American Society of Agricultural and Biological Engineers
2950 Niles Road | St. Joseph MI 49085-9659 | USA
269.429.0300 | fax 269.429.3852 | hq@asabe.org | www.asabe.org

An ASABE Meeting Presentation
DOI: https://doi.org/10.13031/aim.202401277
Paper Number: 2401277

Vision-based Relative Navigation and Drone Swarming Control for Inspection in GPS-denied Environment

Fethi Candan[1], Muhammet Emre Sanci[1], Liujun Li[1,2,3*]

[1] Department of Soil and Water Systems, University of Idaho, 875 Perimeter Drive MS 2060, Moscow, ID 83844-2060, United States

[2] Department of Mechanical Engineering, University of Idaho, Moscow, ID, United States

[3] Department of Computer Science, University of Idaho, Moscow, ID, United States. liujunl@uidaho.edu

Written for presentation at the
2024 ASABE Annual International Meeting
Sponsored by ASABE
Anaheim, CA
July 28-31, 2024

Abstract. *Unmanned Aerial Vehicles (UAVs) play a crucial role in a myriad of agricultural and infrastructural applications, encompassing surveillance, observation, and spraying, etc.. Nevertheless, challenges persist in the realm of limited payload distribution and insufficient operation time, particularly when dealing with large acres of farmland and multiple tasks. The utilization of multiple UAVs in a swarm configuration allows for distributed payload and task capabilities, thereby extending the overall flight duration. However, UAVs forming a swarm, posing issues related to formation and localization, particularly the presence of GPS denied zones. Leader-follower drone system presents a formidable obstacle, necessitating innovative solutions for formation control to address such localization challenges. In addressing these challenges, our research introduces a vision-based relative navigation algorithm for leader-follower formation control. This approach employs machine vision methods for localization with blob operation and machine learning object detection, enabling the follower UAV to seamlessly track the leader drone. Furthermore, the follower UAV can transmit its relative position to the leader UAV, facilitating mutual localization. To validate the efficacy of our proposed method, we conducted experiments wherein inspection UAVs were modeled and implemented in Webots environments. Specifically, the leader UAV was subjected to a GPS denied zone, prompting the follower UAV to send relative position data to aid in re-localization and restore the desired position. This innovative vision-based approach holds promise for enhancing the autonomy and localization capabilities of UAV inspection in challenging operational environments.*

Keywords. *UAV, Swarm, Multiple-UAVs, Formation, Formation Control, Vision Relative Navigation, GPS-denied zone, Machine Learning, Object Detection*

Introduction

Unmanned Aerial Vehicles (UAVs) play a crucial role in a myriad of agricultural and infrastructural applications, encompassing surveillance, and observation, spraying, etc., yet challenges persist in the realm of limited payload distribution and insufficient operation time, particularly when dealing with large acres of farmland and multiple tasks [1], [2], [3], [4]. The utilization of multiple UAVs in a swarm configuration allows for distributed payload and task capabilities, thereby extending the overall flight duration. However, UAVs forming a swarm pose issues related to formation and localization, especially in the presence of GPS-denied zones. The leader-follower drone system presents a formidable obstacle, necessitating innovative solutions for formation control to address such localization challenges. Previous research survey provides a thorough examination of vision-based techniques utilized in Unmanned Aerial Vehicle (UAV) navigation [5], [6], [7].

The literature encompasses three studies on vision-based target detection, localization, and obstacle tracking utilizing Unmanned Aerial Vehicles (UAVs). The first study ([6]) proposes a novel system employing a cooperative team of UAVs and Unmanned Ground Vehicles (UGVs) for target detection and localization in border areas. It employs a customized motion detection algorithm on the UAV-mounted camera to track crowds, with UGVs serving as individual human detectors due to their higher resolution and fidelity. This approach effectively localizes crowds with unknown movement patterns. The ref. [8] research addresses UAV localization using vision-based methods, leveraging georeferenced aerial images. As UAVs gain popularity for various applications, the paper introduces a vision-only localization algorithm. However, it acknowledges the challenge of robustness inherent in vision-based algorithms. In ref. [9], it concentrates on vision-based obstacle detection and tracking for UAV navigation in real-time scenarios. It presents a strategy integrating object detection and tracking using a dynamic Kalman model. The detection phase utilizes a saliency map to locate objects, while the tracking phase employs a Kalman filter for coarse prediction and a local detector for refinement using temporal information between frames. These studies collectively contribute to advancing vision-based techniques for UAV applications, addressing challenges in target detection, localization, and obstacle tracking, with implications for various domains including surveillance, border security, and aerial navigation [9], [10]. By synthesizing existing literature on key components such as visual localization and mapping, obstacle avoidance, and path planning, comprehensive overview of the field, the article delves into the methodologies, advancements, and challenges associated with vision-based UAV navigation. Additionally, it provides insights into the future prospects of UAV navigation while delineating the hurdles that lie ahead in leveraging vision-based approaches effectively. Through this survey, readers gain a nuanced understanding of the current state-of-the-art and the evolving landscape of vision-based UAV navigation.

In addressing these challenges, our research introduces a vision-based relative navigation algorithm for leader-follower formation control. This approach employs machine vision methods for localization with blob operation and machine learning object detection, enabling the follower UAV to seamlessly track the leader. Furthermore, the follower UAV can transmit its relative position to the leader UAV, facilitating mutual localization. In this project, vision-based relative navigation and drone swarming control for inspection in GPS-denied environment has been investigated and applied on Webots simulation environments [11]. To validate the efficacy of our proposed method, we conducted experiments wherein Agricultural UAVs were modelled and implemented in Webots environments. Specifically, the leader UAV was subjected to a GPS-denied zone, prompting the follower UAV to send relative position data to aid in re-localization and restore the desired position. This innovative vision-based approach holds promise for enhancing the autonomy and localization capabilities of Agricultural UAVs in challenging operational environments.

This paper is organised as follows: Methodology section presents an overview of Modelling of the UAV, position-based formation control and vision-based localisation. The next section shows the scenario and the results of the UAV localisation. Finally, conclusion section summarises the main results and ideas for future work.

Methodology

In this section, commercial DJI Tello UAV linear model ([1], [12], [13]), leader follower formation and vision-based localisation have been explained.

In Figure 1, DJI Tello UAV and its coordinate systems have been shown. In the figure, Ω_i is the angular velocity of rotor i. Position and the orientation of the UAV is $\mathrm{p} = [x, y, z]$ and $\mu = [\phi, \theta, \psi]$, respectively.

In Eq. (1), the inputs of the dynamical equations of the UAV (U_i) have been defined using thrust force and orientation torques ($\tau_\phi, \tau_\theta, \tau_\psi$).

$$U = [U_1 \quad U_2 \quad U_3 \quad U_4]^T = \left[F_{thrust}^B \quad \tau_\phi \quad \tau_\theta \quad \tau_\psi\right]^T \tag{1}$$

The thrust has been determined to overcome from the gravity effects. Therefore, mass of the UAV (m) and gravity (g) have been considered in the equation. Moreover, altitude of the UAV has been determined with the dynamical equation and it is shown in Eq. (2).

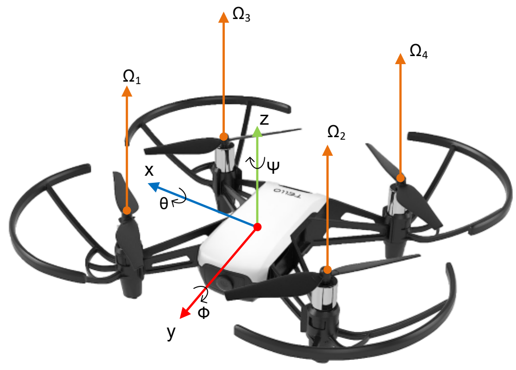

Figure 1. DJI Tello UAV ([14])

$$U_1^0 = \sum_1^4 \Omega_i^2 = mg, \quad \Omega_i^0 = \sqrt{\frac{mg}{4b}} =: \Omega_h \tag{2}$$

After that, detailing of the dynamical equation of the UAV in terms of thrust and torques, the Eq. (3) can be written. It is remarked x-mode flying mode has been used in DJI Tello UAV. In the equation, l distance from center of the UAV mass, b thrust coefficient and d is the drag coefficient of the rotor.

$$U = \begin{bmatrix} U_1 \\ U_2 \\ U_3 \\ U_4 \end{bmatrix} = \begin{bmatrix} b & b & b & b \\ 0 & -bl & 0 & bl \\ -bl & 0 & bl & 0 \\ -d & d & -d & d \end{bmatrix} \begin{bmatrix} \Omega_1^2 \\ \Omega_2^2 \\ \Omega_3^2 \\ \Omega_4^2 \end{bmatrix} \tag{3}$$

In this project, the leader-follower formation system has been designed. In Figure 2, red and blue UAVs have been defined as leader and follower, respectively. Then, to calculate the relative distance for desired formation, the actual positions have been used.

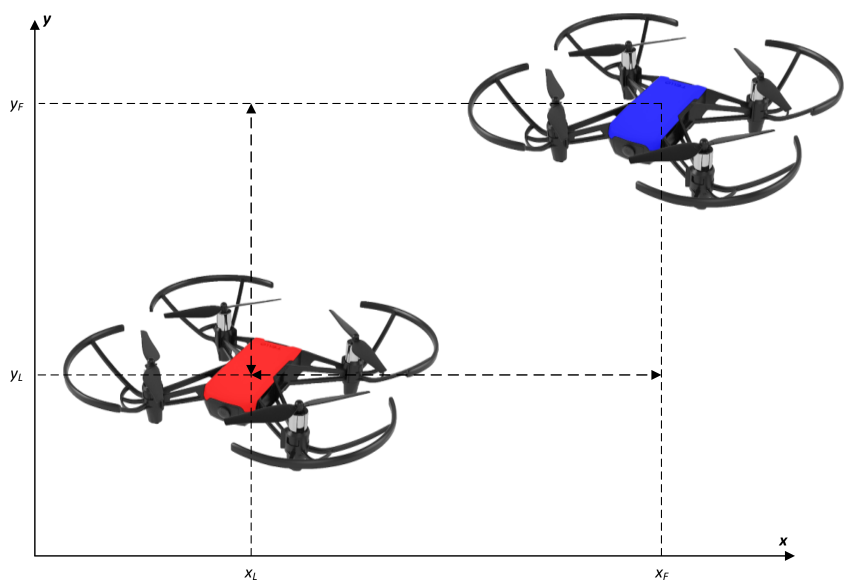

Figure 2. Leader-Follower System

In the Figure 2, leader and follower positions have been defined as (x_L, y_L) and (x_F, y_F), also relative distance between leader follower is (x_r, y_r). In Eq. (4) and (5), relative position and velocity calculations have been written for distance-based formation control [15], [16].

$$\begin{bmatrix} x_r \\ y_r \end{bmatrix} = \begin{bmatrix} \cos(\Psi_L - \Psi_F) & -\mathrm{dsin}(\Psi_L - \Psi_F) \\ -\sin(\Psi_L - \Psi_F) & -\mathrm{dcos}(\Psi_L - \Psi_F) \end{bmatrix} \begin{bmatrix} |x_L - x_F| \\ |y_L - y_F| \end{bmatrix} \tag{4}$$

$$\begin{bmatrix} v_{ry} \\ v_{ry} \end{bmatrix} = \begin{bmatrix} \cos(\Psi_L - \Psi_F) & -\mathrm{dsin}(\Psi_L - \Psi_F) \\ -\sin(\Psi_L - \Psi_F) & -\mathrm{dcos}(\Psi_L - \Psi_F) \end{bmatrix} \begin{bmatrix} v_L - v_F \\ w_L - w_F \end{bmatrix} \tag{5}$$

Figure 3 represents vision-based localization methods for the leader-follower systems under GPS-denied zone. In GPS-denied zone, the GPS sensor values have not given accurate data. To eliminate the error and faults, camera-based localisation has been presented. In the Fig.3, camera field of view is limitation of the detection and region of interest shows the leader position as pixels.

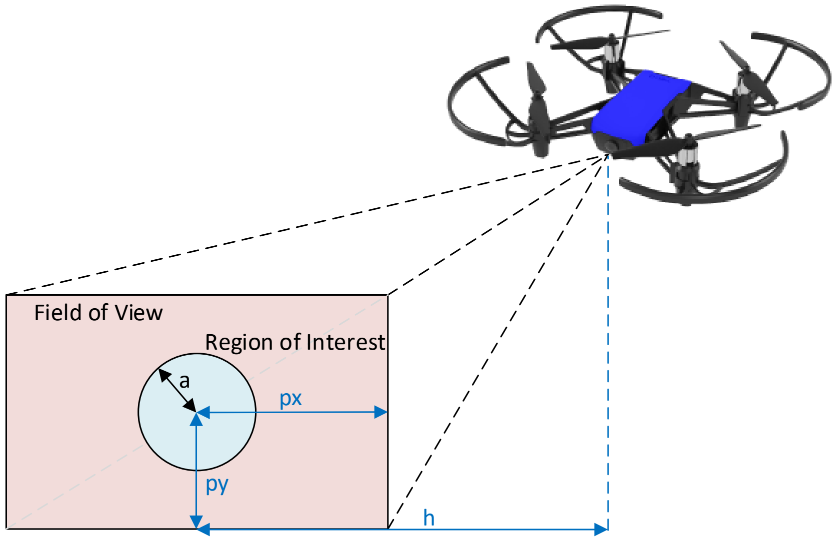

Figure 3. Vision-based localization representation

For the position detection, Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used [17]. The input features of the system are pixel x (px), pixel x (py) and radius (a) and the outputs are x-y positions of the leader UAV.

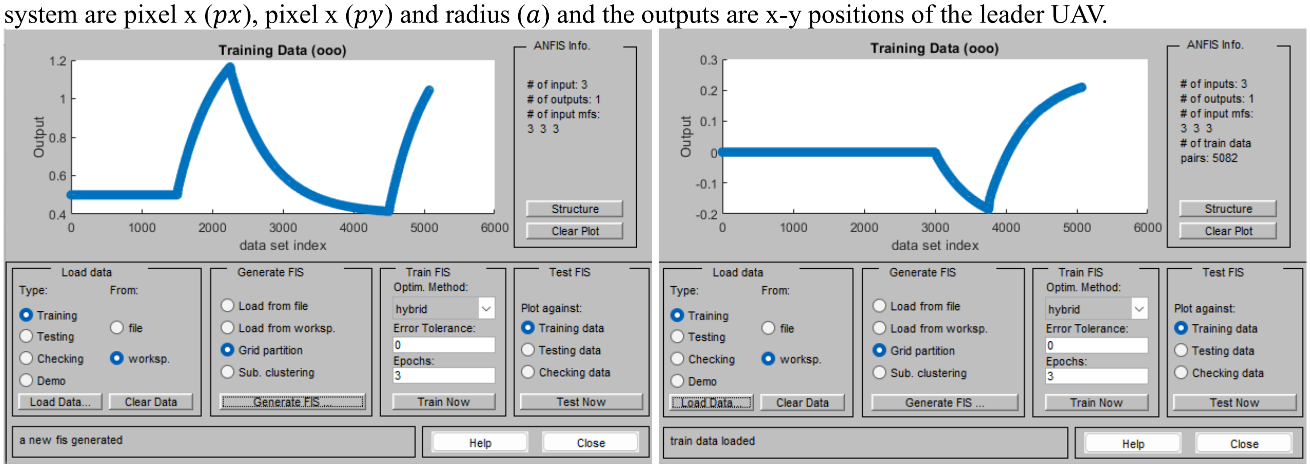

Figure 4. ANFIS Training

In Figure 4, the membership function of ANFIS has been selected as 3x3 triangular. In addition, epoch number has been fixed to 3. It is noticed that each position has been calculated separately. Takagi-Sugeno-Kang fuzzy method has been implemented and crisp singular value has been generated as an output.

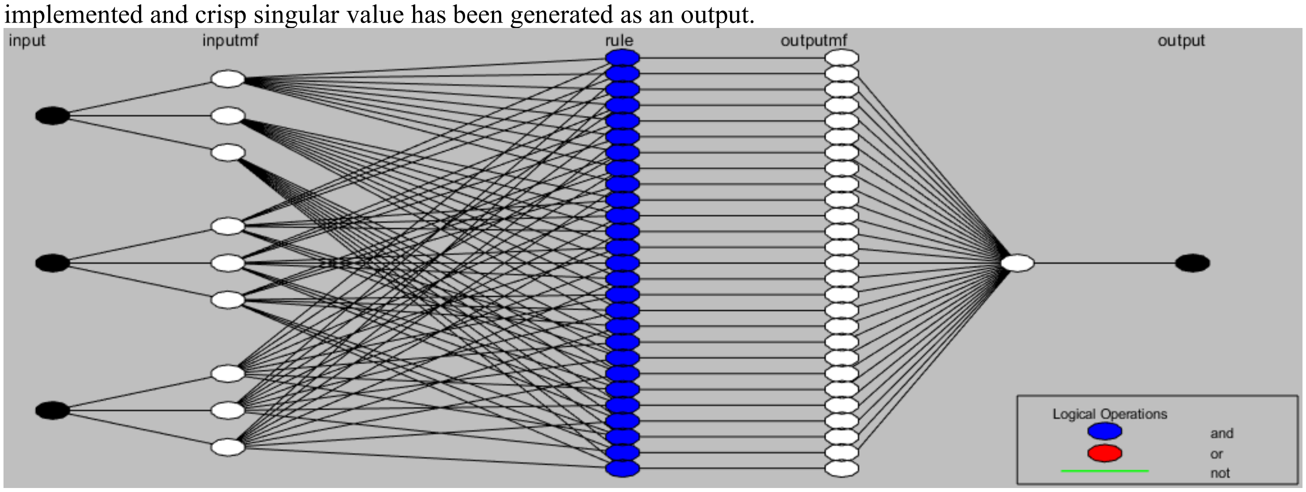

Figure 5. Illustration of the proposed ANFIS Control Structure

In Figure 5, ANFIS structure has been shown. The structure and training have been run on Windows operating system under Intel i7 CPU, 64 GB RAM and RTX 2060Ti GPU.

Simulation Results

After the methodology, scenario and position results have been explained in this section. In Figure 6, the application scenario in Webots environment has been shown, where Leader (red) UAV and its front camera monitor, follower UAV and its front camera monitor, and test area have been represented respectively.

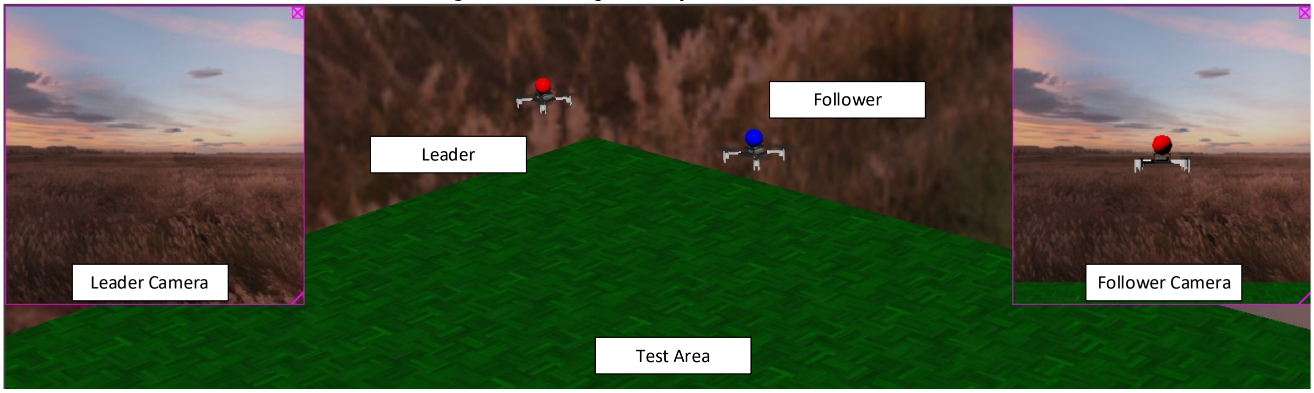

Figure 6. Application scenario in Webots environment

After the designing scenario, data-driven methods have been designed and employed into follower UAV. In Table 1, 5 random selected data have been evaluated. The total collected data has been 5000. It is noted that, pixel x (px), pixel y (py) and radius (a) measure as a pixel data from the camera. Moreover, actual x and actual y are defined as meter and collected from GPS sensor. For the data collecting and testing, Python 3.11 has been used, MATLAB with ANFIS has been used for training and modelling of the position-based localization.

Table 1. Randomly selected some of the collected data

Index	Pixel x (px)	Pixel x (py)	Radius	Actual x	Actual y
1	198	172	10	0.52	0
5	162	150	11	0.53	-0.001
1636	162	154	7	0.691	-0.001
2538	198	174	12	0.852	-0.002
4134	90	76	5	0.418	0.106

In Figure 7, the data-driven modelled results have been plotted separately as x and y axis. In the figure, black lines define actual position of the leader UAV, the red lines define predicted position of the leader UAV.

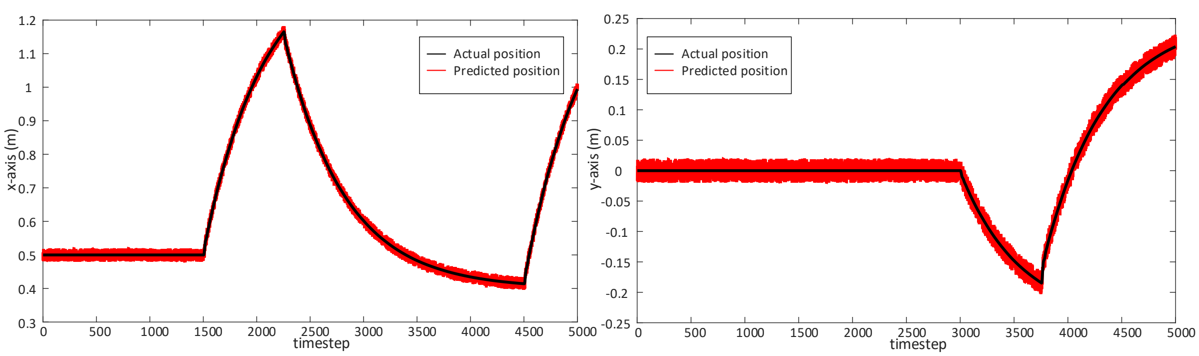

Figure 7. Actual and predicted position results

Considering the output results the root-mean-square-error (RMSE) values can be written 0.0687017 and 0.0687251 for x and y axis, respectively. The result shows that the proposed leader-follower drone swarm formation and the and the vision-based relative navigation and ANFIS control scheme is effective for GPS-denied navigation and inspection operations in a reliable fashion.

Conclusion and Future Works

In conclusion, Unmanned Aerial Vehicles (UAVs) are indispensable tools across various agricultural applications, despite facing persistent challenges such as limited payload distribution and operation time, especially in large farmlands and multifaceted tasks. The adoption of multiple UAVs in a swarm configuration presents a viable solution, enabling distributed payload and task capabilities to extend flight duration. However, issues arise concerning formation and localization within

UAV swarms, particularly in GPS denied zones, necessitating innovative solutions for formation control. Our research addresses these challenges by introducing a vision-based relative navigation algorithm for leader-follower formation control, leveraging machine vision techniques and machine learning object detection. This approach enables seamless tracking of the leader UAV by the follower UAV and facilitates mutual localization through the transmission of relative position data. Through experimentation in simulated environments, we validated the efficacy of our proposed method, demonstrating its potential to enhance the autonomy and localization capabilities of Agricultural UAVs in challenging operational settings. This innovative vision-based approach marks a significant step forward in advancing the capabilities of Agricultural UAVs for improved efficiency and effectiveness in agricultural practices.
After the data-driven methods, the state estimation filters such as Kalman filter, Maximum correntropy Kalman filters will be merged with data-driven models. Moreover, vision relative navigation methods using GPU will be applied and tested on real-world environments.

Acknowledgements

The authors would like to acknowledge the funding support from NSF award (2139025): Drones-Enabled Active Sensing System (DEASS) for Detection of Subsurface Defects in Civil Infrastructure through Synchronized Drone Swarming and Thermal Imaging.

References

[1]F. Candan, O. F. Dik, T. Kumbasar, M. Mahfouf, and L. Mihaylova, ‘Real-Time Interval Type-2 Fuzzy Control of an Unmanned Aerial Vehicle with Flexible Cable-Connected Payload’, *Algorithms*, vol. 16, no. 6, Art. no. 6, Jun. 2023, doi: 10.3390/a16060273.

[2]H. Chen, X. Wang, and Y. Li, ‘A survey of autonomous control for UAV’, in *2009 International Conference on Artificial Intelligence and Computational Intelligence*, IEEE, 2009, pp. 267–271. Accessed: Apr. 05, 2024. [Online].

[3]S. J. Chung, A. A. Paranjape, P. Dames, S. Shen, and V. Kumar, ‘A Survey on Aerial Swarm Robotics’, *IEEE Trans. Robot.*, vol. 34, no. 4, pp. 837–855, 2018.

[4]G. Skorobogatov, C. Barrado, and E. Salamí, ‘Multiple UAV Systems: A Survey’, *Unmanned Syst.*, vol. 08, no. 02, pp. 149–169, Apr. 2020, doi: 10.1142/S2301385020500090.

[5]Y. Lu, Z. Xue, G.-S. Xia, and L. Zhang, ‘A survey on vision-based UAV navigation’, *Geo-Spat. Inf. Sci.*, vol. 21, no. 1, pp. 21–32, Jan. 2018, doi: 10.1080/10095020.2017.1420509.

[6]S. Minaeian, J. Liu, and Y.-J. Son, ‘Vision-based target detection and localization via a team of cooperative UAV and UGVs’, *IEEE Trans. Syst. Man Cybern. Syst.*, vol. 46, no. 7, pp. 1005–1016, 2015.

[7]Y. Xu, L. Pan, C. Du, J. Li, N. Jing, and J. Wu, ‘Vision-based UAVs Aerial Image Localization: A Survey’, in *Proceedings of the 2nd ACM SIGSPATIAL International Workshop on AI for Geographic Knowledge Discovery*, Seattle WA USA: ACM, Nov. 2018, pp. 9–18. doi: 10.1145/3281548.3281556.

[8]Y. Wu, Y. Sui, and G. Wang, ‘Vision-based real-time aerial object localization and tracking for UAV sensing system’, *IEEE Access*, vol. 5, pp. 23969–23978, 2017.

[9]A. Yol, B. Delabarre, A. Dame, J.-E. Dartois, and E. Marchand, ‘Vision-based absolute localization for unmanned aerial vehicles’, in *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*, IEEE, 2014, pp. 3429–3434. Accessed: Apr. 05, 2024.

[10]‘Adaptive Vision-Based Leader–Follower Formation Control of Mobile Robots | IEEE Journals & Magazine | IEEE Xplore’. Accessed: Dec. 31, 2023. [Online].

[11]‘Cyberbotics: Robotics simulation with Webots’. Accessed: Dec. 31, 2023. [Online]. Available: https://cyberbotics.com/

[12]S. Abdelmoeti and R. Carloni, ‘Robust control of UAVs using the parameter space approach’, in *2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, IEEE, 2016, pp. 5632–5637. Accessed: Apr. 05, 2024. [Online].

[13]F. Candan, A. Beke, and T. Kumbasar, ‘Design and Deployment of Fuzzy PID Controllers to the nano quadcopter Crazyflie 2.0’, in *2018 Innovations in Intelligent Systems and Applications (INISTA)*, Jul. 2018, pp. 1–6. doi: 10.1109/INISTA.2018.8466284.

[14]‘Tello’. Accessed: Apr. 05, 2024. [Online]. Available: https://www.ryzerobotics.com/tello

[15]D. V. Dimarogonas and K. H. Johansson, ‘On the stability of distance-based formation control’, in *2008 47th IEEE Conference on Decision and Control*, IEEE, 2008, pp. 1200–1205. Accessed: Apr. 05, 2024. [Online].

[16]S.-M. Kang, M.-C. Park, B.-H. Lee, and H.-S. Ahn, ‘Distance-based formation control with a single moving leader’, in *2014 American Control Conference*, IEEE, 2014, pp. 305–310. Accessed: Apr. 05, 2024. [Online].

[17]‘Tune Sugeno-type fuzzy inference system using training data - MATLAB anfis’. Accessed: Apr. 05, 2024. [Online]. Available: https://www.mathworks.com/help/fuzzy/anfis.html