Agile UAV Flight in low lighting conditions

PhD Dissertation Proposal

by

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Abstract

The autonomous flight of UAVs is a very broad area of research nowadays, as there are several challenges that involve different fields of study and application, such as search and rescue, inspection, or security, in which certain needs have not been resolved, such as agile flight (4 - 5 m/s) in low lighting conditions. There are various methods to ensure that a UAV can perform a flight in these conditions, one can choose to use sensors such as LiDAR, night vision cameras, event cameras, among others. These sensors are used in combination with techniques such as visual odometry, visual-inertial SLAM, and neural-based ego-motion estimation. In this research work, we propose to develop novel methods based on these techniques and a combination of sensors to achieve the drone's pose estimation at high frequency under low lighting conditions in order to enable agile flight for indoor/outdoor scenarios.

1 Introduction

The use of autonomous vehicles is increasingly used for search and rescue missions. In this type of missions the environment is unknown and many times the UAV is outside the pilot's LoS (Line of Sight). Usually drones performing agile flight have a limited payload.

The limited weight of UAVs used in these missions is primarily due to the need for the vehicle to navigate through confined spaces. Therefore, it's advantageous for the UAV to be as small as possible. However, this reduced size necessitates careful selection of components such as sensors, batteries, chassis, onboard computers, among others, as they significantly impact the UAV's flight and behavior.

Agile flight in Unmanned Aerial Vehicles (UAVs) typically ranges from 4 to 5 m/s. In inspection or search and rescue missions, where every minute counts, even minor differences in flight time can have a significant impact. Given the limited payload capacity, it's crucial to carefully select components to ensure the vehicle's performance remains unaffected.

When deciding which components to integrate into the vehicle, it's crucial to highlight that, for agile flight, they must be capable of operating at high frequency. If we don't choose the appropriate sensors to gather data while autonomous flight is being carried out in an agile manner, there's a risk of collision due to the lack of updated environmental data as close to real-time as possible. It's essential that the sensors can provide data with the necessary speed and accuracy to ensure safe and efficient navigation during agile flight.

However, once the vehicle's structure is optimized for agile flight with a limited payload, another significant challenge arises: changes in lighting conditions within the environment. Low-light environments, characterized by illumination levels below 100 lux, present particular challenges. Addressing these lighting changes requires solutions for vehicle positioning, navigation, and ensuring precise control during autonomous agile flight.

Today, there are methods available for achieving autonomous flight in unmanned aerial vehicles, allowing navigation in low-light environments. These methods include the use of LiDAR (light detection and ranging) sensors, IO (Inertial Odometry) algorithms, image enhancement through neural networks, among others [1],[2], [3], [4], [5]. However, implementing these methods often requires substantial computational resources or involves the use of heavy sensors. Shrinking these sensors without compromising their quality can be expensive.

Before addressing the navigation problem, localization must be solved. It's crucial to know the exact position of the vehicle. While GPS is commonly used for UAV positioning, it doesn't work indoors. Instead, sensors for obtaining the vehicle's inertial information (angular velocity and linear acceleration) such an IMU (Inertial Measurement Unit) are often employed to determine its position and orientation. Although these sensors provide a clear picture of the vehicle's state, if not used in conjunction with a recursive system, they can accumulate errors [5]. Additionally, in disaster situations, there are disadvantages such as electromagnetic interference, temperature changes, among other factors, which can affect their proper functioning.

Once the challenge of determining the UAV's position in low-light environments is resolved, we face the navigation challenge. For navigation, there are reactive methods based on SLAM dedicated to unknown environments, as well as methods that use neural networks or RRTs to navigate from one point to another [6], [7]. However, these methods often require external systems such as Vicon cameras to provide the vehicle's position. The goal of this work is to achieve autonomous vehicle navigation without relying on an external system for position estimation.

With all this in mind, it prompts us to ask whether we can achieve autonomous agile flight in low-light conditions using only the inertial information of the vehicle. Developing a recursive system that utilizes neural networks to confirm the vehicle's position and state could help mitigate the accumulated error that previous methods might encounter.

1.1 Motivation

When employing unmanned aerial vehicles for search and rescue missions, it's crucial to acknowledge the unknown and ever-changing environment. This may entail alterations due to disasters, shifts in lighting, adverse weather conditions, among other factors. These missions are subject to critical time constraints, underscoring the importance of agile flight, often reaching speeds of 4 to 5 meters per second. Manual piloting of these vehicles is frequently unfeasible, necessitating autonomous flight.

The utilization of autonomous vehicles in search and rescue missions poses numerous challenges requiring individual consideration. Among the most significant is precise vehicle localization, particularly in indoor environments where GPS (Global Positioning System) may falter due to signal obstructions as it can be seen in Figure 1. To tackle this challenge, localization systems have been devised, amalgamating visual and inertial data. Nevertheless, fluctuating lighting conditions throughout the mission may compromise the efficacy of visual localization methods. While solutions have been proposed to mitigate this issue, current alternatives often entail vehicles that are either too large or too slow to be practical in search and rescue scenarios.

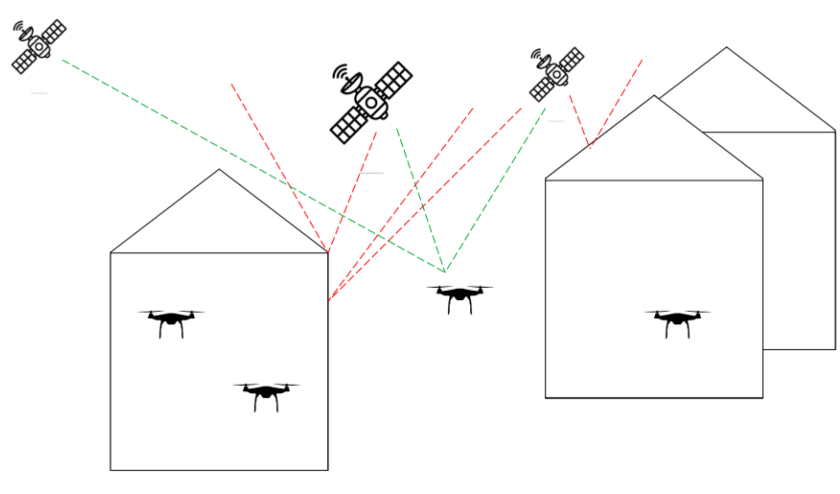

Figure 1: UAV outdoor with good GPS signal and indoor with no signal

The main motivation of this work is to integrate a system capable of performing agile flight under low-light conditions. Currently, existing systems face challenges in navigating such scenarios, either due to their high resource requirements or because their navigation methods do not operate at high frequencies. By developing a system that enables navigation in low-light environments at high frequency, we can begin to consider critical applications such as inspection in dark, time-constrained locations or searching for targets in risky situations for humans, for example closed environments in which access for humans is difficult or a place where the GPS fails completely, such as a forest at night illustrated in Figure 2.

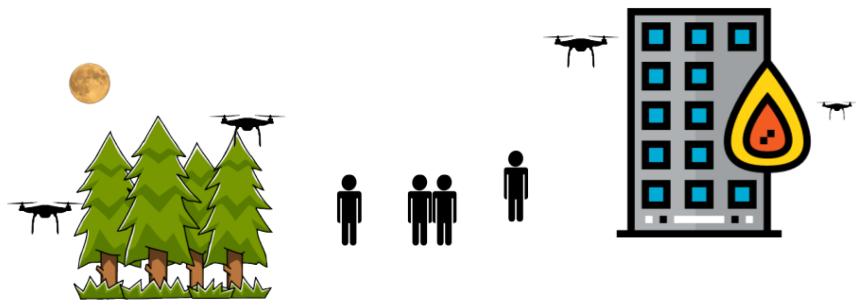

Figure 2: UAVs in risk situations for humans

1.2 Justification

As mentioned earlier, the use of techniques enabling UAVs to autonomously fly in areas with low lighting is in a very early stage of exploration, so venturing into this path using computational techniques combined with control to perform tasks matching the speed of agile flight in these environments is of great interest.

Working on this issue is key to scaling it to other types of needs and challenges that require vehicles to be autonomous and reach the speed of agile flight, such as monitoring and exploration, package delivery, among other tasks that may endanger the integrity of a person performing that task currently.

Currently, we have the necessary technology to achieve quite high speeds when using vision combined with inertial information. However, when removing the field of vision, there is an accumulated error that is difficult to correct in real time. There are image enhancement methods that correct some phenomena that occur in low lighting, an example is the work [8] is a survey of what can be done using learning-based methods, but the disadvantage it presents for this research is that we are looking for sensors that operate at high frequency since in agile flight it is crucial to update the state as soon as possible. Therefore, implementing control and other sensors capable of collecting information to be subsequently processed through a neural network is an area of study that requires attention. Figure 3 shows some phenomena that can occur in low lighting scenarios.

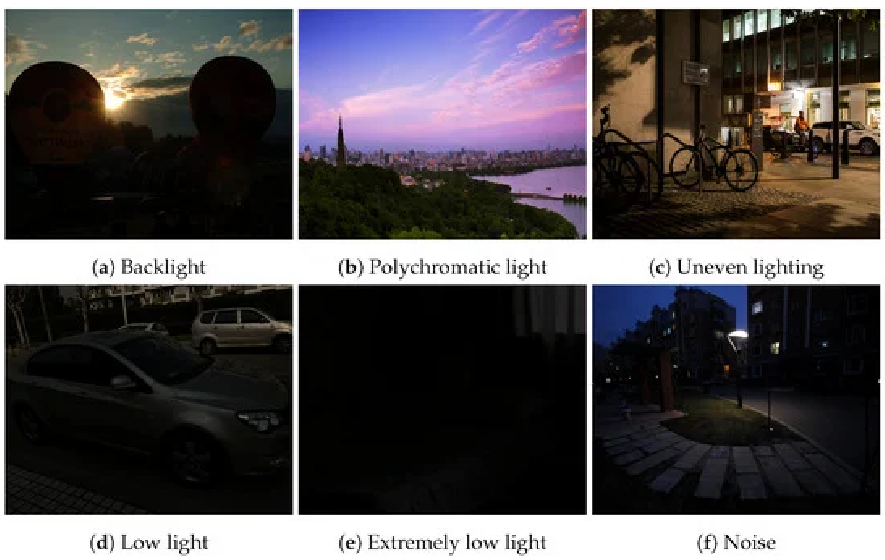

Figure 3: Lowlight scenarios. Image taken from from an image enhacement survey [8]

1.3 Problem Statement

Assuming an unknown indoor/outdoor environment, with low lighting, we want to develop a novel method to enable drone's pose estimation at high frequency in order to enable agile flight, under the following restrictions:

- Low light conditions (less than 100 lux).
- Unexpected changes in the environment.

- External disturbances e.g. wind.

Each of these points needs to be thoroughly studied to contribute effectively to the state of the art. It is essential for the system to operate at high frequency because, in the current state of the art, the problem manifests as vehicles taking too long to conduct inspections without the aid of external systems or relying on large, heavy sensors that consume significant energy and computational resources.

1.4 Research Questions

In order to carry out the research work, it is necessary to answer the following questions:

Question 1: Can we obtain inertial information from different sensors other than an IMU, by estimating it, for autonomous agile flight?

Question 2: Is it possible to achieve autonomous and agile flight in low light scenarios by knowing the vehicle's inertial information?

1.5 Hypothesis

To answer the research questions, the following hypotheses are proposed.

Hypothesis 1: By employing different sensors such as cameras, IR cameras, LiDAR, among others, we can design a computational algorithm to estimate the inertial information.

Hypothesis 2: If we are able to estimate accurately the inertial information, we can design a feedback control algorithm to perform agile flight in low light conditions.

1.6 Objectives

The main objective is to implement a computational strategy that can process information obtained by a UAV so that it can make agile flight in low lighting conditions.

1.6.1 Specific Objectives

To achieve the main objective, there are specific objectives to follow. They are as follows:

- To use data measured by the capable of replacing inertial information, enabling agile autonomous flight.
- To research and propose a control strategy that suits with computational strategy to develop agile flight.
- To achieve high velocities using sensors useing sensors that operate at high frequencies.

1.7 Scope and Limitations

This work has some limitations that need to be mentioned, as the field is vast and needs to be delimited to specific objectives.

- One limitation of this work is the trade-off between sensor precision and cost. As sensors providing inertial information become more precise, their cost increases. Therefore, a limitation will be the capacity of the sensors in relation to their size and weight.
- When aiming to work with neural networks to obtain inertial information from various sensors in addition to an IMU to create a redundant system, the capacity of the onboard computer of the vehicle will be limited.

- In the end, the outcome will be constrained by the capacity of the sensors. This includes factors such as the distance at which they can acquire data from the environment, their operating frequency, material resilience, resistance to external disturbances, and the intended use case.

1.8 Expected Contributions

The goal is to make a contribution such that, upon completion of the thesis, a system capable of autonomously navigating at an agile flight speed in low-light environments will be developed. This system will meet the initially proposed constraints, including a weight limit, battery duration, and resistance to external disturbances. Additionally, it will have the capability to withstand external perturbations. This system will represent an advancement in the state of the art, as there is currently no small-sized UAV capable of performing the aforementioned tasks.

- *Neural Network that uses inertial information to predict pose*: To predict position using a neural network, we chose to utilize the vehicle's inertial information. With this inertial information, it is possible to estimate the position, leveraging the recursive nature of the entire system.

- *Control to mitigate the error*: When performing agile flight in an autonomous vehicle, it is essential to have control that can direct the UAV along the correct route to avoid cumulative error. Therefore, an important contribution will be the integration of tools such as neural networks into a control system that operates at high speed.

- *Open Source Tools*: At the end of each stage of the project, certain tools will be available for study and can contribute to the state of the art. This is with the aim of advancing in this specific research topic.

2 Background

To carry out the methodology of this project, it is necessary to have knowledge about the following tools:

- *Inertial sensors:* To obtain data on the vehicle's linear velocity and angular acceleration that will be the entries to the neural network model.
- *Neural Networks*: Since inertial data obtained from a sensor onboard the vehicle will be known, learning from this data to create a recursive model is essential. The data will be used as input to the model, whether it's a CNN, ResNet, or Transformer capable of processing and learning the data in such a way that the output information obtained from these networks is as close to reality as possible.
- *Flight control:* To steer the UAV along the desired route, using the position predictions generated by the neural networks it is necessary incorporate control, in agile flight we don't have absolute control of the vehicle so it needs a control that mitigates possible accumulated error.
- *Onboard computer:* To perform real-time data processing and execute the control algorithms and neural networks.

Each of these tools will play a fundamental role in the final project.

3 Related work and State-of-the-art

This chapter presents the work related to this research, various methods in which agile flight is carried out were consulted, these methods involve different sensors to carry out the location and localization of the vehicle. This research seeks to be able to position the UAV without using GPS, since indoors the GPS most of the time fails. Likewise, works were reviewed in which the lighting is low or there is no visual sensor with it. objective of seeing the niche opportunity to carry out this research.

In recent years, the use of autonomous drones to facilitate various tasks for humans, whether for safety or convenience, has been increasing. Today, we are addressing challenges that require high computational capabilities, such as location through visual or inertial methods, autonomous navigation of these vehicles in environments that humans would hardly be able to access, agile flight entirely autonomously, among others.

In the literature on agile flight in autonomous vehicles, various methods and approaches exist to achieve this while considering the constraint of not having GPS. Among them, Visual-Inertial Odometry (VIO), visual methods such as SLAM, image enhancement based on neural networks, and navigation based on optical flow stand out. [9]

One of our main focuses of interest among the methods mentioned above is the use of inertial information to achieve high-speed navigation, as has been done in previous works. [5], [10], [11] using recursive systems, high flight speeds ranging from 8 m/s to 20 m/s have been achieved. These speeds are attained through training on the same trajectory and utilizing external systems to achieve agile flight. Additionally, in these scenarios, changes in lighting as the UAV flies over an unknown area have not been taken into account.

There are other works where different sensors than GPS are used to achieve autonomous navigation, such as LiDAR or SLAM [12], . In these works, environments where the vehicle could potentially collide are considered, and thanks to these sensors, autonomous flight can be achieved. However, the speed at which these vehicles operate does not exceed 4 m/s, and the weight of each vehicle exceeds 1 kg, our goal is less than 1 kg.

In work [1] a situation is proposed where satellites cannot provide GPS service, then LiDAR sensors will be used to obtain the position of the vehicle, although LiDAR is a very robust tool in scenarios in which there is no good lighting, the operating frequency of the sensor used in this work is around 5 Hz, to perform agile flight this sensor would not be the most appropriate, it could be used in conjunction with some visual or inertial sensor to fly at higher speeds.

As mentioned, the speed at which these vehicles operate does not exceed 4 m/s, and the weight of each vehicle exceeds 1 kg. Our goal is for the vehicle to be small and its weight to be less than 1 kg.

When it comes to environments with very low illumination, neural networks come into play, as they have been used to create methods such as object tracking under these conditions. An example of this is the work described in [13] despite not directly involving navigation, this work utilizes image processing in conditions of almost zero luminosity. Therefore, exploring computational alternatives for high-speed autonomous flight is important.

The work [4] is a very important reference for the final goal of the project, albeit with some modifications. The work achieves agile flights in environments with variable lighting, but it does so using a heavy system. Additionally, it employs three sensors: an event camera, an infrared camera, and an RGB camera. By combining the information from these sensors, the system can follow a trained trajectory at high speeds in environments with variable lighting.

The work [4] mentions that an event camera has numerous advantages over a standard camera, that is, it is suitable for use in low lighting conditions. What is sought when we talk about this type of environment is that the sensor to be used works at high frequency and has a high dynamic range, this serves to capture the greatest amount of detail in areas where lighting conditions are complicated. The event camera used operates at 140 dB while a standard camera operates around 60 dB.

The main contribution of the work is the combination of three sensors to perform a robust state estimation, they fuse events, frames from a standard camera and inertial information, this combination achieves a reliable estimation in difficult environments, such as low lighting or when perform fast movements, the work of estimating states in low lighting environments using this method can be used for several applications, although there are limitations such as the total cost of the system and the size.

For this reason, other methods have been explored that, in combination with other sensors and computational strategies, can be an alternative to vehicle position estimation.

The work [5], unlike the work [4] that uses a large number of sensors to perform state estimation, uses only inertial odometry. This method is not expensive, can be used in smaller vehicles and is not affected. due to perceptual degradation. However, this work is limited to training a known trajectory, that is, the vehicle can fly at high speeds without the need to use a visual sensor or any proximity sensor, but it fails when flying in unknown spaces in which it is not possible. has trained.

The aforementioned work uses inertial information to learn the route along which the vehicle will fly, after which it passes the information through an extended Kalman filter, in which the updated position is obtained to be able to perform agile flight on a predetermined trajectory. The limitation that this work has with our objectives is that being in an environment in which there is a completely unknown trajectory, the UAV will not be able to pass through it, in addition to having a reference point, in this case a ground thrut an external camera system is needed.

This system has reached very high speeds, it is designed for drone racing and the highest speed reached in the experiments they carried out is 19.44 m/s. The advantage in this research work is found in the network that is uses, this network learns the trajectories that are given to the UAV and when passing through the filter the results obtained measured by the absolute trajectory error are among the best in the state of the art. In this research work, as future work, it is mentioned that the system can be used in routine inspections when visual sensors are affected by low lighting.

Visual sensors, such as standard cameras, are affected when it comes to scenarios in which there is low lighting. In [14], a scenario is proposed in which a quadrotor fails with an engine under these conditions. The UAV presented for this work uses the onboard sensors that it has to help it, these sensors are: an event camera, a standard camera and an IMU, a comparison is made to see which sensors together operate best at the time of perform a desired trajectory. By carrying out a comparison between using a standard camera and an event camera the authors show that the event camera in combination with the algorithm they are using is better when dealing with low lighting conditions. The low illumination is below 100 lux, the experiment in which its algorithm still works still works by subjecting the UAV to 10 lux illumination.

When performing a flight over a box-shaped trajectory comparing the standard camera vs. the event camera in conjunction with their control algorithm, they obtained better results using the event camera, and estimating the state at 50Hz.

The main objective of the aforementioned work is to estimate the position of the UAV in low lighting conditions in a specific circumstance, in this case, the possibility arises that some rotor may be damaged and also without having external sensors to estimate the state of the vehicle, does not mention at what speed it performs the trajectory, so it is not focused on agile flight. Even so, it is taken into account for the research that will be carried out in this thesis work because thanks to this work the idea is reinforced that the visual information as a whole from an algorithm can achieve state estimation in a UAV under these conditions.

In most of the works mentioned above, we talk about the use of the Kalman Filter or Extended Kalman Filter, this is because once we have a measurement, whether it has noise or there is uncertainty in it, the algorithm gives us a good estimate. of the state of the system, especially if there is inertial information accompanied by some other sensor, whether cameras or lasers.

Below are the equations of the Kalman filter and the extended Kalman filter.

Kalman filter mainly focuses on 2 steps, prediction and update.

You have to know the system model, then you predict the future state and error covariance based on the current state and control of the system.

1. State prediction:

$$\hat{x}_{k|k-1} = A\hat{x}_{k-1|k-1} + Bu_{k-1}$$

2. Error covariance prediction:

$$P_{k|k-1} = AP_{k-1|k-1}A^T + Q$$

Where:

- $\hat{x}_{k|k-1}$ is the predicted state at time k given the state at time $k-1$.
- A is the state transition matrix.
- B is the control matrix.
- u_{k-1} is the control vector at time $k-1$.
- $P_{k|k-1}$ is the predicted error covariance at time k.
- Q is the process noise covariance.

To carry out the update task, it requires actual measurements to obtain an accurate estimate of the state. Below are the equations.

Update Equations of the Kalman Filter

1. Kalman Gain:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1}$$

2. State Update:

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - H\hat{x}_{k|k-1})$$

3. Error Covariance Update:

$$P_{k|k} = (I - K_kH)P_{k|k-1}$$

Where:

- K_k is the Kalman gain at time k.
- H is the observation matrix.
- R is the measurement noise covariance.
- z_k is the measurement at time k.
- $\hat{x}_{k|k-1}$ is the predicted state before the update.
- I is the identity matrix.

It is important to know the equations of the Kalman filter because as a measurement, for example in [5], a convolutional neural network is used that aims to learn a given trajectory, the output of this network is the input of the Kalman filter, what the filter does is to mitigate the drift that the network may have by itself

Mention is made of the use of this type of filters since at least in work [5] and [1], the measurement in [5] being inertial information and having used LiDAR sensors in work [1], signal processing is required so that it can be be closer to the desired trajectory.

Below is a table where there is a first column that shows the operating frequency of the sensor, followed by the method used in the second column.

Frequency operation	**Method**
5 Hz	LiDAR based [1]
24 Hz	Events, Frames and IMU [4]
50 Hz	IMU and Events [14]
180 Hz	Inertial Odometry [5]

Table 1: Frequency operation of each method.

To achieve agile flight it is necessary to use sensors that operate at high frequencies, as can be seen in the table 1 the frequency at which the inertial odometry method operates is the highest, despite this, there are We must remember that the objective of this work is to fly agilely in low lighting environments with a low-cost system in terms of sensors and computational resources.

4 Research Proposal

4.1 Methodology

To carry out the research work, it is necessary to follow a methodology. The methodology to be followed consists of the following:

- To propose neural network architectures capable of reconstructing the inertial information based on different sensors' sources.
- To investigate computational strategies that lead us to obtain the pose estimation of the drone.
- To conduct tests with different types of neural networks, selecting the most suitable one for our purposes while considering the constraints.
- To propose a structure that is capable of hosting the system on board while respecting the payload.
- To test that the computational strategy works in low-light scenarios without incorporating agile flight.
- To investigate a control strategy that can be implemented on board of the UAV.
- To select a control strategy according to the mission's complexity, UAV dynamics and available sensors.
- To design an autonomous navigation policy.

4.2 Work Plan

The work plan to be followed is shown in the figure. 4

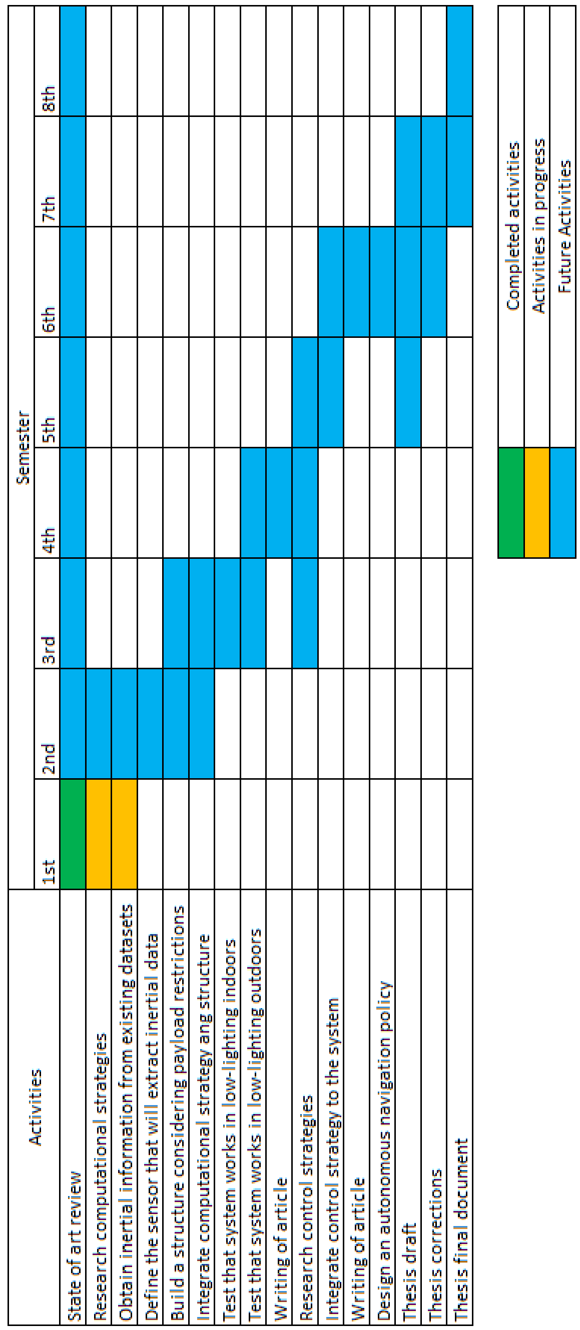

Figure 4: Work Plan for PhD

5 Preliminary Results

So far, we have worked with neural networks to estimate angular velocity from datasets taken from [15], [16], [17] where we have information about the angular velocity, linear acceleration, and the timestamp to which these data correspond. With this, we train a PoseNET-based network to return an estimated value of velocity. Once we have these results, the next step is to utilize a measurement system such as a Vicon system, which provides us with a groundthrut so we will be able to train the network on an actual vehicle, using the vicon in real time will not be possible for this work, since the vicon already provides us with the position, but it does not work in low lighting environments.

We need to solve the following problems:

- **Location Problem**. It will be solved by using a sensor onboard different that GPS to estimate with a sufficient degree of approximation the position of the UAV. So far, experiments have been conducted that take images from diferent datasets and are passed through neural networks where labels are assigned to them. These labels represent inertial information. To assign labels to the images and for the network to fulfill its objective of estimating inertial information, it is necessary to take into account several factors such as temporality, in a single image we cannot know what is happening, we have to have more data such as images that were taken before and after the current image, this helps us know how the vehicle behaved and thus training can be carried out for angular velocity, linear acceleration, among others.

- **Navigation Problem**. Once the localization problem is solved, navigation in a dark environment becomes the next point to address. The estimated position of the UAV will be used to navigate towards the target, the application that the UAV seeks to carry out will be defined later, whether it is carrying out an inspection tour in which it is not possible to fully understand the scenario in low lighting conditions or it is required to reach a specific objective, in both cases the route What the vehicle will follow is not entirely known and methods are required that can use the resources on board the vehicle.

- **Control Problem**. There will be disturbances that need to be mitigated, so control plays a very important role. So far, simulations have been conducted in Gazebo using basic control such as PID on a simple trajectory. Gazebo is a simulation environment often used in robotics, as it allows the sensors and other components of the vehicle in question to be realistically simulated. The wide variety of sensors that this simulator has will allow us to carry out the necessary tests before implementing the control of the UAV. We are looking for a control method that allows the UAV to operate at high velocities.

The diagram shown in Figure 6 shows in a general way how the frames accompanied by inertial information enter the PoseNET algorithm, this with the objective that the network assigns the inertial information as a label to the frames, this will be key to explore if one can omit the use of an inertial sensor and, instead, only a low-cost camera. The results of a first training where the angular velocity of the vehicle was obtained are shown in the Figures 7, 8 and 9.

The trajectory that the network has to train in this case is an ellipse, as shown in the Figure 5. And the training of thrust and gyroscope are shown in the Figure10

Figure 6 shows the diagram of the experiment carried out, at the moment data has been passed through the modified PoseNET algorithm, the input is a set of data in which the UAV records an ellipse-shaped trajectory, the data The forms in the data set are used to train the network, at the end estimated inertial information is obtained. Returning to what was raised in chapter 1 about exploring the possibility of using another sensor that is capable of estimating inertial information other than the IMU in a way that is close to reality, to have an alternative to this sensor in case that it might fail in difficult-to-access environments where conditions give way to these situations.

Once the estimated inertial information is obtained, it is passed through the

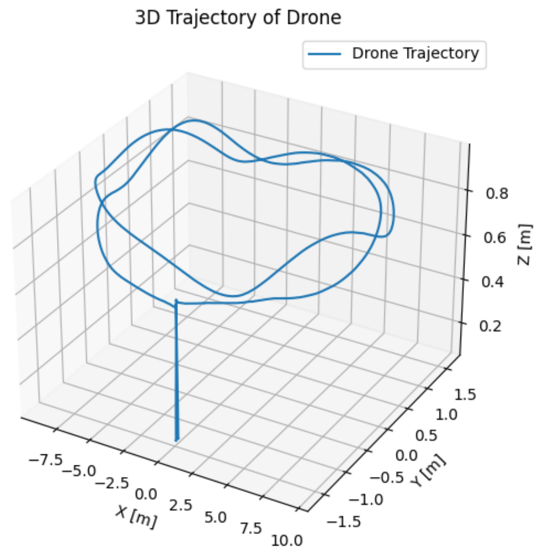

Figure 5: Ellipse trajectory

Inertial Odometry algorithm presented in [5], which only needs that information to estimate the position in which the UAV is located. Work is still continuing to obtain the position. since so far the training data has not been entirely favorable, as can be seen in Figure 1, since it does not have the inertial information coming from a sensor such as the IMU, It becomes a complicated task to use the estimated data. Once you have the data that is most similar to the groundtrut, it will pass through the Kalman filter to improve the position estimation and avoid drift caused by the lack of data information.

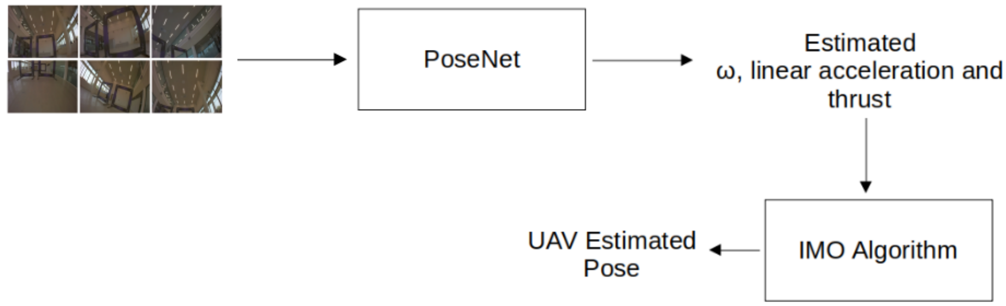

Figure 6: First experiment diagram

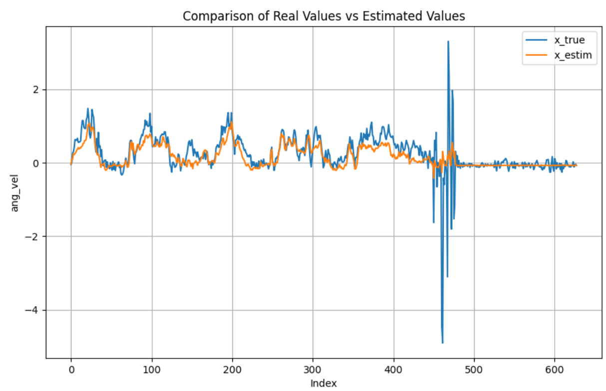

Figure 7: Estimated angular velocity in x axis

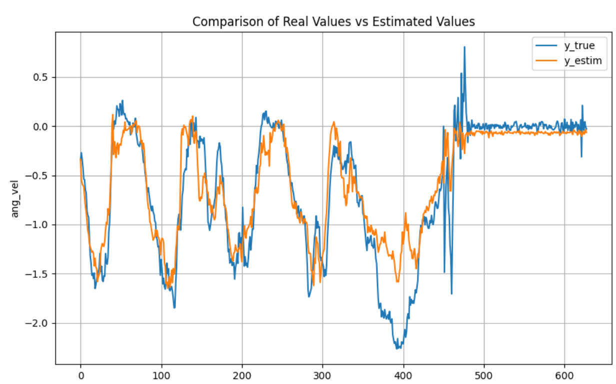

Figure 8: Estimated angular velocity in y axis

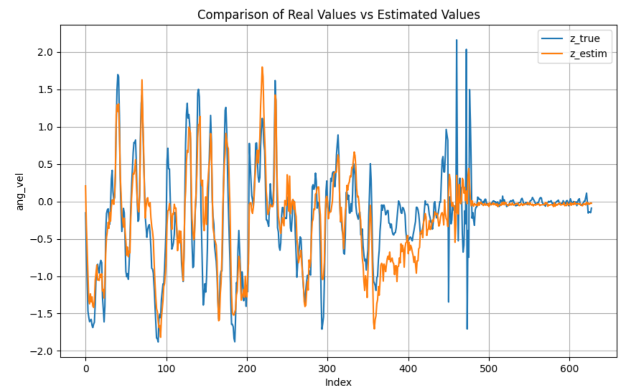

Figure 9: Estimated angular velocity in z axis

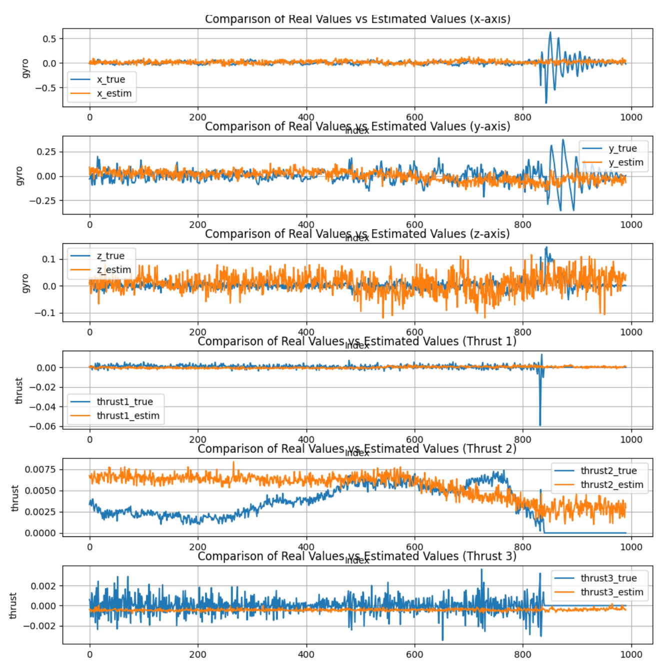

Figure 10: Thrust and linear acceleration measurements

6 Final Remarks

Taking into account that there are works performing agile flight in low-light environments at speeds that do not reach agile flight, working on this problem with the creation of a redundant system capable of reducing the use of some heavy and costly components, and at the same time being able to function in difficult conditions where a sensor such as the IMU may fail, is an important case study.

It should also be noted that the works mentioned in the Chapter 1 that manage to reach high speeds are carried out in drone races. This type of competition opens the door to research that involves complicated lighting environments. These works provide information and ideas on how to solve the problem, but not the total solution, since in a situation there is knowledge about what the runway will be like, in a real case of inspection or search and rescue it is not known if the environment will be known.

The problem of navigation in low-light environments is not yet solved, as the works mentioned in this document require prior training or external sensors to carry it out. The idea is to perform onboard processing that is capable of navigating in these environments without the need for external sensors.

Decisions are still being made about the hardware that will be used for the development of this project. More tools that can be useful for data processing are being explored, and tests with different datasets are ongoing.

References

[1] M. Petrlík, T. Krajník, and M. Saska, "Lidar-based stabilization, navigation and localization for uavs operating in dark indoor environments," in *2021 International Conference on Unmanned Aircraft Systems (ICUAS)*, pp. 243–251, IEEE, 2021.

[2] Y. Jiang, X. Gong, D. Liu, Y. Cheng, C. Fang, X. Shen, J. Yang, P. Zhou, and Z. Wang, "Enlightengan: Deep light enhancement without paired supervision," *IEEE transactions on image processing*, vol. 30, pp. 2340–2349, 2021.

[3] C. Fu, H. Dong, J. Ye, G. Zheng, S. Li, and J. Zhao, "Highlightnet: highlighting low-light potential features for real-time uav tracking," in *2022 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 12146–12153, IEEE, 2022.

[4] A. R. Vidal, H. Rebecq, T. Horstschaefer, and D. Scaramuzza, "Ultimate slam? combining events, images, and imu for robust visual slam in hdr and high-speed scenarios," *IEEE Robotics and Automation Letters*, vol. 3, no. 2, pp. 994–1001, 2018.

[5] G. Cioffi, L. Bauersfeld, E. Kaufmann, and D. Scaramuzza, "Learned inertial odometry for autonomous drone racing," *IEEE Robotics and Automation Letters*, vol. 8, no. 5, pp. 2684–2691, 2023.

[6] G. Torrente, E. Kaufmann, P. Föhn, and D. Scaramuzza, "Data-driven mpc for quadrotors," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 3769–3776, 2021.

[7] W. Youn, H. Ko, H. Choi, I. Choi, J.-H. Baek, and H. Myung, "Collision-free autonomous navigation of a small uav using low-cost sensors in gps-denied environments," *International Journal of Control, Automation and Systems*, vol. 19, no. 2, pp. 953–968, 2021.

[8] Z. Tian, P. Qu, J. Li, Y. Sun, G. Li, Z. Liang, and W. Zhang, "A survey of deep learning-based low-light image enhancement," *Sensors*, vol. 23, no. 18, p. 7763, 2023.

[9] Y. Chang, Y. Cheng, U. Manzoor, and J. Murray, "A review of uav autonomous navigation in gps-denied environments," *Robotics and Autonomous Systems*, p. 104533, 2023.

[10] J. Delmerico, T. Cieslewski, H. Rebecq, M. Faessler, and D. Scaramuzza, "Are we ready for autonomous drone racing? the uzh-fpv drone racing dataset," in *2019 International Conference on Robotics and Automation (ICRA)*, pp. 6713–6719, IEEE, 2019.

[11] P. Foehn, D. Brescianini, E. Kaufmann, T. Cieslewski, M. Gehrig, M. Muglikar, and D. Scaramuzza, "Alphapilot: Autonomous drone racing," *Autonomous Robots*, vol. 46, no. 1, pp. 307–320, 2022.

[12] M. Faessler, E. Mueggler, K. Schwabe, and D. Scaramuzza, "A monocular pose estimation system based on infrared leds," in *2014 IEEE international conference on robotics and automation (ICRA)*, pp. 907–913, IEEE, 2014.

[13] J. Ye, C. Fu, G. Zheng, Z. Cao, and B. Li, "Darklighter: Light up the darkness for uav tracking," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 3079–3085, IEEE, 2021.

[14] S. Sun, G. Cioffi, C. De Visser, and D. Scaramuzza, "Autonomous quadrotor flight despite rotor failure with onboard vision sensors: Frames vs. events," *IEEE Robotics and Automation Letters*, vol. 6, no. 2, pp. 580–587, 2021.

[15] J. Delmerico, T. Cieslewski, H. Rebecq, M. Faessler, and D. Scaramuzza, "Are we ready for autonomous drone racing? the UZH-FPV drone racing dataset," in *IEEE Int. Conf. Robot. Autom. (ICRA)*, 2019.

[16] G. Cioffi, T. Cieslewski, and D. Scaramuzza, "Continuous-time vs. discrete-time vision-based slam: A comparative study," *IEEE Robotics and Automation Letters, (RA-L)*, 2022.

[17] E. Kaufmann, L. Bauersfeld, A. Loquercio, M. Müller, V. Koltun, and D. Scaramuzza, "Champion-level drone racing using deep reinforcement learning," *Nature*, vol. 620, no. 7976, pp. 982–987, 2023.