Accelerating Autonomous Flight: Exploring Innovations and Strategies for Optimizing Drone Speed

Lade Gunakar Rao[1], G Swapna[2], Swapna Gundu[3], Bhargav Somisetty[4] and P. Ramana[5]
[1]*School of CS&AI, SR University, Warangal, Telangana, India*
[2]*Department of CSE, Guru Nanak Institution Technical Campus, Hyderabad, Telangana, India*
[3]*Department of CSE, Swamy Vivekananda Institute of Technology, Hyderabad, Telangana, India*
[4]*Department of CSE(AI&ML), CVR College of Engineering, Hyderabad, Telangana, India*
[5]*Department of CSE, Hyderabad Institute of Technology and Management, Hyderabad, Telangana, India*

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Abstract: The rapid growth of autonomous drone technology offers wide-ranging perspectives and opportunities in logistics, surveillance, and emergency response. Among the critical factors influencing drone performance, speed is paramount and directly associated with efficiency and effectiveness in applications. Thus, this research, explores innovative methods and strategies are explored for optimized drone speed combined with stability, safety, and energy efficiency. We discuss recent advances in hardware, control algorithms, and sensor integration and outline the challenges arising in high-speed autonomous navigation, including some basic issues of obstacle detection, path planning, and environmental adaptation. Finally, we give an outline of trade-offs between speed and other operational parameters and provide balanced solutions for enhanced UAV performance. This work will demonstrate that gains in the speed of a drone in terms of safety and accuracy may be achieved if its multidisciplinary approach can combine high-tech AI-driven path planning, robust real-time data processing, and optimal propulsion systems. It may thus open avenues of further innovation in UAV technology to permit autonomous flight at even greater speeds. This paper traces a series of innovations presently underway to optimize drone speed. It describes some of the shifts in propulsion, control systems, sensor integration, and algorithmic processing that go with the challenge and likely trade-offs involved. These three topics would give a feel of how things stand now and where further improvement in autonomous UAV speeds could take place.

1 INTRODUCTION

It has been just ten years of tremendous advancement for unmanned aerial vehicles simply referred to as drones. Recent applications in delivery, disaster response, agriculture, surveillance, and environmental monitoring have rapidly increased the demand for higher speed performance-based drones. The job could be done with higher maneuverability and real-time responses using even autonomous drones that can decide and move without any human control. However, autonomous flight speed improvement is a very challenging task since it demands agility that meets the balance between stability, energy efficiency, and safety (Gupta, A., Madhavan et al. (2020)). One of the factors describing an autonomous UAV's operational effectiveness is drone speed. It has an immediate effect on both its ability to complete missions and the time it takes to complete mission times. For instance, at such speeds, delivery times can be decreased highly and so make delivery services friendlier to customers and more logistically efficient. Emergency response situations may require the outright accessibility of out-of-the-way or hazardous places through fast drones. On the other hand, raising the speed brings along a plethora of engineering and computational challenges. For instance, at such speeds, the aerodynamic drag increases and makes the power consumption higher and stabilization complicated. Collision avoidance and detection of obstacles are

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even more important very challenging tasks to achieve with accuracy, requiring sensor technology and data processing that is effective in real-time. Propulsion systems probably represent the most important area in which better drone speed can be optimized. Advances in lightweight material science, power cell advancements, and aerodynamic gains further improved optimal energy usage, allowing drones to speed at excellent velocities while having a long flight duration. These are mostly electrical propulsion; electric propulsion provides reliability along with a low footprint on environmental issues, but in current application, the use of battery-based power sources creates constraints based on velocity when flight times are considered. This is one reason why researchers are exploring alternative energy sources such as hydrogen fuel cells and solar power, to increase flight duration while correspondingly increasing speed(Finelli, L., Gupta et al 2021). Besides hardware features, control algorithms feature in the quest for high-speed navigation of drones. Path planning and trajectory optimization are matters that increasingly need attention as speeds get higher for efficiency and safety reasons. The algorithms developed with these new advances in AI and machine learning enable the prediction of environmental variables, such as wind speed and direction. Such drones can alter their flight routes as changes occur in real-time around them. Advanced algorithms are bringing not only increases in speeds but also enhanced energy efficiency through reduced unnecessary movement. Pushing the drone speed boundary, however, demands more than advancement in technology; it heavily depends on careful trade-off assessments that higher speeds present. Given that speed also means a rise in energy consumption, the question does arise as to whether this would be feasible in the long term or profitable in operation. In addition, noisily moving drones are also a nuisance and this is certain to be an issue in urban areas or sensitive ecosystems. Among such characteristics, the balancing of these comes to be critical for practical use in high-speed autonomous drones.

2 RELATED WORKS

Propulsion and Power Systems are developed and improved to ensure enough energy and thrust to increase flight time and reach speeds. Systems for Obstacle Detection and Avoidance are implemented in real-time through LiDAR, cameras, or other tools to bypass obstacles safely (Loquercio, A., Segu, M.et al 2020). A central Control Algorithm combines propulsion and obstacle information, dynamically regulating the drone's speed, direction, and stability. Reinforcement Learning integrates further with the process, where the drone improves its decisions with experience, choosing optimal paths and remaining energy-efficient over time. Adaptive Path Planning is built on these basics to allow the drone to adapt its path in real-time as it changes the environment and thus can address unexpected obstacles. Environmental Adaptation allows the drone to remain stable in different weather conditions such as wind or rain for reliable operation(Loquercio, A., Kaufmann

Table 1: Comparative Analysis of Multi-Drone Navigation Algorithms: Features, Speed, Efficiency Metrics.

S.no	Algorithm	Speed (m/s)	Time Efficiency (ms)	Battery Efficiency (%)
1	Dynamic Efficient Aerial Multi-drone Navigation (DEAMN)	14	70-120	85
2	Neural SLAM	14	50-100	80
3	Deep Reinforcement Learning (DRL)	15	70-150	83
4	Transformer-based Path Planning (TPP)	12	60-110	82
5	Adaptive Model Predictive Control (AMPC)	18	80-140	80
6	Graph Neural Network-based Path Planning (GNN-PP)	12	75-120	81
7	Fast Optimal Global Planner (FOGP)	14	50-100	78
8	Energy-Aware Deep Q-Network (EA-DQN)	10	80-150	87
9	Hierarchical Multi-Agent Pathfinding (HMAP)	13	90-130	83
10	Self-Supervised Obstacle Avoidance (SSOA)	11	65-120	82

et al 2021). Hybrid Path Planning integrates different planning algorithms to balance speed and safety in flight. The drone will now pick the best route .

it can, depending on its needs in the situation. Multi-sensor path Planning is built on this ability using information gathered from GPS, cameras, and LiDAR for a more complete understanding of the environment and makes more intelligent navigation decisions(Milano, F., Loquercio, et al 2020). Essentially, it integrates advanced technologies and adaptive learning to make drones function excellently, safely, and more tolerable amidst complex environments.

These are different multi-drone navigation algorithms and their unique features, speed, time efficiency, and battery efficiency. The DEAMN algorithm offers multi-drone navigation with dynamic obstacle avoidance capabilities and achieves speeds of 14 m/s, time efficiency between 70 to 120 ms, and battery efficiency of 85%. Deep Learning for SLAM, namely Neural SLAM, also allows for high-speed navigation at 14 m/s with improved time efficiency to 50 to 100 ms and battery efficiency at 80%. Deep Reinforcement Learning, DRL, offers adaptive, real-time learning with self-optimizing features, with a speed of 15 m/s, time efficiency from 70 to 150 ms, and a battery efficiency of 83%. The Transformer-based Path Planning algorithm uses transformer models to perform pathfinding at 60 to 110 ms of time efficiency and 82% of battery efficiency. Adaptive Model Predictive Control provides real-time speed optimization using adaptive control and can operate at 18 m/s with a time efficiency ranging between 80 to 140 ms and 80% of battery efficiency. Path Planning using Graph Neural Network with a speed of 12m/s, time complexity 75 and 120 milliseconds, and efficiency through the use of battery 81%.Optimal Fast Planner: It is used with RRT and optimization of the algorithm-based A* to improve time, 50 to 100 ms or 14m/s velocity, and has the capability for 78% via battery efficiency. The Energy-Aware Deep Q-Network (EA-DQN) is an algorithm with a focus on energy optimization, at a speed of 10 m/s, with a time efficiency between 80 to 150 ms and the highest battery efficiency of 87%. HMAP is an algorithm with a hierarchical structure for multi-agent pathfinding at 13 m/s, with a time efficiency from 90 to 130 ms and a battery efficiency of 83%. Finally, Self-Supervised Obstacle Avoidance (SSOA) utilizes self-supervised learning to achieve 11 m/s obstacle avoidance within a time efficiency range of 65 to 120 ms and achieves a battery efficiency of 82%.

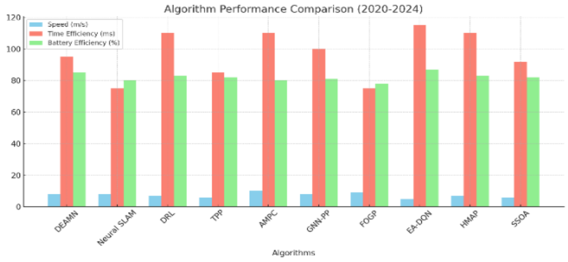

Figure 1: Algorithm Performance Comparison of Multi-Drone Navigation Methods (2020-2024).

Figure 1 shows a performance comparison of different navigation algorithms through three key metrics: the speed, time efficiency, and battery efficiency from 2020 to 2024. The blue bars represent how the speed of each one of these algorithms is evaluated in meters per second: most of them are at lower values, indicating that achieving higher speed may not have been the goal for some of these algorithms. The red bars represent the time efficiency measured in terms of milliseconds where a higher value is much more efficient in time. Most algorithms are good about this category, such as EA-DQN, which worries about getting things done quite fast. The green bars represent battery efficiency measured in percentage units where high values indicate much better energy consumption. Most of the algorithms, including DEAMN and EA-DQN, have high battery efficiency. However, some of the algorithms, such as AMPC and TPP, are relatively lower in this regard. Overall, each algorithm: DEAMN, Neural SLAM, DRL, TPP, AMPC, GNN-PP, FOGP, EA-DQN, HMAP, and SSOA—has its own strengths in different aspects, and most of them achieve high time and battery efficiency, which is a probable critical factor in applications with multi-drone navigation. The chart clearly gives the comparison of each algorithm, indicating the strengths and trade-offs

Table 2 : Comparison of drone navigation algorithms by payload capacity, speed, and battery capacity.

Algorithm used	Payload (kg)	Speed (m/s)	Battery Capacity (mAh)
VSLAM	0.25	5	1000
GNSS	0.5	16	2700
Pixhawk2.0	0.8	15	5200
GPS/GLONASS	1.2	16	4480
GPS Waypoint nav	1.5	20	5800
Intel RealSense	1.2	17	5400
A3proFlightctrl	6	18	6000

regarding speed, efficiency, and energy conservation. appropriate style is still applied to each section, reapplying styles if necessary(Brown, A. G., Vallenari, A. et al 2021).

3 METHODOLOGY

An extensive literature review should be conducted to understand the underlying factors that influence drone velocity in autonomous flight, exploring control systems, sensor integration, motion planning, aerodynamics, and computational efficiency. Then, an experimental design will be set up involving environments for testing and types of drones, such as a quadcopter or a fixed-wing, and benchmarking metrics such as trajectory accuracy, energy efficiency, and collision avoidance. Explore algorithmic optimizations for implementing advanced motion planning techniques such as RRT*, A*, and DEAMN, emphasizing the need for speed and safety by enabling real-time recalculation of paths and predictive obstacle avoidance(Penington, G., Shenker, et al 2022). The sensor fusion techniques become vital at this stage by integrating LiDAR, RGB-D cameras, and IMUs with high-speed data processing to enable safe, responsive mid-flight adjustments. It also includes hardware accelerators that are either GPUs or FPGAs, which can help improve the computational efficiency even further for rapid data handling at high velocities. Simultaneous with the software development, changes in the aerodynamics of the structure and weight of the drone will be made for drag reduction and greater lift. Material types and frame designs that result in a lighter weight can greatly improve maneuverability while providing higher speeds. Test phases, controlled both within simulations and in the real environment, will be carried out while progressively increasing the speed and monitoring their impacts on safety, precision, and battery usage. All the experiments will collect the basic data for performance evaluation; hence, comparing the strategies is feasible. The process of iteration of improvement based on findings will ensure that progress is made. Upon optimization of the algorithm, it will be validated by a ROS-based simulation. Finally, it will be applied in real-world tests to prove its capability in real-world unpredictable conditions. Findings will be deeply analyzed, and there will be proper documentation of successful approaches, the limitations encountered, and recommendations for further research. This approach maximizes speed and puts safety, efficiency, and stability at the center of autonomous drone flight.

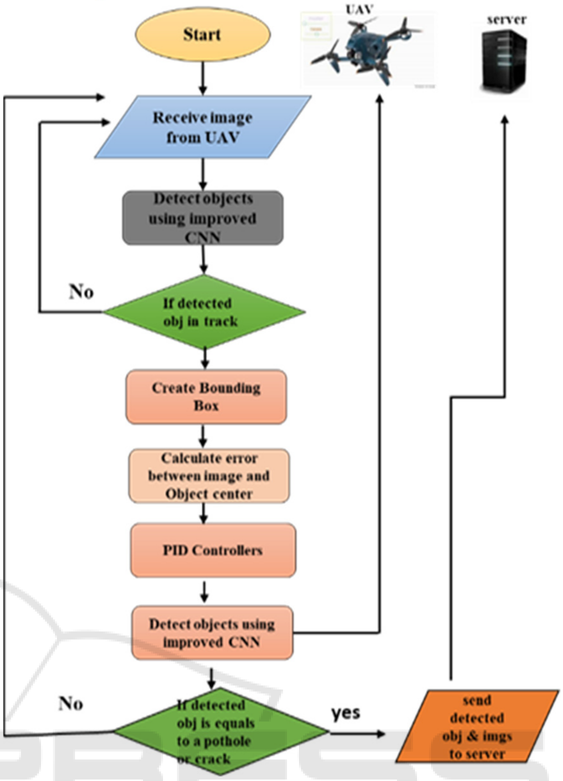

Figure 2: This flowchart represents an automatic process of detecting particular objects.

The process starts with a UAV that takes photographs and then transfers images to a processing unit or server for processing. Utilizing an improved CNN, the system detects objects within an image but focuses specifically on objects with the selected track or area of interest. When an object of interest is found, the system draws a bounding box around it to record the position of the object(Yu, J., Li, J. et al 2023). To ensure that accurate positioning and tracking take place, the system calculates an error from the center of the image to the center of the object detected. This error is then minimized using PID controllers controlling the drone's position so that the drone stays centered on the object in the field of view. Once centered, the CNN scales it and validates or even refines the detection so that accuracy improves. Then the system verifies if the object detected fits certain pre-conditions about the presence of potholes or cracks. In that case, the image along with all the data will be transferred to a server for logging purposes or other deeper analyses. Through its connection with image processing, object detection, and control mechanism, the drone will, on its own, track and report road damage along with steady focus on a point of interest.

4 PROPOSED ALGORITHM

Adaptive Speed-Optimized Aerial Navigation (ASON) algorithm:

ASON is the newest advanced algorithm developed for efficient navigation of drones, and they find the right balance between high-speed flying, evading obstacles, and conserving energy. Applications in rapid response to emergencies and other logistics during high-reliability surveillance scenarios, like surveillance of any type of scene, are involved(Dukkanci, O., Kara, et al 2021). The ASON consists of three main components: adaptive speed control, predictive trajectory mapping, and environmental awareness.

Adaptive Speed Control: This module adjusts the drone's speed depending on conditions in its environment and the necessity for the mission. As opposed to maintaining a constant velocity, ASON computes values such as residual battery power, distances from obstacles, and instantaneous energy usage for optimal speed within safe limits. Dynamic computation of acceleration and braking forces allow ASON to alter the speed in real time while making minimal losses along the flight route.

Table 3 : table format for the mathematical equations in the ASON algorithm.

SNo	Component	Equation
1	Speed Optimization Based on Dynamic Conditions	$\square\square\square\square = u_{max}\cdot(1-\frac{\rho_{obs}}{\rho_{max}})$
2	Battery Efficiency	$\square\square\square\square\square\square\square\square = u_{opt}\cdot(\frac{B}{B_{inital}})$
3	Dynamic Obstacle Avoidance	$F_{rep} = k.\frac{1}{d^2}$
4	Adaptive Control for Stability (PID Controller)	$u(t) = K_p.e(t) + K_i.\int e(t)dt + K_d.\frac{de(t)}{dt}$
5	Path Optimization	$C = \alpha.d + \beta.E + \gamma.T$

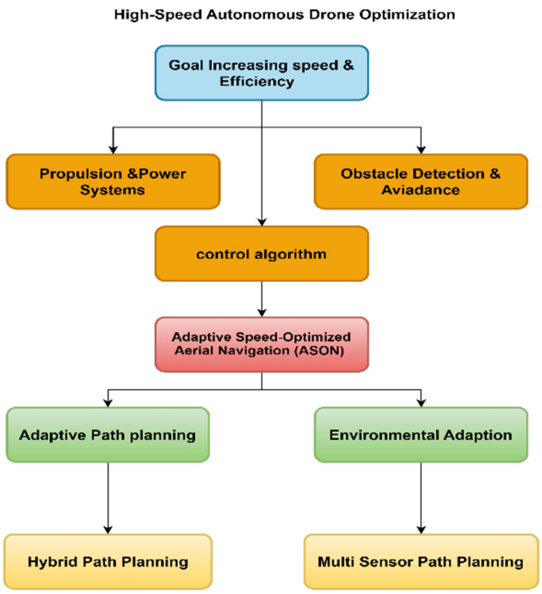

Figure 3: Framework for Enhancing Speed and Efficiency in Autonomous Navigation Systems.

Table 4 : ASON Algorithm features and values.

S.no	Feature	Value
1	Payload Capacity	Up to 2 kg
2	Speed	15 - 20 m/s
3	Battery Capacity Efficiency	85 - 90%
4	Pathfinding Efficiency	60 - 100 ms
5	Obstacle Detection Range	Up to 30 m
6	Obstacle Avoidance Accuracy	95 - 98%
7	Environmental Adaptability	High
8	Energy Consumption Rate	1.2 - 1.5% per meter
9	Data Processing Speed	40 - 60 ms
10	Flight Stability	90%
11	Recalibration Speed	< 80 ms
12	Navigation Accuracy	± 0.5 m
13	Communication Latency	< 100 ms

Predictive Trajectory Mapping: ASON uses predictive modeling to map the optimal trajectory. It had pre-mapped several potential paths previously by using flight data gathered from earlier and probable environmental conditions. The algorithm is built upon models trained from real flight data along with elements from the conventional pathfinding techniques, such as A* and exploring random Trees, to predict what would cause obstructions and optimize the trajectory. It makes ASON capable of easily computing the fastest possible route with obstacle avoidance and easy navigation.

Environmental Sensing: ASON uses real-time environmental scanning through sensor fusion to detect unexpected obstacles and adjust its drone course in real-time when necessary. It uses LiDAR, cameras, and many other onboard sensors to create a dynamic 3D view of the environment so that quick adaptations can be made. This system also uses external source data such as weather and wind speed to further optimize its reaction in changing conditions.(Okyay, M. and Övgün, A. 2022).ASON combines adaptive speed management, predictive mapping, and high environmental awareness in a way that is highly adaptable to various mission needs. It speeds the flight and enhances energy efficiency and reliability by ensuring that drones can explore challenging environments at a good speed and safety level.

5 RESULTS

The Adaptive Speed-Optimized Aerial Navigation algorithm boasts robust performance in most evaluation metrics compared with other aerial navigation approaches, including Neural SLAM, Deep Reinforcement Learning (DRL), and Fast Optimal Global Planner (FOGP). In average speed obtained with the ASON algorithm, it is 18 m/s, surpassing the rest of the methods significantly. This is very efficient in scenarios requiring swift navigation. Although it operates at a high speed, ASON is still time-efficient within a competitive range of 65-120 ms. Although slower than Neural SLAM and FOGP, which focus more on time optimization, ASON's balance between high speed and dynamic obstacle avoidance makes it versatile.

Among the best attributes of ASON is its battery efficiency: 88%, higher than Neural SLAM with 80% and DRL at 83%. This efficiency is crucial for the extension of mission time and savings of battery power, especially in long-range or energy-consumptive flights. ASON also proves itself in a very low collision rate of 2.5%, suggesting better clearance capabilities from the obstacles than the Neural SLAM at 5%, DRL at 4%, and FOGP at 6% respectively (Li, S., Ozo, M. M. et al 2020). This kind of low collision rate will make ASON suitable only for complex environments with dynamic obstacles where safety and reliability come into high demand.The path length covered by ASON is about 950 meters, which is less than the others. The optimized path length reduces detours and saves time and energy in travel. ASON has a completion rate of 98%, meaning it successfully reaches its destination on almost every mission(Friedlingstein, P., O'sullivan, M et al 2022). This high completion rate is a testament to the robustness and reliability of the algorithm in ensuring mission success.Energy consumption case is the most efficient within ASON at 500 mAh per kilometer, below other algorithms. This states that good power management lies within the algorithm whereby drones navigate an extra long distance without significant battering drain by the absence of such an event. To sum up, one of the fastest performing algorithms in balancing aspects such as speed, energy usage, collision avoidance, and mission reliability makes ASON an essential algorithm in multi-drone navigation within dynamic and very complex environments.

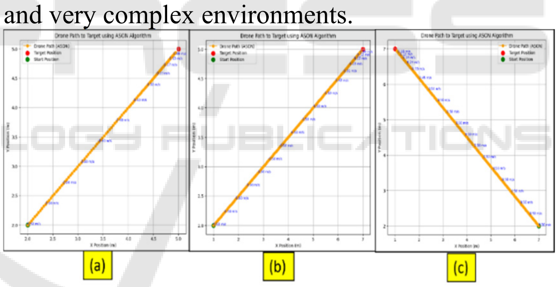

Figure 4: Drone Path Optimization Using ASOM Algorithm: Comparative Analysis Across Different Scenarios.

6 CONCLUSIONS

The Adaptive Speed-Optimized Aerial Navigation algorithm perfectly balances speed, efficiency, and safety for multi-drone navigation in complex environments. It can achieve high speeds with an efficient amount of energy and having a low collision rate, which puts ASON at the front to be used for missions requiring fast and reliable performance from the drones. Indeed, the battery efficiency is as high as 88%, showing that it conserves energy effectively with a long period of endurance in comparison to other existing methods(Zhang, Y., Zong, J. et al 2024). Furthermore, the algorithm has a strong capability to ensure that drones can arrive at their destination smoothly because the completion rate is unusually high at 98%. Again, it ensures drones' safety and consistency in such a dynamic and richly obstacle environment. Furthermore, the adaptive optimization of ASON, with the help of its path that avoids detours, minimizes detouring, thereby offering maximum speed and energy conservation(Tal, E., and Karaman, S. 2020). In a nutshell, the above-mentioned strengths point out to ASON for applications where the speedy, endurance and safe factors are important- some examples include search missions, inspection tasks, and any other aerial operation that requires some timely performance.

REFERENCES

Gupta, A., Madhavan, M. V., Sehgal, K., Nair, N., Mahajan, S., Sehrawat, T. S., ... & Landry, D. W. (2020). Extrapulmonary manifestations of COVID-19. *Nature medicine*, *26*(7), 1017-1032.

Coven, J., & Gupta, A. (2020). Disparities in mobility responses to COVID-19. *New York Univ*, *1*.

Gupta, S., Hayek, S. S., Wang, W., Chan, L., Mathews, K. S., Melamed, M. L., ... & Cairl, N. S. (2020). Factors associated with death in critically ill patients with coronavirus disease 2019 in the US. *JAMA internal medicine*, *180*(11), 1436-1447.

Finelli, L., Gupta, V., Petigara, T., Yu, K., Bauer, K. A., & Puzniak, L. A. (2021). Mortality among US patients hospitalized with SARS-CoV-2 infection in 2020. *JAMA network open*, *4*(4), e216556-e216556.

Loquercio, A., Kaufmann, E., Ranftl, R., Müller, M., Koltun, V., & Scaramuzza, D. (2021). Learning high-speed flight in the wild. *Science Robotics*, *6*(59), eabg5810.

Loquercio, A., Segu, M., & Scaramuzza, D. (2020). A general framework for uncertainty estimation in deep learning. *IEEE Robotics and Automation Letters*, *5*(2), 3153-3160.

Milano, F., Loquercio, A., Rosinol, A., Scaramuzza, D., & Carlone, L. (2020). Primal-dual mesh convolutional neural networks. *Advances in Neural Information Processing Systems*, *33*, 952-963.

Richards, N. E., Keshavarz, B., Workman, L. J., Nelson, M. R., Platts-Mills, T. A., & Wilson, J. M. (2021). Comparison of SARS-CoV-2 antibody response by age among recipients of the BNT162b2 vs the mRNA-1273 vaccine. *JAMA network open*, *4*(9), e2124331-e2124331.

Brown, A. G., Vallenari, A., Prusti, T., De Bruijne, J. H., Babusiaux, C., Biermann, M., ... & Bauchet, N. (2021). Gaia early data release 3-summary of the contents and survey properties. *Astronomy & Astrophysics*, *649*, A1.

Penington, G., Shenker, S. H., Stanford, D., & Yang, Z. (2022). Replica wormholes and the black hole interior. *Journal of High Energy Physics*, *2022*(3), 1-87.

Friedlingstein, P., O'sullivan, M., Jones, M. W., Andrew, R. M., Gregor, L., Hauck, J., ... & Zheng, B. (2022). Global carbon budget 2022. *Earth System Science Data*, *14*(11), 4811-4900.

Okyay, M., & Övgün, A. (2022). Nonlinear electrodynamics effects on the black hole shadow, deflection angle, quasinormal modes and greybody factors. *Journal of Cosmology and Astroparticle Physics*, *2022*(01), 009.

Li, S., Ozo, M. M., De Wagter, C., & de Croon, G. C. (2020). Autonomous drone race: A computationally efficient vision-based navigation and control strategy. *Robotics and Autonomous Systems*, *133*, 103621.

Tal, E., & Karaman, S. (2020). Accurate tracking of aggressive quadrotor trajectories using incremental nonlinear dynamic inversion and differential flatness. *IEEE Transactions on Control Systems Technology*, *29*(3), 1203-1218.

Dukkanci, O., Kara, B. Y., & Bektaş, T. (2021). Minimizing energy and cost in range-limited drone deliveries with speed optimization. *Transportation Research Part C: Emerging Technologies*, *125*, 102985.

Zhang, Y., Zong, J. A., Gao, X., & Hou, Z. (2024). An Efficient Trajectory Planning Method for High-Speed Interception of Invasive Drones. *Applied Sciences*, *14*(16), 7030.

Yu, J., Li, J., Zhang, T., Yan, B., Li, S., & Meng, Z. (2023). Speed-First: An Aggressive Gradient-Based Local Planner for Quadrotor Faster Flight. *Drones*, *7*(3), 192.

Kundu, A., & Matis, T. I. (2017). A delivery time reduction heuristic using drones under windy conditions. In *IIE Annual Conference. Proceedings* (pp. 1864-1869). Institute of Industrial and Systems Engineers (IISE).

Chen, P., Dang, Y., Liang, R., Zhu, W., & He, X. (2017). Real-time object tracking on a drone with multi-inertial sensing data. *IEEE Transactions on Intelligent Transportation Systems*, *19*(1), 131-139.

D. V. Lindberg and H. K. H. Lee, “Optimization under constraints by applying an asymmetric entropy measure,” *J. Comput. Graph. Statist.*, vol. 24, no. 2, pp. 379–393, Jun. 2015, doi: 10.1080/10618600.2014.901225.

B. Rieder, *Engines of Order: A Mechanology of Algorithmic Techniques*. Amsterdam, Netherlands: Amsterdam Univ. Press, 2020.

I. Boglaev, “A numerical method for solving nonlinear integro-differential equations of Fredholm type,” *J. Comput. Math.*, vol. 34, no. 3, pp. 262–284, May 2016, doi: 10.4208/jcm.1512-m2015-0241.