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Abstract: ...

Keywords: ...

1. INTRODUCTION

Multi-agent systems (MASs) are nowadays used in a variety of applications from as they can perform complex tasks, which would otherwise impossible for a single robot. This is even more the case when considering heterogeneous fleet where the strenghts of one type of robot can compensate for the limitations of another. For example, to monitor a large area, multiple ground agents can move from one point to another being supervised from above by a drone with a wide field of view. To deepen the subject and understand both the potential tasks and challenges of MASs, the reader can refer to the work of Maldonado et al. (2024).

One of the fundamental cooperative tasks when working with multi-agents is formation control. This topic has been studied for years. For example, already Lee and Chong (2009) already proposed a decentralized control algorithm for a team of two-wheeled robots to achieve achieve a geometric pattern. However, formation control remains an hot challenging topic to this day. Tran et al. (2021) experimentally validated a robust distributed control based on negative imaginary systems consensus theory, using both ground robots and an air-ground fleet. In the work of Güler and İsa E. Yıldırım (2023), each agent computes its control action in a leader-follower manner using local extended Kalman filter's estimates to achieve a desired shape together with other wheeled robots and a drone. An optimal distributed formation control algorithm for double-integrator multi-agents has been presented and validated through simulations by Huang et al. (2023). Aditya and Werner (2023) defined the formation problem for a group of double-integrator agents as a discrete-time game whose solution is given by a state-dependent Riccati equation. A robust distributed consensus controller is presented by Restrepo et al. (2023) to address the rendezvous problem and applied in simulation to a swarm of drones. In the recent years, reinforcement learning has used in many areas including formation control. Wang et al. (2020) addressed multi-particle formation control by combining

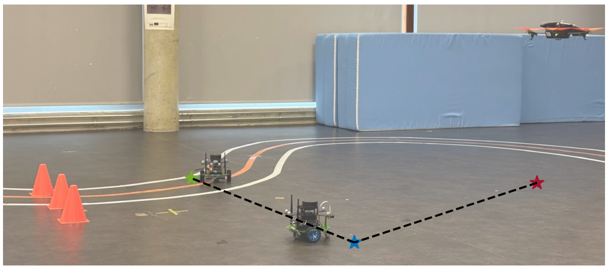


Fig. 1. This paper proposes a formation control for a heterogeneous fleet to attain a desired shape despite obstacles.

graph attention networks and multiple long short-term memories to achieve the desired shape and avoid collisions respectively. A position and an orientation robust controllers based on reinforcement learning are proposed and validated through simulations by Zhong et al. (2025) for the formation of a term of quadrotors.

In this context is placed this work which proposes a novel formation control scheme for a team consisting of a quadcopter and two unicycles, as show in Fig. 1. When addressing the multi-agent formation, there are two main challenges to solve: achieving the desired shape and avoiding collisions. On one hand, for the first challenge, a distributed controller combining Feedback Linearization (FL) and an optimal linear controller based on Linear Matrix Inequalities (LMIs) is presented. LMIs are a powerful mathematical tool used in many applications among which also formation control. In the work of Trejo et al. (2023), an LMI is solved to design the controller and observer gains, guaranteeing stable formation flight for a group of quadcopters. Deshpande et al. (2011) propose a formation control with artificial fixed delays for multiple double-integrators and verify the asymptotic stability of the scheme by checking the solvability of an LMI. Semsar-Kazerooni and Khorasani (2009) present an LMI formulation of the LQR problem to guarantee stable state consensus with an optimal control effort in a multi-agent system.

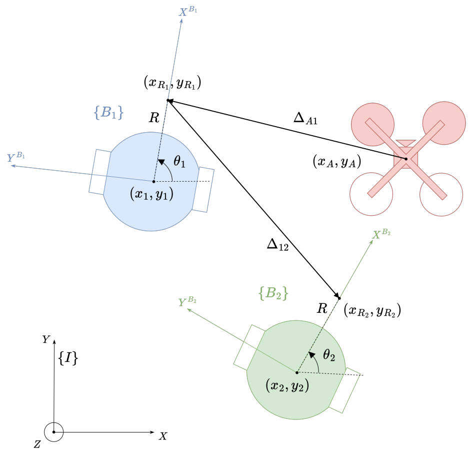


Fig. 2. Air-ground heterogeneous fleet.

On the other end, to avoid collision avoidance, the chosen solution is Artificial Potential Field (APF). In analogy with a particle moving in an electrostatic or gravitational field, virtual repulsive force fields are simulated to ward off the robot from an obstacle. This approach has been widely used in formation control of ground vehicles, see for example the work of Yongshen et al. (2018). However, in more recent works, e.g. Han et al. (2024) and Piet et al. (2025), APFs are employed to navigate around obstacles and prevent collisions while attaining the desired shape.

This paper represents the continuation of the previous work by Morando et al. (2025), where a control architecture combining Feedback Linerarization (FL), a robust LMI-based controller and APFs was proposed and validated through simulations for the formation of three unicycles. The successive developments sought to manage the challenge of a heterogeneous team (replacing a ground vehicle with a quadcopter) by adapting the methodology and then experimentally validating the new solution. The contributions of this work are: a) a controller involving FL, a LMI-based controller and APFs is presented for the stable formation of an air-ground fleet; b) the proposed controller has been validated through MATLAB Simulink simulations and a compresive set of experiments, including both static and dynamic obstacle scenarios. The remainder paper is structured as follows. In Section 2, the mathematical model used to describe the team is stated. The proposed formation controller is detailed in Section 3. The simulations and experiments results are reported and analyzed in Section 4 and in Section 5 respectively. Finally, conclusions are drawn in Section 6.

2. HETEROGENEOUS FLEET MODELING

In this section, the dynamics of the agents composing the team (i.e., of the two unicycles and the quadrotor, as shown in Fig. 2.) are described and adapted to then apply the LMI approach. The well-known kinematic model of a two-wheeled robot R_i is

$$\begin{cases} \dot{x}_i &= v_i \cos\theta_i \\ \dot{y}_i &= v_i \sin\theta_i \\ \dot{\theta}_i &= \omega_i \end{cases} \tag{1}$$

where (x_i, y_i, θ_i) is the pose of the agent and (v_i, ω_i) are the linear and angular velocities respectively. The equations (1) describing the motion of the center of rotation are non-linear. But still, if a point located at distance $R > 0$ from (x_i, y_i) denote as (x_{R_i}, y_{R_i}), is considered and new virtual inputs are defined $(u_{i,x}, u_{i,y})$, the dynamics become linear:

$$\begin{cases} \dot{x}_{R_i} = u_{i,x} \\ \dot{y}_{R_i} = u_{i,y} \end{cases} \tag{2}$$

Moving on to the drone, as in the formation problem deals with the (X, Y)-dynamics, some simplifying hypothesis have been made. First, let us assume that there is an inner attitude controller. Hence, the focus is only on the translational dynamics which are:

$$\begin{cases} m\ddot{x}_A^F = -T\sin\theta \\ m\ddot{y}_A^F = T\cos\theta\sin\phi \\ m\ddot{z}_A^F = T\cos\theta\cos\phi - m\,g \end{cases} \tag{3}$$

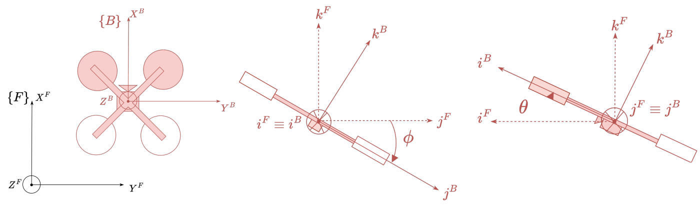


Fig. 3. Quadcopter's roll ϕ and pitch θ angles.

Let analyze the equations with the help of Fig. 3. The state (x_A^F, y_A^F, z_A^F) represents the position of the drone w.r.t. the inertial frame $\{F\}$. The frame $\{F\}$ has been used instead of $\{I\}$ to be aligned with the framework employed to implement the controller for the drone, see Section 5. The angles ϕ and θ are the roll and pitch Euler angles of the body frame $\{B\}$ (fixed to the drone) relative to the inertial frame $\{F\}$. Ignoring the small body forces, the only forces acting on the drone are the trust produced by the motors T along the k^B direction and the gravity mg along the $-k^F$ direction. Let suppose that the Z-controller

$$T = (r_1 + mg)/(\cos\phi\cos\theta) \tag{4}$$

is such that the drone's mass is compensated in a short time by r_1, i.e. $r_1 \to 0$. This implies that the (x, y)-dynamics will not include the mass of the drone, as the Z-controller already compensated it. Finally, let us make the hypothesis that the roll and pitch angles are small, i.e. $\phi, \theta \approx 0$. Then, the translational dynamics simplify to

$$\begin{cases} \ddot{x}_A^F = -g\theta \\ \ddot{y}_A^F = g\phi \end{cases} \tag{5}$$

At this point, all the agents can be described by the linear models (1) and (5). To define the formation problem, let us introduce the quantities

$$\Delta_{A1} = [\Delta_{A1,x}\ \ \Delta_{A1,y}]^T \tag{6a}$$
$$\Delta_{A1,x} = x_{R_1} - x_A = x_{R_1} - y_A^F \tag{6b}$$
$$\Delta_{iA,y} = y_{R_1} - y_A = y_{R_1} - x_A^F \tag{6c}$$

with (x_A, y_A) the position of the drone w.r.t the inertial frame $\{I\}$,

$$\Delta_{A1} = [\Delta_{A1,x}\ \ \Delta_{A1,y}]^T \tag{7a}$$
$$\Delta_{A1,x} = x_{R_1} - x_A = x_{R_1} - y_A^F \tag{7b}$$
$$\Delta_{iA,y} = y_{R_1} - y_A = y_{R_1} - x_A^F \tag{7c}$$

the desired inter-distances Δ_{A1}^d and Δ_{12}^d, and the desired position of the drone (x_A^d, y_A^d) w.r.t the inertial frame

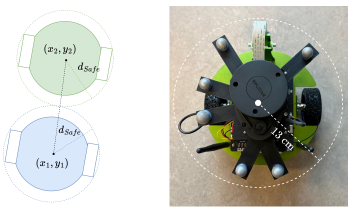
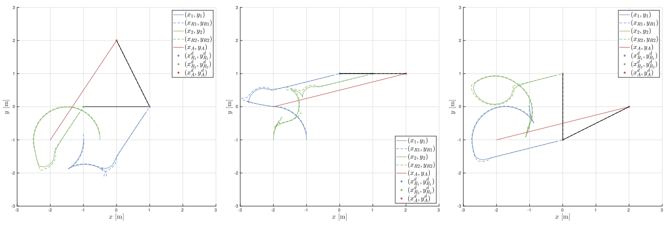


Fig. 4. TODO



(a) Triangle Top (b) Line Segment (c) Triangle Right

Fig. 5. Trajectories of the three agents with desired and actual interdistances in simulation.

$\{I\}$ (constant over time). The overall dynamics of the formation's errors are as follows

$$\begin{cases} \ddot{e}_{A,x} = -g\theta \\ \ddot{e}_{A,y} = g\phi \\ \dot{e}_{\Delta_{A1,x}} = u_{1,x} - \dot{e}_{A,y} \\ \dot{e}_{\Delta_{A1,y}} = u_{1,y} - \dot{e}_{A,x} \\ \dot{e}_{\Delta_{12,x}} = u_{2,x} - u_{1,x} \\ \dot{e}_{\Delta_{12,y}} = u_{2,y} - u_{1,y} \end{cases} \tag{8}$$

with

$$e_{A,x} = x_A^F - y_A^d, \; e_{A,y} = y_A^F - x_A^d \tag{9}$$

$$e_{\Delta_{A1,x}} = \Delta_{A1,x} - \Delta_{A1,x}^d, \; e_{\Delta_{A1,y}} = \Delta_{A1,y} - \Delta_{A1,y}^d \tag{10}$$

$$e_{\Delta_{12,x}} = \Delta_{12,x} - \Delta_{12,x}^d, \; e_{\Delta_{12,y}} = \Delta_{12,y} - \Delta_{12,y}^d \tag{11}$$

Let us define the state and control vectors as follows

$$\boldsymbol{e}^T = \begin{bmatrix} e_{A,x} & \dot{e}_{A,x} & e_{A,y} & \dot{e}_{A,y} & e_{\Delta_{A1,x}} & e_{\Delta_{A1,y}} & e_{\Delta_{12,x}} & e_{\Delta_{12,y}} \end{bmatrix} \tag{12a}$$

$$\boldsymbol{u}_A = \begin{bmatrix} \phi \\ \theta \end{bmatrix}, \; \boldsymbol{u}_1 = \begin{bmatrix} u_{1,x} \\ u_{1,y} \end{bmatrix}, \; \boldsymbol{u}_2 = \begin{bmatrix} u_{2,x} \\ u_{2,y} \end{bmatrix}, \boldsymbol{u} = \begin{bmatrix} \boldsymbol{u}_A \\ \boldsymbol{u}_1 \\ \boldsymbol{u}_2 \end{bmatrix} \tag{12b}$$

Hence, the heterogeneous fleet's dynamics can be written in a matrix form:

$$\dot{\boldsymbol{e}} = A\boldsymbol{e} + B\boldsymbol{u} \tag{13}$$

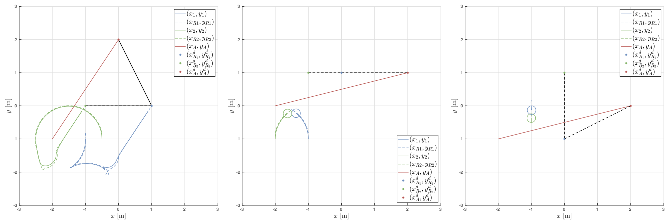
By discretizing with sampling time ΔT using the Euler method:

$$\boldsymbol{e}(k+1) = A_d\boldsymbol{e}(k) + B_d\boldsymbol{u}(k) \tag{14}$$

with $A_d = I + \Delta T A$ and $B_d = \Delta T B$. To model real-world disturbances, it is assumed that an addictive zero-mean disturbance $\boldsymbol{d}(k)$ is acting on the input channel, i.e.

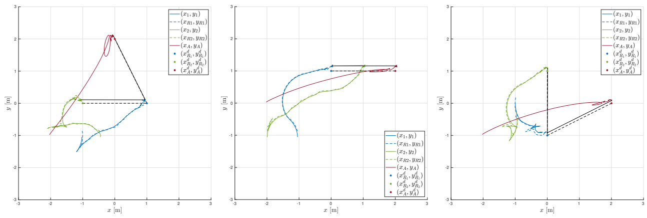
$$\boldsymbol{e}(k+1) = A_d\boldsymbol{e}(k) + B_d\boldsymbol{u}(k) + B_d\boldsymbol{d}(k) \tag{15}$$

Let us make the following hypothesis: a) the drone knows its position; b) the robot R_1 knows its position w.r.t the quadcopter; c) the robot R_2 knows its position w.r.t the other agent R_1; d) all unicycles are aware of their distance from any obstacles on the ground.



(a) Triangle Top (b) Line Segment (c) Triangle Right

Fig. 6. Trajectories of the three agents without APF in simulation.



(a) Triangle Top (b) Line Segment (c) Triangle Right

Fig. 7. Trajectories of the three agents with desired and actual interdistances in the experiments.

3. FORMATION CONTROLLER

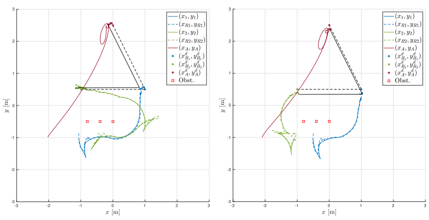
4. SIMULATIONS RESULTS

5. EXPERIMENTAL VALIDATION

dire che usi FL-AIR per il drone, pensa se incrementare ε a 20cm invece di 17cm

For each obstacle, just add a corrective APF term: add formula

Increased y_A^d of 0.5 m, formation reached after 55.30 s(the drone takes some time, but R_2 achieve the formation w.r.t R_1 after 16.02 s), when swapped the formation is achieved after 9.74 s (drone after 8.32 s while R_2 after 9.74 s).



(a) R_2 on the right (b) R_2 on the left

Fig. 8. TODO

6. CONCLUSION

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