Dynamic Position Estimation and Flocking Control in Multi-Robot Systems

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Abstract: This paper presents a novel approach to improve flocking algorithms for terrestrial Multi-Robot Systems (MRS) featuring defective or inaccurate sensors by using the Adaptive Value Tracking (AVT) algorithm. The idea behind the usage of the AVT is to estimate the positions of robots with poor GPS connectivity. Such estimation is then furnished as an input for the flocking controller, which is a method ensuring the movement even when some robots lack of GPS data. The proposed framework is tested in simulation using several robots, and found that the AVT effectively preserves accurate positioning and consequently flocking behavior.

1 INTRODUCTION

Flocking (He et al., 2018), inspired by the collective behavior observed in natural systems such as bird flocks and fish schools, has been used in recent years, particularly within the field of multi-agent systems. This phenomenon, where individual agents follow simple rules based on the positions and velocities of their neighbors, results in emergent, collective behavior that holds big potential for applications in robotics, autonomous vehicles, and distributed sensing networks.

Despite the progress made in developing flocking algorithms, several challenges remain, particularly in ensuring scalability, real-world applicability, communication efficiency, energy optimization, robustness, and decentralization. These challenges needs the development of more sophisticated and practical approaches to enhance the functionality and deployment of multi-agent systems.

Reza Olfati-Saber (Olfati-Saber, 2006) introduced fundamental algorithms for flocking in both free-space and constrained environments, setting the stage for subsequent research. Recent advancements have seen the emergence of innovative strategies, such as hybrid metric-topological interactions (He et al., 2018), which enhance the flexibility and convergence properties of flocking algorithms. Additionally, various optimal flocking strategies have been used to specific objectives and environmental constraints, aiming to optimize energy consumption, ensure spatial coverage, and navigate complex terrains.

However, these advancements also introduce a set of challenges. Ensuring scalability while maintaining practical computational constraints is a significant challenge. Moreover, the integration of theoretical insights with practical considerations remains a critical area of focus to develop robust, efficient, and scalable flocking algorithms.

This paper addresses the aforementioned challenges by proposing novel solutions and methodologies that advance the theoretical foundations of flocking and facilitate practical implementation in real-world settings. Specifically, we present a framework for improving robot positioning in flocking, focusing on the synchronized movement of autonomous agents with no GPS connection in open space. Our approach uses the Adaptive Value Tracking (AVT) for dynamic adjustment and tracking, enabling efficient communication and coordination among agents equipped with different sensor capabilities.

Through theoretical analyses and numerical simulations, we show the benefits of using the AVT method for the flocking control of multi-robot systems evolving in open but complex environments.

The outline of the paper is as follows. Section 2 presents the related works. Section 3 explains the different methods used for achieving flocking behavior in multi-agent systems. Section 4 describes our

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proposed framework, including the integration of the AVT for position estimation of GPS-denied agents. Section 5 presents the obtained results from our simulation studies, demonstrating the effectiveness of our approach. Section 6 concludes the paper, summarizing the key improvements and future research implications.

2 RELATED WORK

The study of flocking algorithms in multi-agent dynamic systems has evolved significantly over the years, with numerous contributions advancing our understanding and application of these algorithms. One of the foundational works in this field is the paper by Reza Olfati-Saber (Olfati-Saber, 2006). This work explores flocking behavior in both free-space and environments with multiple obstacles, introducing three specific algorithms: two for free-flocking and one for constrained flocking. The extensive analysis of the first two algorithms reveals their incorporation of Reynolds' rules of flocking, addressing critical issues such as fragmentation in flocking behavior. The authors also proposes a "universal" definition of flocking, supported by various simulation results demonstrating the effectiveness of the algorithms in scenarios such as 2-D and 3-D flocking, split/rejoin maneuvers, and squeezing maneuvers for hundreds of agents. This work has significantly advanced the understanding of multi-agent systems and their potential applications in robotics and autonomous vehicle systems.

Building upon these foundational concepts, more recent research has continued to refine and improve flocking algorithms. Other researchers (He et al., 2018) study on a flocking algorithm for multi-agent systems that emphasizes connectivity preservation under hybrid metric-topological interactions. This algorithm utilizes a range-limited Delaunay graph for interaction topology, reducing the cost of information exchange among agents while increasing the flexibility of the flocking algorithm. This approach allows the multi-agent system to converge to a more regular quasi-lattice formation without additional constraints on sensing range or desired distances between agents. Implemented in a distributed manner, this algorithm leverages local information for each agent to construct its neighbor set. Theoretical and numerical analyses have demonstrated the superiority of this approach compared to traditional disk and Delaunay graph-based algorithms.

Further advancements in optimal flocking have been explored, with various methodologies addressing specific objectives and environmental constraints. For instance, Ergodic Trajectories Flocking ensures agents cover a spatially distributed area evenly over time, though it requires periodic information sharing, which can be challenging in large swarms (Beaver and Malikopoulos, 2020). Optimal Shepherding for Flock Influencing is useful for steering real flocks of birds away from hazards, but its complexity increases with flock size and environmental factors (Lee, 2013). Constraint-Driven Flocking focuses on minimizing energy consumption and avoiding collisions, necessitating sophisticated sensing and computation capabilities (Beaver and Malikopoulos, 2020). Dynamic Peloton Formation optimizes aerodynamic effects for energy efficiency, primarily validated in simulations, raising questions about real-world effectiveness (Beaver and Malikopoulos, 2020). Line Flocking with Model Predictive Control maximizes velocity matching and upwash benefits but is designed for idealized conditions (Zhan and Li, 2013). Pareto Front Selection in Multi-objective Control effectively balances multiple objectives but requires significant computational resources (Kesireddy and Medrano, 2024).

Despite these work, several challenges persist in the field of flocking algorithms for multi-agent systems. Scalability remains a significant issue, as managing large numbers of agents presents numerous logistical and computational hurdles. The real-world application of these algorithms often reveals a gap between simulation results and practical effectiveness. Communication overhead is another critical challenge, as ensuring effective communication in large swarms without saturating the network is essential for cohesive flock behavior. Balancing energy efficiency, particularly the costs of communication, computation, and movement, is a persistent concern. Robustness is crucial, as maintaining performance in the face of environmental uncertainties and system failures is paramount. Additionally, developing algorithms that allow for decentralized decision-making and autonomy while ensuring cohesive flock behavior poses a complex challenge. Embedding these approaches necessitates reducing computational time, emphasizing the need for efficient and practical implementations.

Our proposed framework aims to address these challenges by integrating the AVT for dynamic position estimation, particularly for GPS-denied agents. This innovation enhances the ability of multi-agent systems to maintain flocking behavior under varying conditions and sensor capabilities, for more robust and efficient flocking algorithms suitable for real-world applications.

3 PRELIMINARIES

3.1 Graph Theory for MRS

In this work, the MRS is described via the graph theory. An undirected graph is defined as $\mathcal{G} = \{\mathcal{V}, \xi\}$, such that $\mathcal{V}$ represents the group of robots (nodes), where $\mathcal{V} = \{1, 2, ..., N\}$. ξ is a collection of communication channels (edges), represented as $\xi = (i, j)\ \forall\ i, j \in \mathcal{V}$. Furthermore, ξ is employed to characterize the connectivity of multi-robot systems. (i, j) implies that there exists a communication channel between robot i and robot j. The neighborhood group of vehicle i is given as

$$\mathcal{N}_i^{\alpha} = \{j \in \mathcal{V}_{\alpha} : (i, j) \in \xi\} = \{j \in \mathcal{V}_{\alpha} : ||q_j - q_i|| < r\} \quad (1)$$

with $r > 0$ is the interaction range between robots and $||.||$ stands for the Euclidean norm. q_i and q_j are the Cartesian coordinates of robots i and j, respectively.

3.2 Flock Modelling

Flocking refers to the coordinated movement and formation of multiple agents, where each agent follows simple rules based on the positions and velocities of its neighbors, resulting in emergent, collective behavior. Using the flocking control algorithm allows each agent to apply a force input, embodying the collective dynamics of the flock through interactions with its surroundings and neighboring agents.

Consider a set of n agents evolving in a m dimensional space ($m = 2$ in our case), with the following dynamics

$$\begin{aligned} \dot{q}_i &= v_i \\ \dot{v}_i &= u_i \quad i = 1, 2, \dots, n \end{aligned} \quad (2)$$

where $q_i, v_i, u_i \in \mathbb{R}^m$ are the position, velocity and control input of the agent i. The geometric formation, which is a quasi α-lattice pattern (Olfati-Saber, 2006), can be expressed as

$$||q_j - q_i|| = d \ \ \forall j \in \mathcal{N}_i^{\alpha} \quad (3)$$

with d representing the distance between neighbors i and j. To avoid the singularity caused when $q_i = q_j$, the control in (Olfati-Saber, 2006) is based on the $\sigma-$norm which maps $\mathbb{R}^m \to \mathbb{R}^+$ and is expressed as $||z||_{\sigma} = \frac{1}{\varepsilon}(\sqrt{1 + \varepsilon||z||^2} - 1)$. Its gradient is given by $\sigma_{\varepsilon}(z) = \frac{z}{\sqrt{1+\varepsilon||z||^2}} = \frac{z}{1+\varepsilon||z||_{\sigma}}$. Furthermore, let $a_{ij}(q)$ be elements of an adjacency matrix $\mathcal{A}(q)$, defined as

$$a_{ij}(q) = \begin{cases} 0 & i = j \\ \rho_h\left(||q_j - q_i||_{\sigma}/r_{\alpha}\right) & j \neq i \end{cases} \quad (4)$$

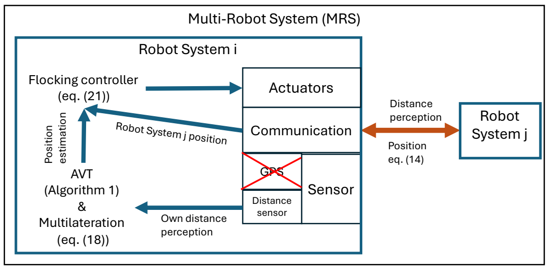

Figure 1: Illustration of the developed Multi-Robot System (MRS) framework.

where $\rho_h : \mathbb{R} \to [0, 1]$ is a bump function to obtain smooth interaction for $a_{ij}(q)$ in the MRS with $h \in (0, 1)$ and $r_{\alpha} = ||r||_{\sigma}$. $\rho_h(z)$ is defined as

$$\rho_h(z) = \begin{cases} 1 & z \in [0, h) \\ \frac{1}{2}\left(1 + \cos\left(\pi\frac{z-h}{1-h}\right)\right) & z \in [h, 1] \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

The set of neighboring obstacles ($\beta-$agents) of node i (robot i), can be expressed by

$$\mathcal{N}_i^{\beta} = \{k \in \mathcal{V}_{\beta} : ||\hat{q}_{i,k} - q_i|| < r'\} \quad (6)$$

Thus, additionally to (3), the desired formation includes the interaction between agents and obstacles, given by

$$||\hat{q}_{i,k} - q_i|| = d' \ \ \forall k \in \mathcal{N}_i^{\beta} \quad (7)$$

where r' and d' are the interaction range and the distance between an $\alpha-$agent i and a $\beta-$agent k and $\hat{q}_{i,k}$ is the estimated position of the closest point from robot i to obstacle k. Consequently, the elements $b_{i,k}$ of a heterogeneous adjacency matrix $\mathcal{B}(q)$ is expressed as

$$b_{i,k}(q) = \rho_h\left(||\hat{q}_{i,k} - q_i||_{\sigma}/d_{\beta}\right) \quad (8)$$

where $d_{\beta} = ||d'||_{\sigma}$ represents the distance between an α-agent and an obstacle. Then, recalling the flocking control from (Olfati-Saber, 2006), this is developed as

$$u_{pi} = u_{pi}^{\alpha} + u_{pi}^{\beta} + u_{pi}^{\gamma} \quad (9)$$

Such a design ensures that the MRS is capable of avoiding obstacles while maintaining a quasi α-lattice configuration pattern (Olfati-Saber, 2006). The term u_{pi}^{α} is responsible for maintaining an inter-distance between $\alpha-$agents, u_{pi}^{β} is a term comprising an obstacle avoidance algorithm for α and β-agents, and u_{pi}^{γ} is the navigation feedback term, which drives the group towards a collective objective. The terms are then given as

$$u_{pi}^{\alpha} = \sum_{j \in N_i^{\alpha}} \phi_{\alpha}(||q_j - q_i||_{\sigma}) n_{ij} + \sum_{j \in N_i^{\alpha}} a_{ij}(v_j - v_i) \quad (10)$$

$$\begin{aligned} u_{pi}^{\beta} =& K_1^{\beta} \sum_{k \in N_i^{\beta}} \phi_\beta(\|\hat{q}_{i,k} - q_i\|_\sigma)\hat{n}_{i,k} \\ &+ K_2^{\beta} \sum_{j \in N_i^{\beta}} b_{i,k}(q)(\hat{v}_{i,k} - v_i) \end{aligned} \quad (11)$$

$$u_i^{\gamma} = -c_1(q_i - q_d) - c_2(v_i - v_d) \quad (12)$$

where

- q_d and v_d are the desired position and velocity, respectively
- $\hat{v}_{i,k}$ is the velocity between robot i and obstacle k
- v_i is the linear velocity of robot i
- $K_1^{\beta}, K_2^{\beta} > 0$ are constant gains
- $\hat{n}_{ij} = \sigma_\varepsilon(q_j - q_i)$, $\hat{n}_{i,k} = \sigma_\varepsilon(\hat{q}_{i,k} - q_i)$
- $\phi_\alpha(z) = \frac{1}{2}\rho_h(z/d_\alpha)[(a+b)\sigma_1(z+e) + (a-b)]$
- $\phi_\beta(z) = \rho_h(z/d_\beta)(\sigma_1(z-d_\beta) - 1)$ is a repulsive action function
- $\sigma_1(z) = z/\sqrt{1+z^2}$
- $0 < a \le b$ and $e = |a-b|/\sqrt{4ab}$
- $c_1, c_2 > 0$ are the navigation gains

4 PROPOSED FRAMEWORK

Consider a set of terrestrial robots embedding different sensors (e.g., GPS, ultrasonic sensors). To perform a collective navigation, the communication between the agents is crucial. In this vein, every member group embedding a GPS device will share with its neighbors its position, which will be used by a distributed controller (in our case the flocking algorithm). Then, if a member group does not feature a GPS device or this one is defective, one method should be applied to determine the position.

Considering the cited issue, this work proposes the usage of the AVT algorithm as a distance estimator followed by a multilateration method for position estimation. As an example, agent i may have a GPS and can estimate the distance to agent j, while agent j might only have distance sensing capabilities and no GPS. Then, the AVT retrieves the measured noisy distances and processes them to obtain values closer to the real ones. The output signal is then used by the multilateration method to estimate the global position, which is employed as an input for the flocking strategy of robot j.

In the next subsections, we carefully explain the proposed framework. For this, we briefly present the mathematical model of the used robots, followed by the distance estimation using the AVT. Robot position estimation and the control of the MRS is explained later, completing the loop for the proposed framework. Fig. (1) presents a block-diagram showing the interaction between the elements of our proposed architecture.

4.1 Multi-Robot System

Consider a multi-robot system composed by N unicycle robots. $(x_i, y_i) \in \mathbb{R}^2$ and θ_i represent the Cartesian positions and orientations w.r.t. the i-th robot. r and e are the radius of the wheels and the distance between these ones, respectively, see Figure 2. The equations

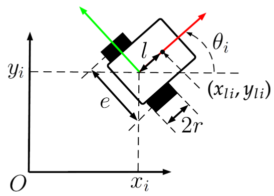

Figure 2: Wheeled mobile robot.

of motion for the i-th robot, containing the nonholonomic constrains are expressed as

$$\dot{q}_i = \begin{pmatrix} \dot{x}_i \\ \dot{y}_i \\ \dot{\theta}_i \end{pmatrix} = \begin{pmatrix} \cos\theta_i & 0 \\ \sin\theta_i & 0 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} v_i \\ \omega_i \end{pmatrix} \quad (13)$$

with $q_i = (x_i, y_i, \theta_i)^T$ the state vector of the robot i. v_i and ω_i stand for the linear and angular velocities.

For control purposes, let us redefine the system output at an offset point l, where $l \neq 0$, see Figure 2. With this, the new position output is as follows

$$q_{li} = \begin{pmatrix} x_{li} \\ y_{li} \end{pmatrix} = \begin{pmatrix} x_i + l_i\cos\theta_i \\ y_i + l_i\sin\theta_i \end{pmatrix} \quad (14)$$

By differentiating (14) w.r.t. time and using (13), it is possible to obtain

$$\dot{q}_{li} = \begin{pmatrix} \dot{x}_{li} \\ \dot{y}_{li} \end{pmatrix} = \begin{pmatrix} \cos\theta_i & -l\sin\theta_i \\ \sin\theta_i & l\cos\theta_i \end{pmatrix} \begin{pmatrix} v_i \\ \omega_i \end{pmatrix} = \Lambda(\theta_i)v_i \quad (15)$$

Therefore, $\det(\Lambda(\theta_i)) \neq 0$. Solving for the auxiliary input, the following is obtained

$$v_i = \begin{pmatrix} \cos\theta_i & -l\sin\theta_i \\ \sin\theta_i & l\cos\theta_i \end{pmatrix}^{-1} \begin{pmatrix} u_{xi} \\ u_{yi} \end{pmatrix} = \Lambda^{-1}(\theta_i)u_i \quad (16)$$

With the latter, (15) can be approximated to a simple integrator model, given as

$$\dot{q}_{li} = u_{pi} \quad (17)$$

where $u_{pi} = (u_{xi}, u_{yi})^T \in \mathbb{R}^{2N}$ the control input vector, with N the number of agents conforming in the multi-robot system.

4.2 Drone Ranging Estimation Using Adaptive Value Tracking (AVT)

Adaptive Value Tracking (AVT) (Yildirim and Gürcan, 2014) is a technique used to find and track a dynamic value within a given search space as efficiently as possible. This method has been successfully implemented in various scientific and industrial projects (Belbachir and Pasin, 2019; Belbachir et al., 2018; Belbachir et al., 2019; Agliamzanov et al., 2015; Yildirim and Gürcan, 2014; Gürcan, 2013).

From the perspective of software engineering, an AVT is a software component that implements a robust and efficient search algorithm in order to search and track a dynamic value v^* (Yildirim and Gürcan, 2014) (see Figure 3).

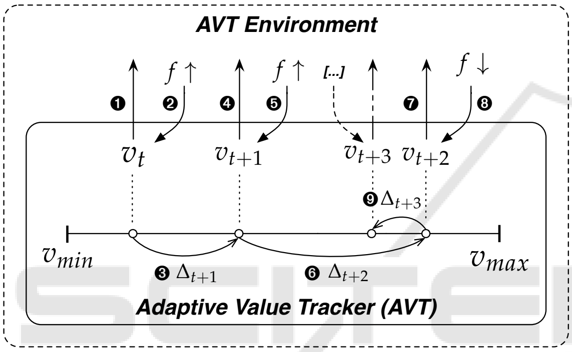

Figure 3: Interaction between an AVT and its environment (Yildirim and Gürcan, 2014).

The search algorithm requires information about the search space:

$$[v_{min}, v_{max}] \subset \mathcal{R}$$

where v_{min} is the lower boundary and v_{max} is the upper boundary for the searched value v^*. At any time t, the owner component can interact with the AVT to obtain the current proposed value v_t and guide the search direction, ensuring convergence to v^* by providing feedback: INCREASING (↑), DECREASING (↓), or PRESERVING (≈). The AVT adjusts its proposed value by Δt based on the feedback, where

$$\Delta t \in [\Delta_{\min}, \Delta_{\max}]$$

$\Delta_{\min}$ represents the minimum adjustment step and is considered the precision, ensuring $|v_t - v^*| \leq \Delta_{\min}$. Δt represents the adjustment value.

In scenarios where a vehicle loses GPS coverage, it initiates an adaptive localization protocol (ALP) with the first critical step being ranging estimation. Here, the vehicle communicates with nearby infrastructure to estimate its relative distances, treating ranging as a search process using AVT to increase the robustness against noise measurements.

Algorithm 1: Ranging Estimation Algorithm.

Obtain a new range estimate $\hat{d}$ using any ranging method
$error = avt.getValue() - \hat{d}$
if $error < 0$ **then**
  $avt.adjust(f \uparrow)$
else if $error > 0$ **then**
  $avt.adjust(f \downarrow)$
else
  $avt.adjust(f \approx)$
end if

In this algorithm, the distance estimate $\hat{d}$ taken from a different sensor is compared to the AVT's proposed value. Depending on whether the estimate is higher or lower, the AVT adjusts the feedback to converge to the actual distance. This iterative process ensures that the estimated distance stabilizes over time, allowing the vehicle to accurately determine its relative distance despite noisy measurements.

By using AVT in ranging estimation, vehicles can maintain accurate localization, even in the absence of GPS signals, enhancing the overall robustness of the navigation system.

4.3 Multilateration Method

As it was previously stated, the multi-robot system embeds different sensors (e.g., GPS, ultrasonic sensors). Thus, within the group of robots, consider agents featuring only distance sensors. The multilateration strategy allows to these robots to estimate their positions $(\hat{x}_i, \hat{y}_i)$, if these ones have a set of m reachable neighborhoods featuring GPS signal with information (x_j, y_j, d_j), where (x_j, y_j) is the location of the neighborhood j and d_j is the measured distance to it. Thus, by minimizing the difference between the measured noisy distances and the estimated Euclidean distances, it is possible to obtain the minimum mean square estimate (MMSE). The computation, with the form $y = bX$, outputs the location estimation $(\hat{x}_i, \hat{y}_i)$ by employing the matrix solution for MMSE (Savvides et al., 2001), given as

$$b = \begin{pmatrix} \hat{x}_i \\ \hat{y}_i \end{pmatrix} = (X^T X)^{-1} X^T Y \quad (18)$$

where

$$X = \begin{pmatrix} 2(x_1 - x_2) & 2(y_1 - y_2) \\ 2(x_1 - x_3) & 2(y_1 - y_3) \\ \vdots & \vdots \\ 2(x_1 - x_m) & 2(y_1 - y_m) \end{pmatrix} \quad (19)$$

$$Y = \begin{pmatrix} \delta - x_2^2 - y_2^2 - d_2^2 \\ \delta - x_3^2 - y_3^2 - d_3^2 \\ \vdots \\ \delta - x_m^2 - y_m^2 - d_m^2 \end{pmatrix}; \;\; \delta = x_1^2 + y_1^2 + d_1^2 \quad (20)$$

4.4 MRS Distributed Control

Consider the position output q_{li} in (13), such that the i-th robot can be treated as a simple integrator system, given in (17). Then, the control signal computed by the flocking algorithm is modified as follows:

$$\begin{aligned} u_{pi} =& u_{pi}^{\alpha} + u_{pi}^{\beta} + u_{pi}^{\gamma} \\ u_{pi}^{\alpha} =& \sum_{j \in N_i^{\alpha}} (K_p^{\alpha} \phi_{\alpha}(\|q_{lj} - q_{li}\|_{\sigma}) n_{ij} \\ &+ K_i^{\alpha} \int \phi_{\alpha}(\|q_{lj} - q_{li}\|_{\sigma}) n_{ij} dt) \\ u_{pi}^{\beta} =& K_p^{\beta} (\sum_{k \in N_i^{\beta}} \phi_{\beta}(\|\hat{q}_{i,k} - q_{li}\|_{\sigma}) \hat{n}_{i,k} \\ &+ \sum_{j \in N_i^{\alpha}} \sum_{k \in N_j^{\beta}} \phi_{\beta}(\|\hat{q}_{j,k} - q_{lj}\|_{\sigma}) \hat{n}_{j,k}) \\ u_{pi}^{\gamma} =& -\operatorname{sat}(K_p^{\gamma}(q_{li} - q_d)) \end{aligned} \quad (21)$$

where $K_p^{\alpha}, K_i^{\alpha} > 0$ are gradient-based consensus gains, $K_p^{\beta} > 0$ and $\operatorname{sat}(*)$ is a saturation function, such that

$$\operatorname{sat}(z) = \begin{pmatrix} \operatorname{sat}(z_1) \\ \vdots \\ \operatorname{sat}(z_n) \end{pmatrix}; \operatorname{sat}(z_i) = \begin{cases} z_{imin} & z_i \leq z_{imin} \\ z_i & z_{imin} < z_i < z_{imax} \\ z_{imax} & z_i \geq z_{imax} \end{cases} \quad (22)$$

Additionally, $K_p^{\gamma} > 0$ is a gain for the navigation feedback force. u_{pi}^{α} is a PI decentralized control law of the gradient-based term from the flocking algorithm. Such a term was originally proposed as a PID controller for double integrator systems in (Saif et al., 2019). u_{pi}^{β} is the term comprising the obstacle avoidance algorithm initially proposed by (Olfati-Saber, 2006) and then modified in (Koung et al., 2020), which is the approach used for this work. u_{pi}^{γ} is the navigation feedback term, which drives the group towards a collective objective. The saturation function allows to control the navigation term weight. Hence, this one does not dominate over the other components, specially when the desired position is far away from the formation's barycenter.

In summary, the multi-robot system considered in this work consists of a group of nonholonomic terrestrial robots. The main objective is to perform a trajectory tracking mission while maintaining the quasi α-lattice formation considering the communication limitations coming from the sensors.

5 SIMULATION RESULTS

The current presents the tests of the proposed strategy using the Matlab/Simulink® environment. The simulation consists of six terrestrial robots performing a trajectory-tracking mission while maintaining a quasi α-lattice formation using the proposed architecture.

5.1 Simulation Scenario

The simulation scenario focuses on a trajectory tracking mission involving a set of robots. The objective is to evaluate the effectiveness of the Adaptive Value Tracking (AVT) algorithm for inaccurate measurements (GPS signal lost), working in conjunction with the flocking controller.

Initially, the group of robots start at random positions within the simulation environment, ensuring a spread-out initial configuration to avoid clustering. Then, a desired trajectory is generated and the flocking controller is activated to self-organize the agents into the desired pattern. The set of parameters used for the simulation are given in Table 1

Table 1: Simulation parameters for MRS formation control with obstacle avoidance.

Parameter	Value	Parameter	Value
a, b	1.0	x^*, y^* [m]	1.75
ε	0.1	d [m]	0.41
h	0.2	d' [m]	0.45
K_p^{α}	5.5	r [m]	0.6
K_i^{α}	0.5	l [m]	0.01
K_p^{β}	0.3	$\dot{\phi}_{max}$ [rad/s]	π
K_p^{γ}	0.4	$\dot{\phi}_{min}$ [rad/s]	$-\pi$

The complete mission includes the trajectory, which is given by a circular pattern of 4m radius. Then, at $t = 850s$, a final desired position $q_d = (-4, 4)^T$ m is provided. In our experiments, Robot 6 is not equipped with a GPS device, providing an initial challenge for the AVT algorithm. Likewise, Robot 3 embeds a GPS device, however the signal is lost at $t = 600$s, switching to the AVT estimation.

5.2 Simulation Results

Fig. (4) shows the trajectories performed by the different robots during the simulation. We can see that the MRS reaches the formation and avoids the obstacle. The completion of the mission is confirmed in Fig. (5), where we can visualize how the positions of the robots keep constant once they have reached the final position. Due to the loss of the GPS signal

(Robot 3 at $t = 600$s), the MRS adapts the formation as disturbances appear because of the switching to the AVT estimation.

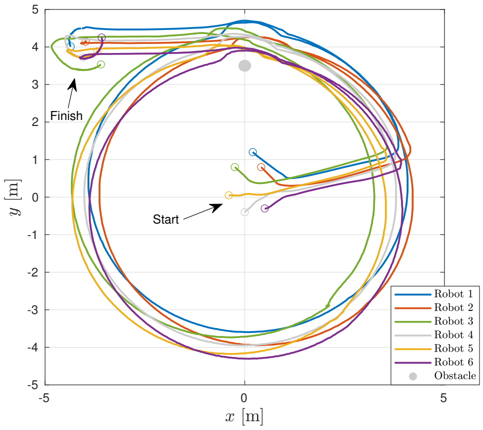

Figure 4: Performed trajectories.

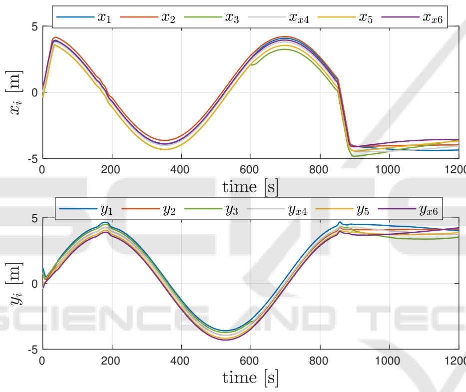

Figure 5: Linear trajectories for *x* and *y*-axis, respectively.

Fig. (6) depicts examples of the measured distances and estimated distances by the AVT from robots 6 to 1 and 4 and 3 to 2 and 5. Such examples were chosen since they correspond to the defective robots featuring the AVT estimation. Additionally, we can visualize the effectiveness of the estimation as it reduces the noise coming from the embedded distance sensors.

The inter-distances are shown in Fig. (7). The curves confirm how the formation adapts after the loss of the GPS signal coming from **robot 3**. It is important to remember that the flocking controller works for undirected graphs, implying that every robot must know the positions of its neighbors. Likewise, if one of the members is disturbed, such disturbance will affect the rest of the group.

Fig. (8) and Fig. (9) show the trajectories performed by the robots as well as the inter-distances when the AVT algorithm is not applied. The flocking

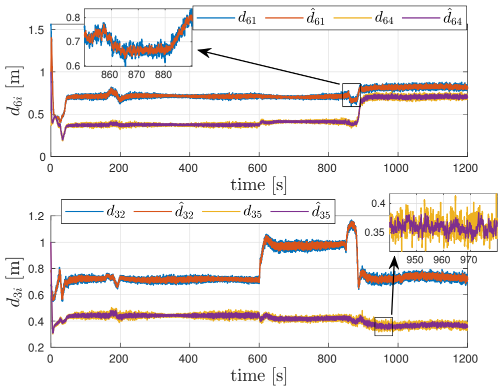

Figure 6: [Top] Inaccurate and estimated distances from Robot 6 to Robots 1 and 4, respectively. [Bottom] Inaccurate and estimated distances from Robot 3 to Robots 2 and 5, respectively.

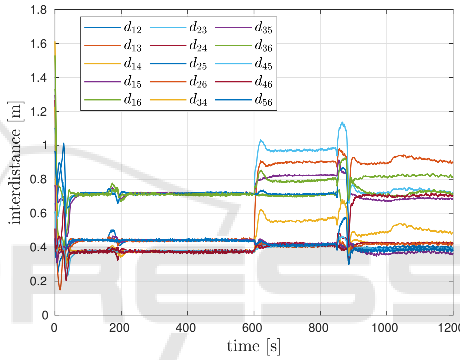

Figure 7: Robots inter-distances during the simulation.

controller manages to carry out part of the mission, however, for the last part, the formation disseminates and robot 3 diverges because of the noisy sensors and the disturbances. Thus, we can conclude that the proposed framework provides a robust performance for MRS.

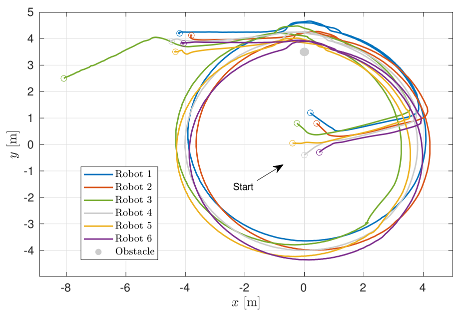

Figure 8: Performed trajectories without AVT estimation.

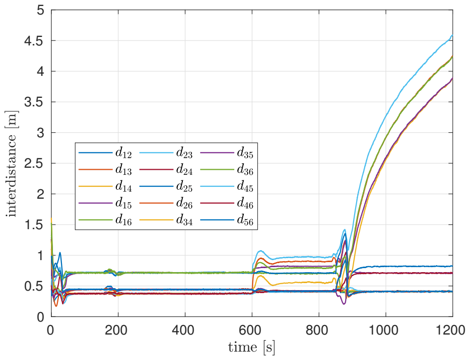

Figure 9: Robots inter-distances during the simulation without AVT estimation.

6 CONCLUSIONS

This paper has proposed a novel framework aiming at improve the robustness and scalability of flocking algorithms in multi-agent systems. Particularly focusing on scenarios where agents lose GPS connectivity. The integration of Adaptive Value Tracking (AVT) for dynamic position estimation in GPS-denied environments represents a significant advancement. This approach enables agents to estimate their positions accurately using ranging information from neighboring agents, thereby maintaining synchronized movement and safe flocking behavior.

Through theoretical analysis and numerical simulations, we have demonstrated the effectiveness of our framework for MRS featuring defective sensors and evolving in complex environments. By using the AVT, our approach not only enhances the reliability of multi-agent systems but also lays the groundwork for future developments in autonomy and collective intelligence.

Future research directions include further optimization of communication protocols and integration of additional sensor versatility. Additionally, the real-time implementation of the proposed strategy, as well as performance comparisons with the Kalman filter and observers.

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