Centralized Distance-based MPC Strategy for Local Formation Tracking of a Multi-Robot Fleet

Augustin Point[1] and David Vieira[1] and Michel Basset[1] and Rodolfo Orjuela[1]

***Abstract*— In this paper, a centralized control strategy is proposed to perform the formation tracking (FT) of a multi-robot fleet, without using absolute position information. The core of the approach lies in the predictive regulation of inter-agent distances using model predictive control (MPC) to improve robustness against deformations. The proposed strategy allows the formations to be efficiently maintained around the moving leader, even in GPS-denied conditions. To evaluate the advantages of using a distance-based formalism for local formation tracking, the proposed strategy is then compared with another approach inspired by the literature, in which robots maintain positions with respect to the fleet centroid. Simulation results show the efficiency of the proposed MPC framework in maintaining a local formation around the leader and highlight the benefits of using the distance-based formalism in constrained settings. To conclude the study, further discussions are made about the specification of each formalism.**

***Keywords*: formation-control, formation tracking, leader-follower, model predictive control, centralized architecture**

I. Introduction

Recent years have seen significant advancements in the study of the coordinated work among autonomous robots [1]. Through coordination, a wide range of tasks benefit from improved efficiency and fault tolerance as well as reduced costs. In particular, the formation tracking (FT) task in which a fleet of robots maintains a given geometric formation along a trajectory has received large interest from the research community. As having precise robot localization is the key to an efficient FT, many strategies rely on absolute positioning systems to localize the robots. While these absolute positions can be used directly as the control features [2], the use of relative positions obtained from the subtraction between agents' global states can offer improved collaborative results [3]. However, in practice, these absolute strategies require pre-existing infrastructure or involve lengthy calibration processes, making their deployment in unknown environments difficult. Instead, relying only on relative position measurements between robots can lead to more flexible FT strategies, beneficial to GPS-denied operations applicable to search and rescue [4], target trapping [5] or collaborative object transportation [6]. Considering the need to develop efficient control and coordination algorithms for local FT, the objective of this paper is to study the strengths and weaknesses of different formation formalisms through the comparison of centralized control laws.

*This work was funded by the European Interreg Rhin-Superieur program through the RobotHub Academie and RobotHub Transfer projects.

[1]Authors are with the Institute of Research in Computer-Science, Mathematics, Automatic and Signal (IRIMAS UR7499), Mulhouse, France. name.surname@uha.fr

Formation control (FC) (and by extension FT) strategies can be categorized into three formalisms depending on the sensing capabilities of the agents [7]. In position-based strategies, agents are required to sense their own absolute positions, while displacement-based and distance-based strategies require agents to sense the relative positions of their neighbors in a shared and individual reference frame respectively. While position-based strategies can not be considered local as they require agents to know their absolute positions, displacement and distance-based approaches are suited for local FT.

Displacement-based FC strategies are extensively investigated using consensus theory following the initial developments in [3]. In this paper, agents modeled as double-integrators converge to an agreement on their position errors which allows the desired formation to be achieved. As the choice of reference frame only impacts the agreed value and not the FC performance, the desired formation can be defined locally and set to move along with the robots. These strategies are often referred to as virtual-structure [8]. In [9], this virtual structure is attached to a leader robot to make a group of UAVs maintain relative distances with it, and a non-linear model predictive control (MPC) controller is used. In [10] instead, a virtual leader is used to move the virtual structure and a neurodynamic optimization-based non-linear MPC strategy is developed. While deciding the virtual leader movement is straightforward in centralized architectures, it is much more difficult for distributed architectures as its position must be collaboratively decided by the robots. For this reason, [11] explores another consensus strategy for local FT where single-integrator robots agree on the virtual leader position defined as the formation centroid. In [12], this centroid-position-based formalism is applied to distributed MPC. Despite the important communication required for each robot to compute the centroid, this formalism is seen to produce efficient local FT controllers.

Distance-based formations also arouse significant research interests since they do not require robots to share a common reference frame. Indeed, the formation is described as a set of desired inter-distances to be maintained between robots. The important coordination required has motivated the use of graph-based methods to analyze their interactions. Gradient-based control laws are used in [13] and [14] to minimize a global potential function involving distance errors made between each robot and its neighbors in a distributed manner. The asymptotical convergence to the desired formation is later proven by [15] for rigid interaction graphs using Lyapunov theory. To additionally allow robots to perform reference tracking, distributed velocity [16] and centroid [17] estimators are designed for distance-based formations. Beyond the many results obtained in distributed contexts, centralized architectures, while less scalable, are also employed for distance-based FC for efficiency purposes. A centralized FT strategy using hierarchical quadratic programming to optimize multiple objectives including maintaining prescribed robot inter-distances is recently presented in [6].

It seems, however, that the integration of the distance-based formalism with recent control strategies such as MPC remains largely unexplored [18]. Nonetheless, the ability of MPC to inherently consider system constraints and predict the system's future behavior can prove beneficial [19]. For these reasons and following the works in [6] in applying optimization techniques to distance-based FC, the main contribution of this paper is to propose a distance-based centralized MPC strategy (CMPC) to enhance the predictive regulation of inter-robot distances. With the objective of studying the advantages of different local FT formalisms, the proposed strategy is then compared with a recent centroid-position-based approach inspired by the literature [12]. For the sake of a fair comparison, both strategies are based on a leader-follower approach to perform trajectory tracking, and MPC is employed for FC.

In the remainder of the paper, Section II presents the robots modeling and the formation formalisms used in the study. Then, Section III details the expression of the proposed distance-based strategy and the centroid-position approach for FT. Section IV outlines the comparative study and presents the simulation results and finally Section V gives concluding remarks and perspectives of future works.

II. Problem statement

The FT problem consists on making a fleet of robots maintain a given geometric formation along a trajectory. Additional specifications related to the fleet are then presented before detailing the two formation formalisms selected for comparison.

A. Robot fleet specifications

In this paper, a homogeneous fleet of N holonomic robots modeled with single-integrator dynamics is considered:

$$\dot{\boldsymbol{p}}_i = \boldsymbol{u}_i \tag{1}$$

where $\boldsymbol{p}_i$ refers to the 2D position vector of robot i and the control signals $\boldsymbol{u}_i$ to its 2D velocity, both expressed in a local reference frame R. Considering fast-enough low-level actuators, this can be a good approximation of a holonomic ground robot. Still, saturations on the absolute input signal value $||\boldsymbol{u}_i(k)|| \leq v_{lim}$ and its variation $||\boldsymbol{u}(k)-\boldsymbol{u}(k-1)|| = ||\Delta\boldsymbol{u}(k)|| \leq a_{lim}$ are considered to account for actuator limitations.

In centralized architectures, a single entity is responsible for aggregating the information obtained from the whole fleet and computing the control inputs of each agent. Here, this role is endorsed by the leader with two goals: 1) following the desired trajectory; and 2) computing the followers' input signals using the provided local measurements. In the following, the leader robot is assumed to precisely measure the relative positions of its followers, expressed in its own reference frame R. It is also supposed to communicate the computed control signals to its followers without time delays. As FT often requires close proximity between robots, LIDARs and cameras can be used to offer precise relative position measurements at close range. Additionally, standard protocols such as WiFi or Bluetooth can provide an efficient explicit communication of this information with reduced latency, alleviating the strong hypotheses. To apply their control signals, follower robots are expected to either share this same reference frame or be able to transform them in their own local frame for instance using relative bearing angle measurement.

B. Considered formation formalisms

As the leader's second objective, the FC consists of regulating the individual robot positions to maintain a set of predefined constraints, which depends on the chosen formalism. Their differences are pictured in Figure 1.

- In a centroid-position-based formalism, the predefined constraints correspond to a set of desired positions $P^* = \{\boldsymbol{p}_1^*, \ldots, \boldsymbol{p}_n^*\}$ to be reached by the robots, and defined with respect to a reference frame centered on the robots average positions. The frame orientation can be chosen by the leader as constant in R but also as the angle tangent to a point of interest on the trajectory or following more complex schemes. For simplicity, the first solution is employed here. Also, R is chosen as the angle tangent to the trajectory as the leader follows it.
- In a distance-based formalism, the predefined constraints are a set of desired inter-distances $D^* = \{d_{ij}^*, (i,j) \in \mathbb{R}^2\}$ to be maintained between robots i and j. For 2D points, only a subset of those is required to define a locally rigid formation, that is, such that the total number of degrees of freedom amounts to three: 2 translations and 1 rotation [20]. A graph representation is often employed to represent the robot interactions as $\mathcal{G}^* = (\mathcal{N}, \mathcal{E}^*, \mathcal{W}^*)$ where the nodes set $\mathcal{N}$ represents the N agents and $\mathcal{W}^* = \{d_{ij}^* \,|\, (i,j) \in \mathcal{E}^*\} \subset D^*$ the distances to be maintained. In this formalism, no common reference frame is required and therefore, no desired orientation is specified.

Having presented the robots model as well as the two formation formalisms, Section III presents the centroid-position and the distance-based FT strategies, both using MPC.

III. Formation tracking strategies

Recently, MPC [19] has become a very popular strategy for the FC problem by allowing the design of robust algorithms while accounting for system constraints. Its fundamental principle lies in the use of a system model to predict future outputs Y over a prediction horizon N_p. At each sample time $k_t = T_e \cdot n$, with T_e the discretization step and

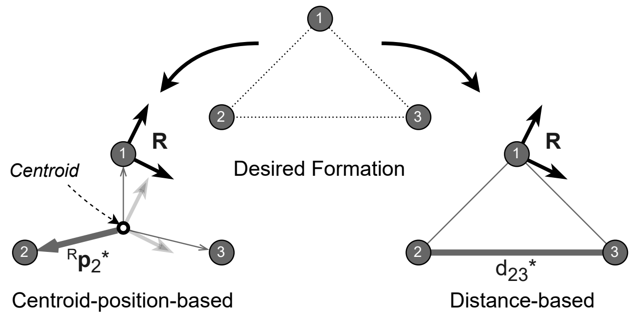


Fig. 1: Centroid-position and distance-based formalisms

$n \in \mathbb{N}$ an integer, the objective is to determine the sequence of future inputs that minimizes a given cost function while respecting a set of constraints, with the use of an optimizer. To reduce the computational costs, this sequence $\boldsymbol{U}(k_t) = [\boldsymbol{u}(k_t)^T, ..., \boldsymbol{u}(k_t + N_c - 1)^T]^T$ is optimized over a control horizon N_c such that $N_c \leq N_p$, by assuming that the inputs remain constant beyond N_c, i.e., $\boldsymbol{u}(k) = \boldsymbol{u}(k_t + N_c - 1)$ for $k = k_t + N_c \ldots N_p$. According to the receding horizon principle, only the first optimized control input $\boldsymbol{u}(k_t)$ is fed to the system at the instant k_t. This MPC framework is subsequently employed to define both distance-based and centroid-position-based FT strategies.

A. Distance-based strategy

Let $\boldsymbol{x}$ aggregate the relative positions measured between robots, expressed in the leader frame R. These can be computed from absolute positions $\boldsymbol{p} = [\boldsymbol{p}_1^T, \ldots, \boldsymbol{p}_N^T]^T$ as:

$$\boldsymbol{x}(k) = \begin{bmatrix} \vdots \\ \boldsymbol{p}_{i/j}(k) \\ \vdots \end{bmatrix} = (H^T \otimes I_2)\boldsymbol{p}(k) \ , \quad (i,j) \in \mathcal{E}^* \tag{2}$$

Here, the incidence matrix H is used to represent the inter-robot distances to be controlled, given by the edge set $\mathcal{E}^*$ of the weighted graph $\mathcal{G}^*$. Each column vector references an edge $(i, j) \in \mathcal{E}^*$ with -1 in the i^{th} row, 1 in the j^{th} row and 0 elsewhere. Denoting $\boldsymbol{u} = [\boldsymbol{u}_1^T, \ldots, \boldsymbol{u}_N^T]^T$ as the concatenation of the vectors $\boldsymbol{u}_i$, the discretized model allowing the prediction of the robots relative positions is given in its centralized form by:

$$\begin{aligned} \boldsymbol{x}(k+1) &= \boldsymbol{x}(k) + T_e(H^T \otimes I_2)\, \boldsymbol{u}(k) \\ &:= A\boldsymbol{x}(k) + B\boldsymbol{u}(k) \end{aligned} \tag{3}$$

As the leader independently computes its control inputs to track the desired trajectory, matrix B is split to separate the followers' and leader's control inputs $\boldsymbol{u}_F$ and $\boldsymbol{u}_L$:

$$\boldsymbol{x}(k+1) = A\boldsymbol{x}(k) + B_F\boldsymbol{u}_F(k) + B_L\boldsymbol{u}_L(k) \tag{4}$$

Instead of controlling the $\mathscr{L}_2$ norm of the inter-robot distances, the squared norms are used as the control features. Removing the square root allows for simplification of the model while additionally improving convergence speed. Using the Hadamart (or elementwise) product $\circ$, the squared norms are computed from the state variables as:

$$\begin{aligned} \boldsymbol{y}(k) &= C(\boldsymbol{x}(k) \circ \boldsymbol{x}(k)) \\ \text{with} \quad C &= I_m \otimes [1 \ \ 1] \end{aligned} \tag{5}$$

with I_m the identity matrix of dimension $m = |\mathcal{E}^*|$, to obtain the outputs $\boldsymbol{y}$. Following the model definition given by (4) and (5) and introducing the vector of desired squared inter-distances $\boldsymbol{y}_d = [\cdots d_{ij}^* \cdots]^T$, $d_{ij}^* \in \mathcal{W}^*$, the cost function to be minimized is expressed as:

$$\begin{aligned} &J(\boldsymbol{u}_F(k_t), \ldots, \boldsymbol{u}_F(k_t + N_c - 1), \\ &\quad \boldsymbol{u}_L(k_t), \ldots, \boldsymbol{u}_L(k_t + N_c - 1), \boldsymbol{p}(k_t), \boldsymbol{y}_d) = \\ &\sum_{k=1}^{N_p} ||\boldsymbol{y}_d - \boldsymbol{y}(k_t + k|k_t)||_Q^2 + \sum_{k=1}^{N_c} ||\Delta\boldsymbol{u}(k_t + k)||_R^2 \end{aligned} \tag{6}$$

It consists of two terms to be minimized at once, with the positive-definite weight matrices Q and R allowing to prioritize one over the other. The first term penalizes the formation error through the inter-distances, while the other penalizes the variation of the inputs $\Delta\boldsymbol{u}(k) = \boldsymbol{u}(k) - \boldsymbol{u}(k-1)$ which can lead to a smoother control law. Making use of the cost function (6), the optimization problem to be solved at each time instant k_t by the MPC can be formulated as:

$$\begin{aligned} \boldsymbol{U}_F^*(k_t) = \arg\min_{\boldsymbol{U}_F} \ & J(\boldsymbol{U}_F(k_t), \boldsymbol{U}_L(k_t), \boldsymbol{p}(k_t), \boldsymbol{y}_d) \\ \text{s.t.} \ 1) & \ -a_{lim} \leq \Delta\boldsymbol{U}_F(k_t) \leq a_{lim} \\ 2) & \ -v_{lim} \leq \boldsymbol{U}_F(k_t) \leq v_{lim} \end{aligned} \tag{7}$$

The objective is to minimize the cost function with respect to the follower's inputs $\boldsymbol{U}_F$ and under the set of linear inequality constraints limiting both the input and its variation to the intervals $[-v_{lim}, v_{lim}]$ and $[-a_{lim}, a_{lim}]$ respectively. The computation of squared distances introduces non-linearity in the prediction model which consequently makes the optimization problem non-quadratic. Conversely, the leader predicted inputs $\boldsymbol{U}_L$ are not optimized but rather given as initial parameters of the optimization problem. They correspond to the control sequence allowing to track the trajectory, which can be obtained from a short-term predictive planner. An accurate estimate of the leader's future inputs can help remove the static error caused by the leader's movements, however, this feed-forward term is not equivalent to an integral action as it is not able to correct other constant disturbances.

Another important consideration is that the choice of reference frame does not impact the outputs. Consequently, distance-based strategies offer a large range of solutions to compute the optimal control inputs of the robots, as any preferred formation orientation can be chosen. Depending on the application, releasing the orientation constraint may or may not be desired. It should be noted however that this degree of freedom can be removed by the addition of supplementary constraints in the optimization problem, as in [6], without losing the locality property.

The proposed distance-based strategy therefore allows the leader robot to locally compute the followers' control inputs in order to maintain desired inter-robot distances. Under the same MPC framework, Section III-B presents the second strategy based on the centroid-position formalism.

B. Centroid-position-based strategy

Following the system modeling presented in [12], this section details the centroid-position-based strategy to be compared with the proposed distance-based method. From initial measurements of the followers' positions $\boldsymbol{p}$ relative to the local frame R, the leader robot predicts their evolution in a centralized manner using the discretized model:

$$\begin{aligned} \boldsymbol{p}(k+1) &= \boldsymbol{p}(k) + T_e\, \boldsymbol{u}(k) \\ &:= A\boldsymbol{p}(k) + B\boldsymbol{u}(k) \end{aligned} \tag{8}$$

Similar to (4), the B matrix is split to separate the followers' and leader's control inputs as follows:

$$\boldsymbol{p}(k+1) = A\boldsymbol{p}(k) + B_F\boldsymbol{u}_F(k) + B_L\boldsymbol{u}_L(k) \tag{9}$$

In the centroid-position-based MPC approach, the system model informs about how the control inputs act on the robots' positions relative to the formation centroid. In [12], the following output equation is employed

$$\boldsymbol{y}(k) = (C \otimes I_2)\, \boldsymbol{p}(k) \tag{10}$$

where $\otimes$ relates to the Kronecker product and

$$C = \begin{bmatrix} 1-1/N & -1/N & \cdots & -1/N \\ -1/N & 1-1/N & \cdots & -1/N \\ \vdots & \ddots & \ddots & \vdots \\ -1/N & \cdots & -1/N & 1-1/N \end{bmatrix}$$

allows to transform $\boldsymbol{p}$ into local positions relative to the formation centroid. Using this model, followers attempt to maintain both the leader and their own desired position with respect to the formation centroid. This is important as for a large number of robots, the leader has a minimal impact on the centroid position and relying solely on it to move the formation may prove inefficient. By ensuring that followers explicitly regulate the leader position error, this issue can be minimized as its impact on the global error is more significant.

Following the model definition given by (9) and (10), the cost function defining the different costs to be minimized is chosen to be the same as the distance-based strategy, given by (6). Similarly, the optimization problem is given by (7). However, with respect to the distance case, it can be expressed as a quadratic programming problem, for which more efficient solvers exist. It should be noted that during the prediction, the formation is supposed to keep the same orientation. However, as seen in Section IV presenting the simulation results, this assumption still allows for good performance.

IV. Simulation results

This section presents the simulation results of the comparison between the distance-based and the centroid-position-based formalisms, using the local FT strategies detailed in Section III.

N	H	v_{leader}	v_{lim}	a_{lim}	Formation
5	Complete graph	2 m/s	5 m/s	15 m/s^2	Isosceles 1.5 m side
T_e	Q	R	N_p	N_c	
0.05s	$1 \cdot I$	$0.05 \cdot I$	20	4	

TABLE I: Parameters used during the simulation

	Formation conv time (s)	Formation conv energy
Distance	0.45	42
Centr-pos	1.05	91

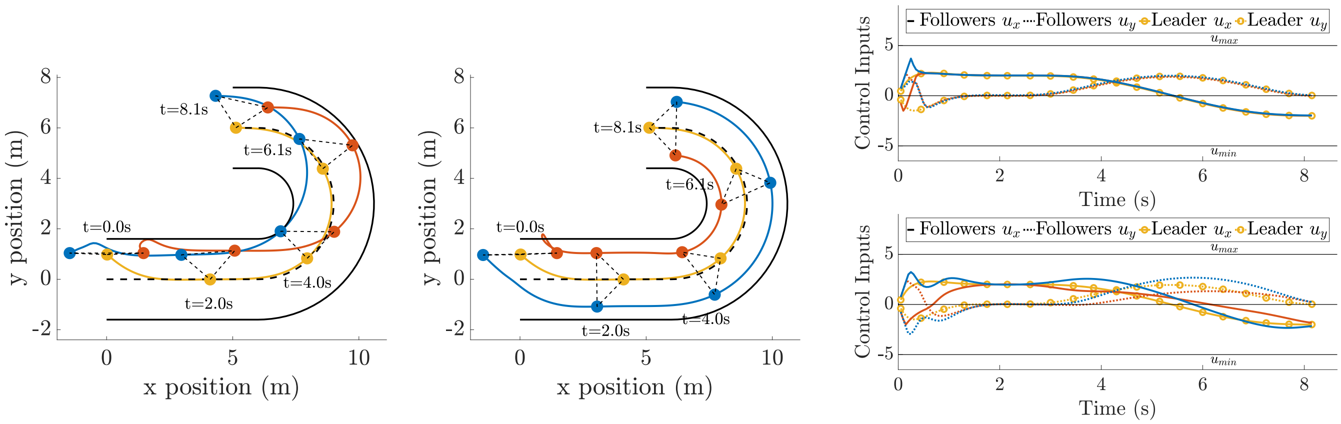
TABLE II: Quantitative results with $v_{lim} = 5$ m/s

A. Simulation results

The test scenario involves a leader robot following a path at a constant speed of 2 m/s while 2 follower robots maintain a triangular formation around it. The leader uses a trajectory tracking algorithm and centrally computes the followers' control signals by solving the optimization problems defined by (7) using the *interior point* algorithm. The robot models used for validation are single integrators as defined in Section II, subject to the saturations $||\boldsymbol{u}_i(k)|| \leq v_{lim}$ and $||\Delta\boldsymbol{u}_i(k)|| \leq a_{lim}$. Table I summarizes the parameters specific to the simulation and the control strategies. For comparison purposes, both the centroid-position and distance-based strategies use the same set of MPC parameters, chosen experimentally to maximize performances.

Figure 2a illustrates the formation evolution for both the distance-based and centroid-position-based strategies. The trajectory to be tracked by the leader is represented by the dashed line, enclosed in a corridor representing a safe zone where the robots can evolve freely. It should be noted that its purpose is solely to enhance visualization and to facilitate comparison. Therefore, the area outside of this corridor does not constitute an obstacle for the robots to avoid. The radius of the corridor is chosen as the desired distance of 1.5 m separating the leader from each of its followers.

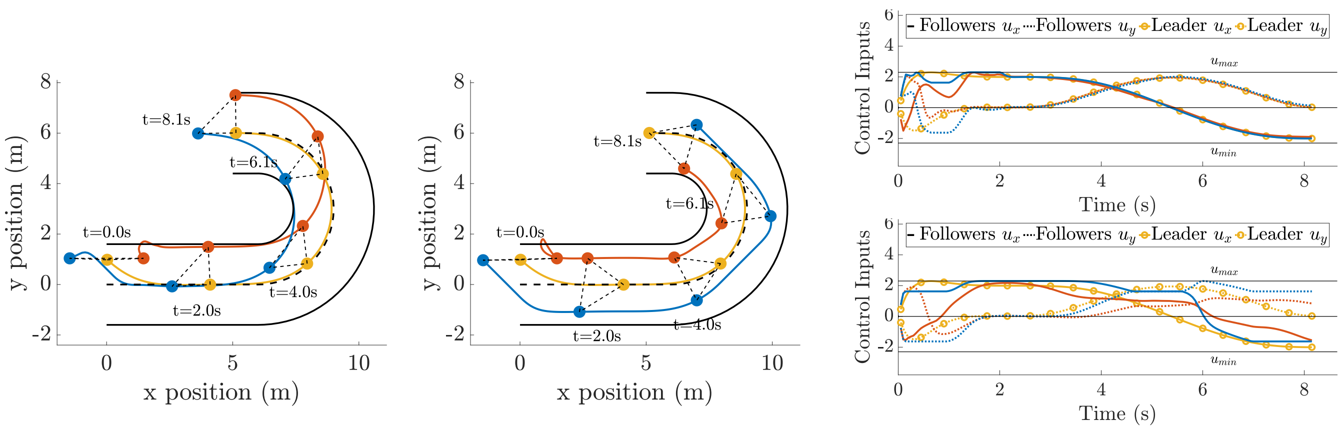
The robots are initially placed along a horizontal line 1 m above the trajectory. As the leader begins following it, followers are seen to efficiently reach the desired triangular formation. By considering the leader's movements during the computation of the followers' control inputs, both strategies are able to precisely maintain the formation around the leader. However, as the formation orientation is not explicitly specified in the distance-based approach but rather decided implicitly during the MPC, follower robots pursue seemingly arbitrary trajectories. Conversely, in the centroid-position-based strategy, the robots' movements are better coordinated along the desired trajectory. Despite this behavior, the formation control performance of the distance-based strategy allows followers to efficiently maintain a maximum distance of around 1.5 m with the leader. Additionally, because robots chose their preferred orientation, the formation can be reached quicker and with less energy as seen in Table II. This is also observed in Figure 2b as the robots' input signals converge faster to a stable value in the distance-based case.



(a) Distance-based (left) and centroid-position-based (right) formation maintenance

(b) Distance-based (top) and centroid-position-based (bottom) control signals

Fig. 2: Robots trajectories and control inputs for both strategies with $v_{lim} = 5$ m/s



(a) Distance-based (left) and centroid-position-based (right) formation maintenance

(b) Distance-based (top) and centroid-position-based (bottom) control signals

Fig. 3: Robots trajectories and control inputs for both strategies with reduced saturation $v_{lim} = 2.3$ m/s

The energy criterion is computed as the sum of all follower inputs until convergence. Conversely, the centroid-position-based MPC strategy offers faster computation with the use of a linear predictive model. In the simulations performed, it is found to be, on average, five times faster than its counterpart in calculating the followers' control inputs.

B. Simulation results with saturated inputs

In order to further observe the formalisms disparities, Figure 3b presents the evolution of the robots' control inputs when the v_{lim} saturation is lowered from 5 m/s to 2.3 m/s. At this limit, the followers' speeds are very close to the leader's cruising speed of 2 m/s and often reach velocity saturations. This happens for the robot starting left in Figure 3a which is unable to track the trajectory intended by the centroid-position strategy, as it requires it to move faster than the saturations permit. Consequently, the strategy is unable to properly maintain the specified formation. While the desired orientation could be explicitly chosen to consider these limitations, its computation can be difficult especially when considering more complex robot dynamics and non-holonomic robot constraints. Conversely, the additional degrees of freedom of the distance-based strategy allow it to maintain the desired formation by letting the MPC choose the formation orientation. This implicit decision provides an easier problem formulation while also allowing the strict prioritization of formation maintenance over strict path tracking, not always necessary in practice.

C. Discussions

To conclude the comparative study, Table III summarizes the main properties of the centroid-position and the distance FC formalisms, as well as the absolute-position for comparison purposes. Specifically, the formalisms are characterized by their ability to regulate specific aspects of the formation: its shape, scale, position, orientation and the robots' individual headings, which all indicate a certain responsibility level. Taking as an example the absolute-position formalism, its high authority on the formation can be beneficial for many applications as only the robots' headings cannot be specified. However, it possesses a high responsibility level as the desired value of every regulated aspect of the formation

	Measurements	Control feature	Shape Regulation	Scale Regulation	Position Regulation	Orientation Regulation	Headings Regulation	Responsibility level
Absolute-position [2]	Robots' absolute positions	Robots' absolute positions	Yes	Yes	Yes	Yes	No	High
Centroid-position [11], [12]	Robots' relative positions	Robots' positions w.r.t centroid	Yes	Yes	No	Yes	No	Medium
Distance [6], [16]	Neighbors' relative positions	Neighbors' inter-distances	Yes	Yes	No	No	No	Low

TABLE III: Qualitative comparison between the centroid-position, the distance and absolute-position formalisms

must be defined. As it is observed in Section IV-B for the distance-based formalism, depending on the application, a lower responsibility level can be beneficial as the removal of some formation constraints increases the set of possible solutions. However unpredictable behaviors can happen when leaving some aspects of the formation unregulated such as the orientation of distance-based strategies. To help solve this issue, the leader-follower approach can be useful to recover some control over free aspects of the formation such as position and orientation. This proves particularly useful when coupled with local formalisms which by definition cannot regulate the absolute position of formations. It is used here as a means to perform local FT by assuming the use of a local trajectory planner by the leader.

V. Conclusion and future works

In this paper, a local FT algorithm based on the predictive regulation of inter-robot distances is presented. Following a leader-follower scheme, the leader centrally computes the followers' control signals using MPC. Simulations demonstrate the algorithm's effectiveness in maintaining the formation around the leader. Through a comparative study conducted against a centroid-position-based MPC strategy inspired by the literature, the superiority of the distance-based formation formalism in performing FT in constrained settings is also highlighted. The study concludes with a discussion about the qualitative advantages of both formalisms and, in particular, the inability of the distance formalism to regulate the formation's orientation. Therefore, perspectives aim to improve the orientation maintenance of the proposed strategy, as well as improve the MPC control law by adding an integral action to remove the static error. It should be mentioned that the presented work lacks realism due to the use of single-integrator robot models and the assumption of perfect communication. To address these limitations, more complex robot models are intended to be used for validation, and the implementation of a distributed MPC algorithm is also considered to better acknowledge the information exchanges occurring in the fleet.

References

[1] J. Cortés and M. Egerstedt, "Coordinated Control of Multi-Robot Systems: A Survey," *SICE Journal of Control, Measurement, and System Integration*, vol. 10, pp. 495–503, Nov. 2017.

[2] Q. Wu, X. Wang, and X. Qiu, "Embedded technique-based formation control of multiple wheeled mobile robots with application to cooperative transportation," *Control Engineering Practice*, vol. 150, p. 106002, Sept. 2024.

[3] W. Ren, "Consensus based formation control strategies for multi-vehicle systems," in *2006 American Control Conference*, (Minneapolis, MN, USA), pp. 6 pp.–, June 2006.

[4] M. Saska, V. Vonásek, T. Krajník, and L. Přeučil, "Coordination and navigation of heterogeneous MAV–UGV formations localized by a 'hawk-eye'-like approach under a model predictive control scheme," *The International Journal of Robotics Research*, vol. 33, pp. 1393–1412, Sept. 2014.

[5] X. Liu, D. Zhang, Q. Zhang, and T. Hu, "Formation Control for Enclosing and Tracking via Relative Localization," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 61, pp. 1–12, 2025.

[6] D. Koung, O. Kermorgant, I. Fantoni, and L. Belouaer, "Cooperative multi-robot object transportation system based on hierarchical quadratic programming," *IEEE Robotics and Automation Letters*, vol. 6, pp. 6466–6472, Oct. 2021.

[7] K.-K. Oh, M.-C. Park, and H.-S. Ahn, "A survey of multi-agent formation control," *Automatica*, vol. 53, pp. 424–440, Mar. 2015.

[8] V. S. M. Rosa and E. M. Belo, "Virtual Structure Formation Flight Control Based on Nonlinear MPC," in *2021 International Conference on Unmanned Aircraft Systems*, (Athens, Greece), pp. 1383–1390, June 2021.

[9] Jongho Shin and H. Kim, "Nonlinear Model Predictive Formation Flight," *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, vol. 39, pp. 1116–1125, Sept. 2009.

[10] H. Xiao and C. L. P. Chen, "Leader-Follower Consensus Multi-Robot Formation Control Using Neurodynamic-Optimization-Based Nonlinear Model Predictive Control," *IEEE Access*, vol. 7, pp. 43581–43590, Mar. 2019.

[11] W. Ren and N. Sorensen, "Distributed coordination architecture for multi-robot formation control," *Robotics and Autonomous Systems*, vol. 56, pp. 324–333, Apr. 2008.

[12] H. Ebel and P. Eberhard, "A comparative look at two formation control approaches based on optimization and algebraic graph theory," *Robotics and Autonomous Systems*, vol. 136, p. 103686, Feb. 2021.

[13] L. Krick, M. E. Broucke, and B. A. Francis, "Stabilisation of infinitesimally rigid formations of multi-robot networks," *International Journal of Control*, vol. 82, pp. 423–439, Mar. 2009.

[14] D. V. Dimarogonas and K. H. Johansson, "Stability analysis for multi-agent systems using the incidence matrix: Quantized communication and formation control," *Automatica*, vol. 46, pp. 695–700, Apr. 2010.

[15] K.-K. Oh and H.-S. Ahn, "Distance-based undirected formations of single-integrator and double-integrator modeled agents in n-dimensional space," *International Journal of Robust and Nonlinear Control*, vol. 24, pp. 1809–1820, Jan. 2014.

[16] M. Khaledyan, T. Liu, V. Fernandez-Kim, and M. de Queiroz, "Flocking and Target Interception Control for Formations of Nonholonomic Kinematic Agents," *IEEE Transactions on Control Systems Technology*, vol. 28, pp. 1603–1610, July 2020.

[17] Q. Yang, M. Cao, H. Garcia de Marina, H. Fang, and J. Chen, "Distributed formation tracking using local coordinate systems," *Systems & Control Letters*, vol. 111, pp. 70–78, Jan. 2018.

[18] Y. Liu, J. Liu, Z. He, Z. Li, Q. Zhang, and Z. Ding, "A Survey of Multi-Agent Systems on Distributed Formation Control," *Unmanned Systems*, vol. 12, pp. 913–926, Sept. 2024.

[19] J. M. Maestre and R. R. Negenborn, eds., *Distributed Model Predictive Control Made Easy*, vol. 69 of *Intelligent Systems, Control and Automation: Science and Engineering*. Dordrecht, Netherlands: Springer, 2014.

[20] B. D. Anderson, C. Yu, B. Fidan, and J. M. Hendrickx, "Rigid graph control architectures for autonomous formations," *IEEE Control Systems Magazine*, vol. 28, pp. 48–63, Dec. 2008.