
\]

Taking the derivative, we have

\[
\dot{\varphi}_{ij}^d = f_d'(t\beta_{g,ij}^T v)\beta_{g,ij}^T v.
\]

The claim then follows from the properties of \(f_d\). □

We can now combine these two lemmata and give the main result of this section.

Proposition 3: The function \(\varphi\) has global minimizers at configurations equivalent to \(x\) which are consistent with \(\mathcal{F}\) and no other critical points.

Proof: As before, let \(x_g\) be a configuration consistent with \(\mathcal{F}\). Consider any arbitrary configuration \(x_0 \neq x_g\) and define \(\dot{x}(t) = x_g + t(x_0 - x_g)\). Notice that \(\dot{x}(0) = x_g\) and \(\dot{x}(1) = x_0\). By linearity, we have

\[
\begin{align*}
\frac{d}{dt} \varphi(\dot{x}) & \bigg|_{t=1} = \sum_{(i,j) \in E_0} \frac{d}{dt} \varphi_{ij}^b(t) \bigg|_{t=1} + \sum_{(i,j) \in E_d} \frac{d}{dt} \varphi_{ij}^b(t) \bigg|_{t=1}.
\end{align*}
\]

(35)

From Lemmata 2 and 3, each term on the RHS of (35) will be non-negative. We then have two cases.

1) All the terms on the RHS are zero and, hence, so is the LHS. However, from the same lemmata, this implies that \(\varphi(\dot{x}) \equiv 0\) at least for \(t \in [0, 1]\) (and possibly for \(t \in [0, \infty)\)). This means that \(\varphi(x_1) = \varphi(x_0) = 0\). Therefore, \(x_0\) is also a global minimizer.

2) At least one of the terms on the RHS of (35) is strictly positive. In this case, \(\frac{d}{dt} \varphi(\dot{x}) \bigg|_{t=1} \neq 0\). Then, by the definition in (1), \(\text{grad} \varphi(x_1) \neq 0\), and \(x_0\) is not a critical point. □

B. Convergence analysis

Our final goal is to show that the basin of attraction of the equilibria of the closed loop system is the entire space \(\mathbb{R}^N\). From a technical standpoint, there is a small obstacle on the way to this goal: the gradient (13), and hence our control law, is not defined when two neighboring agents \(i\) and \(j\) have coincident positions \(x_i = x_j\). This situation has scarce practical relevance, but it needs to be considered from a theoretical standpoint.

Fortunately, this difficulty can be easily sidestepped: we extend the definition of the gradient by setting to zero the terms corresponding to the edges \((i, j)\) where \(x_i = x_j\). The following lemma shows that this is equivalent to computing a sub-gradient of \(\varphi\).

Lemma 4: The discontinuities of the function \(\varphi_{ij}^b(x_i, x_j)\) on the subspace \(x_i = x_j\) can be removed by letting \(\varphi_{ij}^b(x_i, x_j) = 0\). Then, a subgradient of \(\varphi_{ij}^b\) at any point on the same subspace is given by \(\text{grad} \varphi_{ij}^b(x_i, x_j) = 0\).

Proof: From Definition 1, one can deduce that \(f_b\) is bounded above. Since \(d_{ij}(x_i, x_j) = 0\) when \(x_i = x_j\), we then have that \(\lim_{x_i \to x_j - 0} \varphi_{ij}^b(x_i, x_j) = 0\), independently of the path taken by \(x_i\) and \(x_j\). This shows that the discontinuities can be removed. Then, since \(d_{ij} \geq 0\) and \(f_b(c) \geq 0\), \(\varphi_{ij}^b(x_i, x_j) \geq 0\). This means that \(f(x_i') - f(x_i, x_j) \geq 0\) for any \(x_i', x_j' \in \mathbb{R}^n\) and \(x_i = x_j\). Hence, by definition, \(0_{2n}\) is a subgradient of \(\varphi_{ij}^b\) at \(x_i = x_j\). □

We are now ready to show our main convergence result:

Theorem 1: Any trajectory of the closed-loop system

\[
\dot{x} = -\text{grad} \varphi(x)
\]

asymptotically converges to a configuration which is equivalent to the desired one \(x_g\).

Since our closed-loop is a gradient system, standard arguments give us convergence to the set of critical points of \(\varphi\). However, there are a couple of technical aspects which we need to consider, mostly due to the fact that, for leaderless pure hearing formations, the level sets of \(\varphi\) are not compact. First, we need to show that the trajectories do not diverge. Then, we need to show their convergence to a single point (as opposed to infinitely wandering in a set). Since the proof is rather
technical, the details can be skipped on a first reading without loss of continuity.

Proof: Step 1: For bearing+distance formations, we apply a change of variables in $\mathbb{R}^{Nn}$ such that $x_g = 0$. For pure bearing formations, we set $\bar{x} = 0$. Step 2: We show that the closed loop trajectories do not diverge to infinity, i.e., $\lim_{t \to \infty} |x(t)| \neq \infty$. Define the line $\tilde{x}(s,v) = sv$, where $s \in \mathbb{R}$ and $v \in \mathbb{R}^{Nn}$, $\|v\| = 1$. For fixed $s$, $\tilde{x}$ describes a sphere of radius $s$ centered at the origin. For fixed $v$, the curve $\tilde{x}$ describes a radial line normal to any of these spheres. Using the same argument from the proof of Proposition 3, one has that, for any arbitrary $v$,

$$\frac{d}{ds} \varphi(\tilde{x}(s,v)) = v^T \text{grad} \varphi(\tilde{x}) \geq 0.$$  \hspace{1cm} (37)

By way of contradiction, if a trajectory $x(t)$ diverges to infinity, then (by definition of limit) there exists a time $T > 0$ for which the trajectory escapes the ball of radius $s = \|x(T)\|$. This implies that the inner product between the normal to the ball and the trajectory direction is positive, i.e.,

$$v^T \tilde{x} = -v^T g > 0,$$  \hspace{1cm} (38)

where $v$ is given by $v = \frac{\tilde{x}}{|\tilde{x}|}$. However, (38) contradicts (37). Hence the trajectories of the closed system are compact.

Step 3: For rigid bearing+distance formations, this and Lyapunov’s theorem show that the trajectories of the system converge to the unique formation which is congruent with the desired one and has the same centroid. For non-rigid formations, compactness only implies convergence to a set of accumulation points. Step 4: From compactness of $x(t)$, there exists a constant $d_{max}$ such that $d_{ij} < d_{max}$ for all $t > 0$ and $(i,j) \in E_b$. Since the quantities $\{c_{ij}\}$ and $\{d_{ij}\}$ are, respectively, invariant and directly proportional to scaling, one can show that:

$$\|\text{grad} \varphi(\alpha v)\| = \|\text{grad} \varphi(v)\|, \quad \varphi(\alpha v) = \alpha \varphi(v) \hspace{1cm} (39)$$

for any $\alpha > 0$. By taking the maximum of these quantities over $x = \alpha v$ restricted to $\{x \in \mathbb{R}^{Nn} : d_{ij} < d_{max} \forall (i,j) \in E_b\}$ (which is compact), we can always choose $c > 0$ and $\mu \in [0,1)$ (as a function of $d_{max}$ such that

$$\|\text{grad} \varphi(x)\| > c|\varphi(x)|^\mu \hspace{1cm} (40)$$

on a compact set containing $x(t)$. Eq. (40) has the form of a Lojasiewicz gradient inequality, which can be used in the Lojasiewicz theorem to show the convergence of the trajectory $x(t)$ to a single point (see the review article [1]).

As mentioned in the introduction, the result of Theorem 1 does not require the notion of rigidity. However, when the two are combined, we obtain the following:

Corollary 1: Assume that the desired formation $(\mathcal{F},x_g)$ is rigid. Then any trajectory of (36) converges to a configuration which is similar (for pure bearing formations) or congruent (for bearing+distance formations) to the desired one.

VI. EXTENSIONS

In this section we use the fact that our solution is gradient-based to include leaders and a collision avoidance mechanism.

A. Leaders

Consider one or two leader nodes (say, nodes $i$ and $j$) that are kept stationary ($u_i = u_j = 0$). With two leaders, we assume that their relative positions are consistent with the desired formation. Intuitively, the purpose of the first leader is to fix the translation of the final formation, and the purpose of the second one is to fix the scale (when distance measurements are not available). In the one-leader case (resp., two-leader case), we remove the variable for $i$ (resp. $i$ and $j$) from (6) and define $\varphi_{leader}$ to be equal to $\varphi$ restricted to the $d(n-1)$-dimensional (resp., $d(n-2)$) affine subspace of $\mathbb{R}^{dn}$ where $x_i$ (resp., $x_i, x_j$) is constant. One can then easily verify that, for all the nodes $i$ that are not leaders, the gradient $\text{grad}_{x_i} \varphi_{leader}$ is still given by (13). The results of Proposition 3 and Theorem 1 still hold, with the only difference that $x_g$ is now restricted to have a particular value for $x_i$ (respectively, $x_i, x_j$). Thus, we still have global asymptotic convergence of the control law. The only real difference between this extension and the case of leaderless formations is that the centroid invariance established in Proposition 2 does not hold anymore because the stationary leaders partially break the symmetry between the updates of the agents. Instead, the translational ambiguity of the entire formation is fixed by the initial position of the leaders.

To move the formation, one can either apply the desired controls to the leaders and use the controller to track this time-varying reference (with a possible steady-state error) or apply feed-forward terms that, however, need to be assigned to all the agents at the same time (see [14] for details).

B. Collision avoidance

We now present a proof-of-concept collision avoidance mechanism. This mechanism is loosely inspired by [10] in the fact it uses optimization-in-the-loop, but with simple integrator models and without the need to introduce distance measurements. Consider two agents $i$ and $j$ as in Figure 1a. Notice that the cone $S_{ij}$ can be determined without knowing $d_{ij}$, and that $S_{ij}$ represents an overestimate of the area of radius $r$ to avoid around agent $j$. Therefore, as long as agent $i$ does not enter the cone $S_{ij}$, collision will be avoided. We therefore propose to modify the control $u_i$ derived from (13) as follows. First, find a unit vector $q_i$ that is closest to $u_i$ but does not belong to any of the cones $S_{ij}$:

$$\max_{q_i} q_i^T u_i, \text{ s.t. } \|q_i\| = 1, q_i \notin \bigcup_{j:(i,j) \in E_{ca}} S_{ij}, \hspace{1cm} (41)$$

where $E_{ca}$ are the set of neighbors for collision avoidance (in general situations, we would like $E_a = V \times V$, as agents that are not sensed cannot be avoided). Note that, $u_i' = u_i$ when $u_i$ does not belong to any cone. For 2-D agents, the optimization problem (41) can be solved efficiently by sorting the cones $\{S_{ij}\}_{(i,j) \in E_{ca}}$ according to their angles and checking for intersections. Second, obtain a new control $u_i'$ by projecting $u_i$ on $q_i$, that is, $u_i' = q_i u_i^T u_i$. Note that this choice implies that the controller will be stable, because the derivative of
We compare the results with those of other controllers to show (results for 3-D formations are omitted due to space reasons). In general, all methods converge to the desired formations. With respect to [38], our method can converge to the correct scale by incorporating just one distance measurement for the scenarios with zero and one leaders. We can also use Theorem 1, to prove convergence with leaders (see Section VI). With respect to [14], our work and the work from [38] do not require a particular graph structure. However, the control [14] provide straight trajectories and generally faster convergence.

Finally, we include a numerical example of the behaviour of the bearing-only controller with and without collision avoidance in Figure 2. As expected, the modified controller avoids inter-agent collisions. Although for this case the agents have reached the desired configuration, we have found this not to be the case for more complicated graphs, where the agents get stuck in suboptimal positions. This is most likely due to the non-convexity of the constraints given by $S_{ij}$.

VIII. DISCUSSION AND CONCLUSIONS

In this paper, we proposed a globally convergent solution for leaderless, bearing-based formation control. This gradient-based controller can be naturally complemented with additional inter-agent distance measurements and with or without the presence of leader agents. We tested our approach through simulations. The main advantage of our approach with respect to competing solutions [14], [38] is in its flexibility: we can prove global convergence for both pure bearing and bearing+distance formations with or without leaders, and include a collision avoidance mechanism, all under the same framework. This is because it is based on the exact gradient of a Lyapunov function. However, [14], [38] have their advantages in their specific domains: the control law of [38] has exponential convergence guarantees, and maintains the scale of the formation, while the use of triplets of agents in [14] results in very simple and fast straight trajectories. As future work, we plan to investigate strategies to incorporate these ideas in our framework.

REFERENCES

Our controller; Controller from [38]; Controller from [14].


