

Adaptive algorithm for visual positioning of UAVs in the local environment

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Abstract

This paper proposes an adaptive localization algorithm for unmanned aerial vehicles (UAVs) operating in indoor, GPS-denied environments. The approach is based on the analysis of visual features extracted from the surrounding environment and employs a cascade structure that integrates four classical local positioning techniques—Proximity, Centroid, Weighted Centroid, and Lateration — into a unified decision-making module. The system adaptively switches between these methods based on real-time signal characteristics and estimated positioning error. An embedded accuracy control mechanism monitors localization quality and triggers a transition to a map-based visual positioning mode when necessary, ensuring high robustness in dynamic or cluttered spaces. The algorithm is lightweight and does not require extensive pre-mapping or environmental calibration, making it well-suited for rapid deployment in unknown indoor areas. The proposed system was experimentally validated using the DJI Tello platform in real-world indoor settings. Results demonstrate that the method achieves reliable and accurate localization with minimal computational requirements, offering a practical solution for indoor UAV navigation, inspection, and monitoring tasks.

Keywords

visual localization, adaptive algorithm, indoor positioning, UAV, Tello, Proximity, Lateration

1. Introduction

Unmanned aerial vehicles (UAVs) have become increasingly important in a wide range of civilian and industrial applications, including indoor inspection, surveillance, inventory tracking, search-and-rescue operations, and infrastructure monitoring. A critical enabler for the autonomous operation of UAVs in such tasks is the ability to navigate reliably without relying on external satellite-based systems like GPS, which are often unavailable or unreliable in enclosed, obstructed, or densely built environments.

Traditional navigation systems designed for outdoor use lose their effectiveness indoors due to signal attenuation, multipath effects, and interference from walls and structures. To compensate for the absence of GNSS, researchers have explored a variety of local positioning solutions such as LiDAR-based mapping, visual SLAM, inertial odometry, and hybrid sensor fusion methods. Although these approaches provide high precision, they come with significant limitations — LiDAR and depth sensors are expensive and bulky; visual SLAM demands high computational power and detailed scene mapping; deep learning-based methods require large annotated datasets and often lack real-time responsiveness on low-power platforms.

This study is motivated by the need to design a localization system that offers a practical trade-off between accuracy, efficiency, and affordability. Our proposed solution is an adaptive visual positioning algorithm that leverages classical signal-based localization techniques in a cascading fashion. Specifically, the system integrates Proximity, Centroid, Weighted Centroid, and Lateration methods into a single adaptive decision module capable of switching strategies dynamically based on real-time signal characteristics and error thresholds. The lightweight nature of the proposed methods allows

CMSE'25: International Workshop on Computational Methods in Systems Engineering, June 12, 2025, Kyiv, Ukraine

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for fast deployment and real-time operation on embedded platforms without the need for extensive environmental calibration or pre-mapped datasets.

To further enhance reliability, an error monitoring mechanism is embedded into the algorithm, enabling the system to switch to a more advanced visual map-based localization mode if the accumulated error exceeds an acceptable threshold. This hybrid approach ensures both adaptability in unknown environments and sufficient precision in cluttered or dynamic indoor spaces.

The algorithm has been implemented and tested on a low-cost UAV platform — DJI Tello — to evaluate its performance in real-world indoor scenarios. Experimental results confirm that the system maintains a high level of localization accuracy while keeping computational demands minimal, making it well-suited for small-scale autonomous aerial robots.

2. Related work

Current indoor positioning systems often use Wi-Fi fingerprinting, Visual SLAM, or sensor integration. However, they require pre-training, complex calibration, or high computing power. The proposed approach aims to provide acceptable positioning accuracy with minimal overhead by using classical visual landmark-based methods with adaptive logic.

Achieving reliable and accurate localization of unmanned aerial vehicles (UAVs) in indoor environments, where satellite-based navigation systems are inaccessible, has been a long-standing research challenge. Over the years, a variety of strategies have emerged, leveraging wireless infrastructure, vision-based tracking, and sensor fusion to approximate or estimate UAV position in real time.

One of the foundational techniques is Wi-Fi fingerprinting, introduced by Bahl and Padmanabhan [1], which uses signal strength maps created from received signal strength indicators (RSSI) at various known locations. This method enables low-cost localization using existing Wi-Fi networks and is still widely used in commercial indoor navigation applications. However, it suffers from inherent limitations: the requirement for extensive site surveys, sensitivity to environmental dynamics (furniture rearrangement, human movement and other), and the need for frequent recalibration reduce its scalability and adaptability to dynamic real-world conditions.

In contrast, visual odometry and visual SLAM (Simultaneous Localization and Mapping) methods have become a major focus in robotic navigation. MonoSLAM [2] was among the first systems to perform real-time 3D tracking using a single camera. Subsequent advancements, such as Visual-LiDAR Odometry and Mapping (V-LOAM) [3], offered higher robustness and lower drift by combining camera and LiDAR data. These methods have proven their value in structured indoor environments and autonomous driving; however, they require high processing power, finely tuned sensor fusion, and often do not scale well to low-cost UAVs with limited onboard computational capacity [4].

Several studies propose hybrid systems where navigation is achieved by combining multiple types of sensory input. Kulik and Dergachev [5], and later Dergachov et al. [6], presented computer vision-based navigation and autonomous landing algorithms that utilized environmental patterns. These techniques are particularly effective when landmarks or floor patterns are clearly visible. Nonetheless, they often rely on stable lighting and high camera resolution, both of which may vary during indoor flights. Additional works explored object identification using polarization signals [7] and real-time adaptive control systems driven by swarm-based metaheuristics [8, 9], underlining the multidisciplinary nature of modern UAV navigation.

More recently, the integration of UAVs into networked systems has led to the development of cooperative localization and communication strategies. Examples include LiFi-enabled swarm deployment [10], and onboard adaptive management of UAV clusters for autonomous task distribution in constrained environments [11]. These architectures are complex but open the door to large-scale aerial coordination in GPS-denied contexts.

As the demand for scalable and computationally light systems increases, attention has turned toward methods that minimize environmental dependence and pre-configuration. Ivanenko and Petrov [12], Sydorenko and Hrytsenk [13], and Melnyk and Romanenko [14] proposed lightweight visual landmark-

based localization algorithms suitable for rapidly changing layouts and unknown environments. These models do not require extensive offline training, which makes them attractive for time-critical and resource-constrained missions.

Machine learning-based approaches also continue to expand, with Bondarenko and Chernenko [15] demonstrating how visual cues can be interpreted by adaptive models to improve flight trajectory corrections in response to environmental obstacles. Such systems balance adaptability with limited computational overhead, providing a middle ground between deep SLAM and classical geometry-based methods.

Parallel to this, high-complexity AI models such as AGCosPlace [16, 17] use transformer-based architectures to analyze spatial visual scenes. These methods can generalize across environments with minimal domain-specific training and are promising in terms of scalability. Likewise, control architectures based on control barrier functions (CBFs) have been used to manage UAV path constraints under uncertainty [18, 19]. Yet their computational intensity and hardware demands make them more suited for research-grade UAV platforms than for embedded commercial drones [20, 21].

Event-based odometry [22], visual-inertial navigation systems (VINS) [23], and adaptive SLAM pipelines [24] represent continued effort to optimize navigation accuracy in degraded visual conditions. Each of these systems introduces improved robustness to motion blur, lighting changes, or textureless areas but at the cost of increased complexity in parameter tuning and system calibration.

Other researchers explored global-to-local hybrid strategies. For example, Wei et al. [25] combined satellite imagery with local UAV sensor data to generate adaptive maps. Although useful for large-scale or transition spaces (e.g., semi-outdoor environments), these methods lack the responsiveness needed for fully enclosed dynamic spaces like warehouses or industrial interiors.

Vasarhelyi et al. [26] provide a comprehensive survey of visual odometry techniques in GPS-denied scenarios, emphasizing the need for scalable, hardware-agnostic approaches. However, the field continues to lack simple, lightweight systems that can adaptively trade off accuracy and complexity in real time without preloaded maps or neural models.

In this context, the proposed solution — an adaptive cascade of classical localization algorithms (Proximity, Centroid, Weighted Centroid, and Lateration) — seeks to bridge the gap between accuracy and efficiency. Unlike heavyweight methods requiring map generation or neural inference, our approach dynamically switches between fast geometric estimators depending on signal quality and accumulated error. If the system detects significant drift or inconsistency, it triggers fallback to more robust visual reference-based modules. This logic enables practical, scalable deployment of indoor navigation on lightweight UAVs without complex setup or calibration procedures.

3. Purpose and objectives of the research

The main goal of this research is to develop and experimentally verify an adaptive algorithm for visual positioning of UAVs based on the cascade use of inexpensive methods.

The main objectives of the research are:

1. Analyze classic methods of visual positioning.
2. Design a cascade algorithm with dynamic error estimation.
3. Implement a system based on the DJI Tello drone.
4. Evaluate positioning accuracy and processing efficiency.
5. Compare the results with other approaches (Fingerprinting, Visual SLAM).

4. Methodology

The proposed visual localization algorithm for UAVs is designed to operate in GPS-denied indoor environments by sequentially applying a cascade of classical geometric methods based on camera-captured landmarks. The algorithm leverages lightweight computation and adaptivity to dynamically

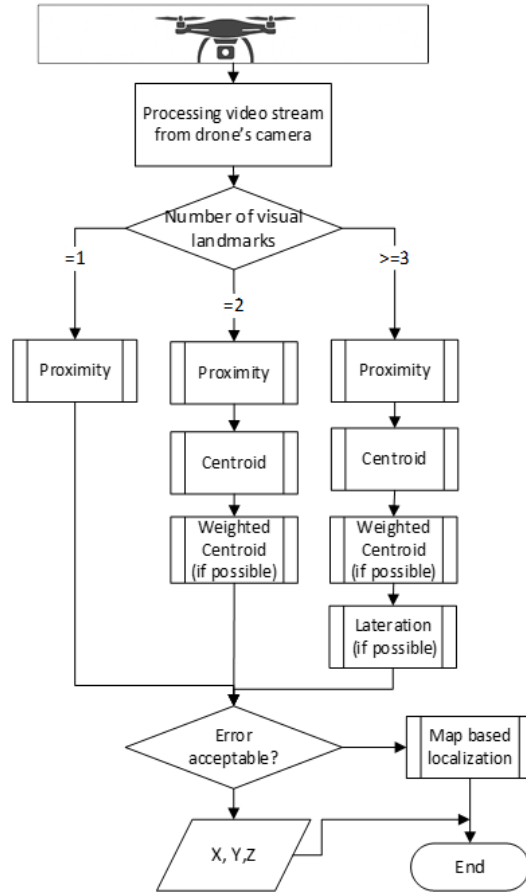


Figure 1: A comprehensive overview of the cascade algorithm, covering the architecture of calculation flows with a number of available benchmarks.

select the most appropriate localization technique depending on signal quality and environmental complexity.

4.1. Overview of the cascade structure

This architecture offers a balanced trade-off between computational efficiency and localization accuracy. By attempting the simplest methods first and escalating only when necessary, the system minimizes latency and energy consumption, making it well-suited for real-time use on lightweight UAV platforms with limited processing capacity.

The principle of operation of the cascade mechanism for the drone's perception of visual information by the onboard camera is shown in Figure 1.

In real time, image processing and recognition of objects around the UAV based on their texture, size, and shape are performed. Preliminary localization is based on the use of classical methods, when the system estimates the optimal location of the UAV among four methods used sequentially:

1. Proximity selects the closest object in distance from the surrounding objects, then calculates its coordinates and assigns them as the current location of the UAV. The advantages of the method are simplicity in software implementation, as well as speed of data processing, along with the ability to work with a limited set of landmarks.

2. Centroid is the process of finding the coordinates of the center point of a shape formed based on a fixed number of landmarks. It is used when there are two or more objects around.

3. Weighted Centroid is an improved version of the previous method due to weighting coefficients that significantly affect the coordinates of the position in space by taking into account distance values.

4. Lateration calculates the coordinates of the UAV position based on distances and sets of coordinates, and the method works only when data is available for three or more landmarks. Higher positioning accuracy is achieved by solving a system of nonlinear equations using the least squares method.

During the flight mission, each of the methods is calculated several times every second without delay. This allows the acquired values to be averaged and normalized when artifacts appear, caused by a sharp change in lighting or an error in the display of pixel values. The system is quite flexible when interacting with different sequences of captured objects, their number or sizes.

Adaptive accuracy assessment is a cycle during which each of the presented methods provides its calculation result, after which the error is estimated and compared. The algorithm stops working and provides a result if the determined position of the UAV passes the acceptable verification threshold, or is redirected to the next method in the cascade.

In the event that none of the methods offered an accurate result, or if there are not enough landmarks or they are unreliable, the system is redirected to a backup current position localization module that works on the basis of a pre-created map or landmark position records and uses pattern matching and visual recognition methods.

The advantages of the algorithm are adaptability to environmental conditions and dynamic selection of the required method, which shows higher accuracy and is easier to implement, as it does not require deep learning models, too powerful resources (sensors or additional equipment for computing), as well as additional calibration.

The application on a small-sized quadcopter model such as the DJI Tello EDU shows high efficiency and performance when used on platforms with limited hardware capabilities. Moreover, all this occurs in conjunction with pre-processing of video frames, a process that also requires resources for calculation and analysis.

4.2. Experimental setup and evaluation procedure

To evaluate the performance of the baseline indoor positioning algorithms under controlled conditions, a test rig was implemented using a DJI Tello drone equipped with a 720p camera. The experiment was conducted in a closed 5x5 meter room with four visual markers mounted on the walls and stands, and a 1x1 meter reference grid painted on the floor. The entire setup was designed to reproduce a simplified but realistic indoor positioning scenario, allowing for consistent evaluation of positioning accuracy using different methods. Data on the UAV position, rotation, and object parameters served to calculate the actual test results and further calibration of methods during of development.

The software stack included Python, the TelloPy API for communicating with the drones, and OpenCV for image processing and marker detection. The drone was sequentially moved to predefined static positions in the room. At each position, a set of positioning algorithms were independently applied to estimate the drone's location based on visual landmarks and environmental constraints. The estimation procedure involved comparing the algorithmically estimated position with the known true location determined using the reference floor grid.

Modeling the conditions of the absence of GPS and taking measurements of the drone's presence space allowed not only to accurately compare the results of actual measurements with the original calculation data, but also to calculate the localization error, which is described as the Euclidean distance between the estimated and actual coordinates.

5. Research results

To properly evaluate the proposed approach, a set of experiments was conducted in different situations and numbers of objects around the UAV. All acquired values during real-time video stream processing were recorded in data arrays, which were collected and exported to .xlsx and .txt files for parsing and further analysis at each stage of development and application.

The Radar Chart in Figure 2 shows the localization error of the quadcopter in an unknown space based on four positioning algorithms: Proximity, Centroid, Weighted Centroid and Lateration. The

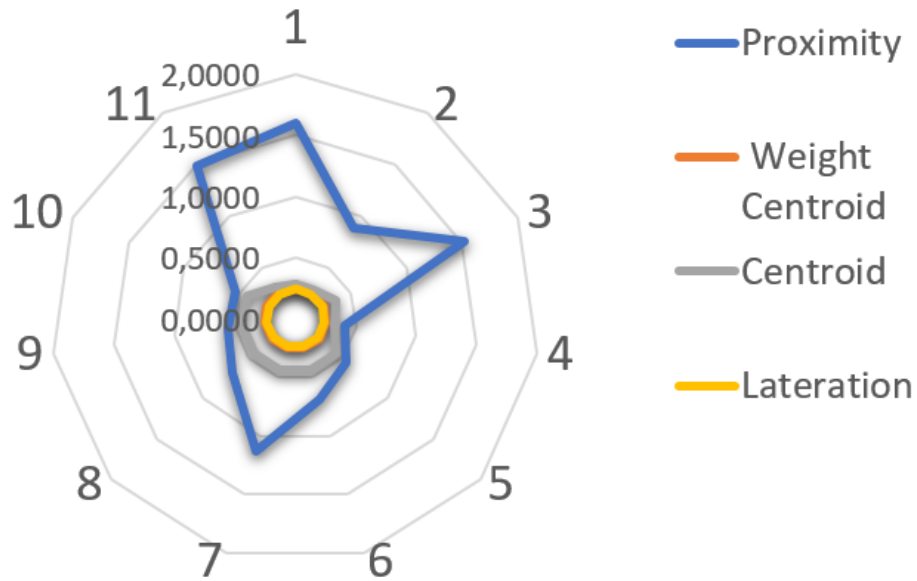


Figure 2: Localization error (in meters) for four indoor positioning algorithms.

evaluation was carried out on the basis of eleven static control points in the room.

As a result, the Proximity method has quite large impulse deviations, reaching 1.6 m. Despite the high speed of calculation and ease of integration, this indicates limited accuracy, but it is advisable to use it as a preliminary approximation or in situations with a limited number of landmarks. Unlike the previous one, the centroid demonstrates more stable error values, however, due to the simplicity of the relations used, in some cases the error reaches 0.44 meters.

The presence of more information describing the recorded objects increases the probability of accurate identification of the UAV position. Thus, the use of weighting factors in Weighted Centroid provides an advantage in the accuracy of calculations, because the coefficients are calculated, the values of which are inversely proportional to the distance to the objects. The largest indicator of this method reaches 0.25m.

At the same time, Lateration has a low level of error (0.24 m) due to the least squares method level calculation system and a sufficient set of data (position coordinates, distance, dimensions) according to each landmark, and the accuracy of the method can only increase with an increase in the number of objects around.

In general, the choice of adaptive algorithm methods is based on a balance between the desired accuracy, the number of available landmarks, and computational resources. A comparative analysis of the error of the methods confirms that Centroid and Weighted Centroid are suitable for scenarios with limited information, while Real-time Lateration provides the highest accuracy of drone positioning in a complex local environment.

The line chart on Figure 3 shows the standard deviation versus height (in meters) for four standard positioning algorithms and the proposed adaptive method. The evaluation was based on finding fifteen test positions.

The results of Proximity have sharp impulses, reaching up to 0.1 m. The centroid showed a fairly stable, but at the same time high level of error, about 0.08 m. Due to the weighting factors, the error rate of Weighted Centroid is lower than previous methods and is 0.06. Lateration demonstrates a fairly static trend of 0.04 meters. The adaptive algorithm not only adopts the values obtained through calculations by one or another method, which provides impulse loads at the beginning, but also provides data interpolation, due to which its error decreases over time and in some places reaches less than 0.04 m.

The results of comparison the accuracy of the Proximity and Centroid methods in the horizontal OXY plane are shown in the scatter plot (Figure 4), where each point represents the determined position of the UAV after a second-by-second calculation cycle. The result shows, Proximity has a larger area

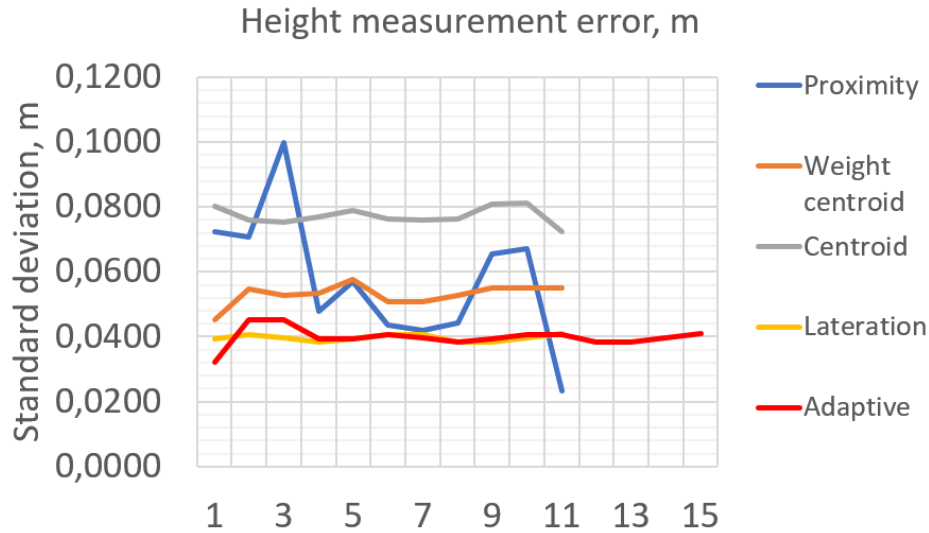


Figure 3: Standard deviation of height measurements for five positioning algorithms.

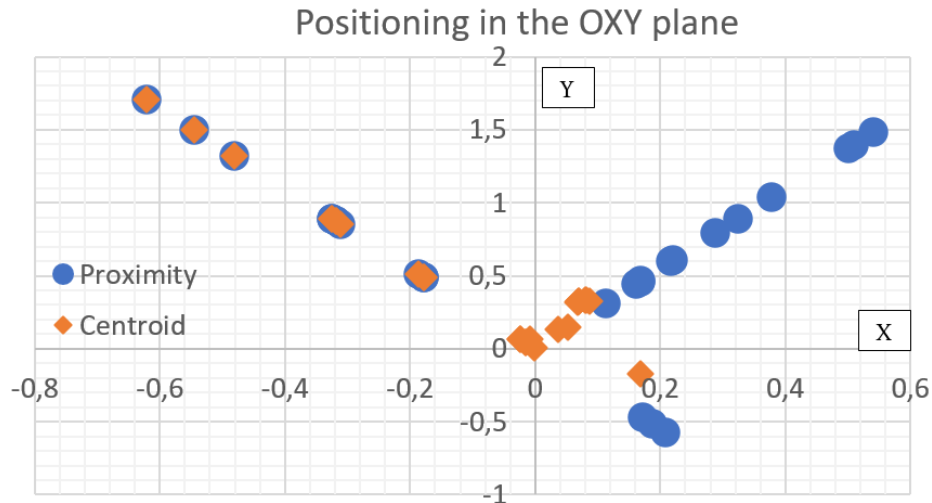


Figure 4: Estimated positions using Proximity and Centroid methods in the horizontal OXY plane.

of distribution of values than Centroid, which still stabilizes the distribution of values over time and creates a local cluster between the extreme values.

Based on the fact that the Lateration method is possible if there are at least 3 objects on the scatter diagram (Figure 5), a comparison of the estimation of the current position of the quadcopter in a room is shown, where each of the ten steps represents both the recognition of landmarks around and the instantaneous determination of the position in real time.

Weighted Centroid generalizes the possible position area, creating a cluster of values that almost do not change over time. Moreover, the larger the number of clusters, the less likely they are to change further in the process of acquiring new values. Lateration, on the contrary, takes into account data about each object and shows the exact position of the UAV at each moment of time, taking into account possible deviations in the acquisition or calculation of values.

The result of the adaptive algorithm is shown in Figure 6, where the quadcopter position points are placed on the horizontal OXY plane during the determination of optimal coordinates by comparison the results of the main visual navigation methods. The spatial relationship scale is indicated in meters.

The use of an adaptive method based on interpolation reduces the spread of values, since significant

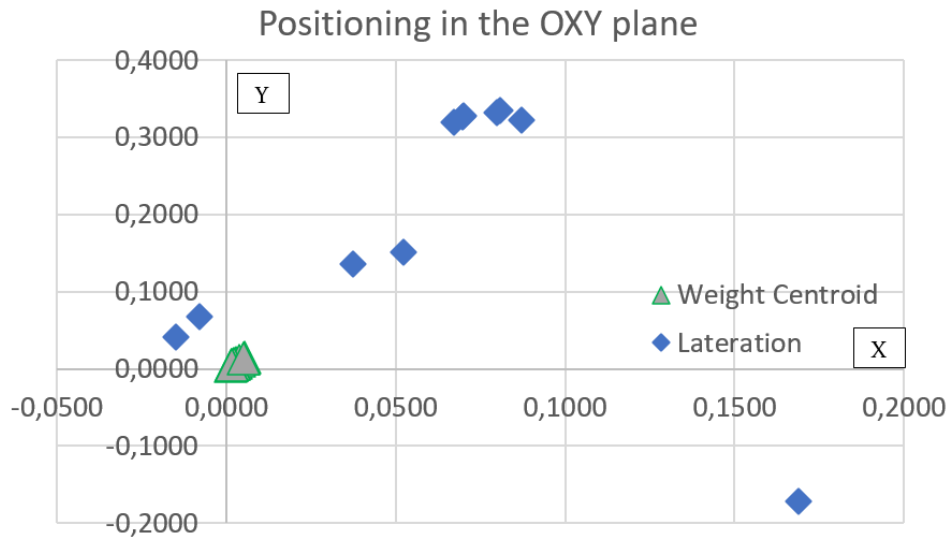


Figure 5: Localization results on the OXY plane using Weighted Centroid and Lateration.

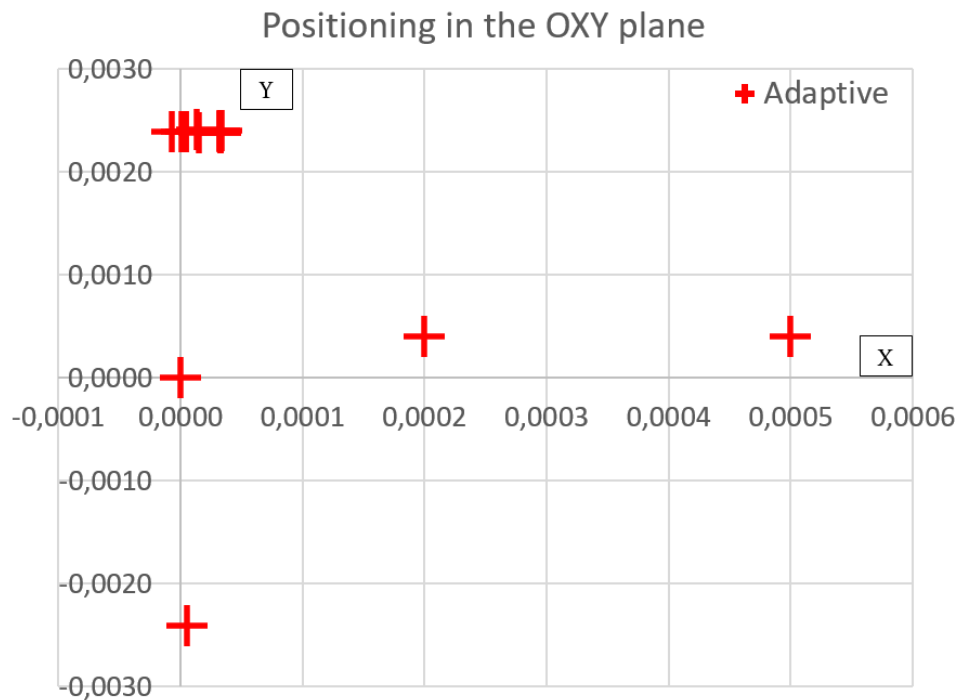


Figure 6: Position estimates using the Adaptive algorithm on the OXY plane.

noise is eliminated both at the beginning of processing and during the calculations, when empirically selected kernel parameters are applied to the matrices, which reduce the influence of random variables on the final result. Thus, the adaptive algorithm has undergone a shift from the initial position mainly within the range of ± 0.003 meters, which indicates its stability and accuracy in the complete absence of external signals.

Each subsequent method is more complex than the previous one, as it contains additional calculation and verification steps and is autonomous, and the system itself operates in switch mode, which allows for modular implementation of calculations, multiple parallel threads, and flexibility in settings.

To conduct a content analysis of the efficiency during each stage and determine the speed, an

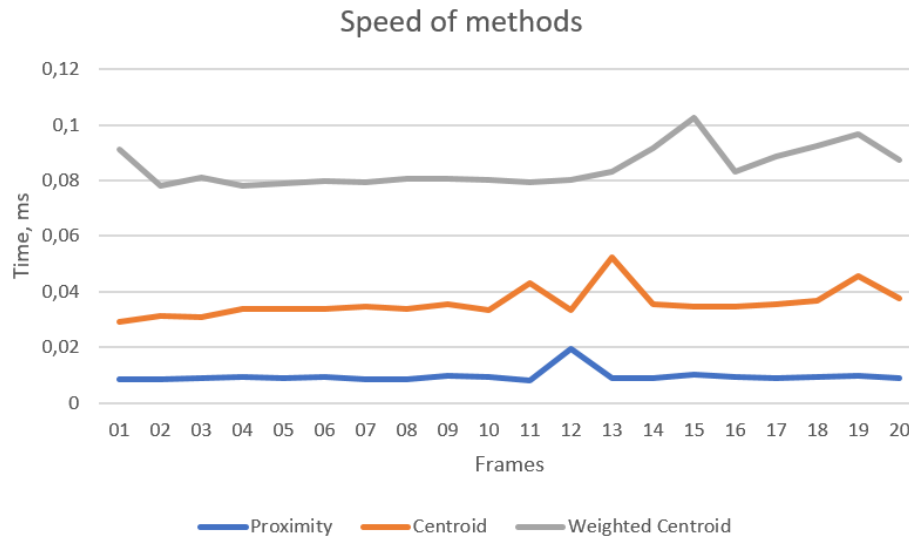


Figure 7: Estimated positions using Proximity and Centroid methods in the horizontal OXY plane.

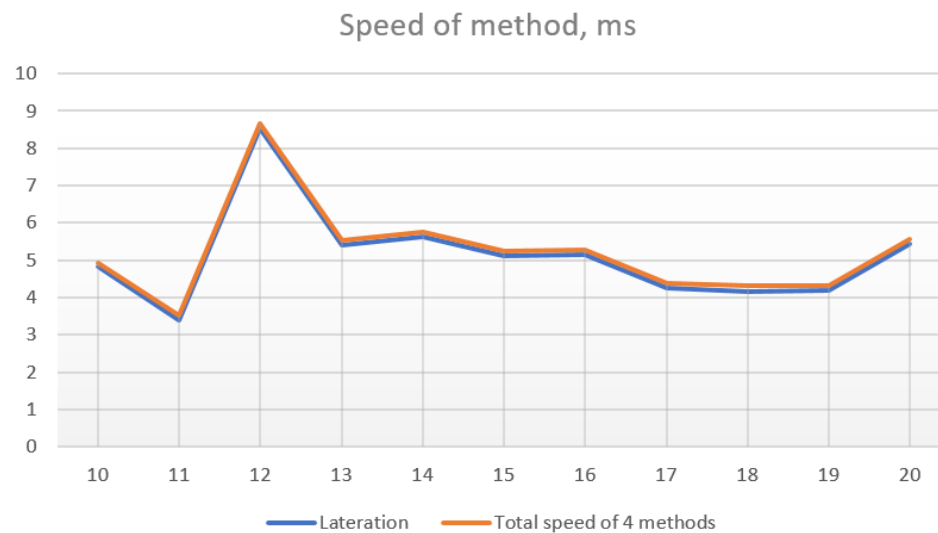


Figure 8: Localization results on the OXY plane using Weighted Centroid and Lateration.

additional calculation speed determination module was integrated into each of the methods. Based on the export results, a line chart was constructed, that presented in Figure 7, showing the change in the speed value of the three visual navigation methods during the full cycle of the program.

Since the Lateration calculation requires at least three landmarks and is an iterative calculation of a nonlinear system of equations for each frame, it is worth noting that as the number of landmarks increases, the processing time also increases. Thus, the diagram in Figure 8 shows the speed of the method when recognizing landmarks every second and determining the current location of the UAV.

As a result, the calculation speed is the advantage of Proximity, Centroid and Weight Centroid, while Lateration brings greater accuracy due to complex computational processes, so the calculation time is significantly longer. In both cases, impulse fluctuations are usually caused by changing one object in the frame to another or by sensitivity to lighting, but they normalize over time.

6. Directions for future research

So far, our work has focused on the architecture of a cascade mechanism that combines methods with varying degrees of complexity. From faster in calculations to more complex ones that require additional checks to ensure a reliable basis for mechanisms for detecting the current position of the quadcopter in an unknown space. Each of the methods is focused on high accuracy and optimal loading, taking into account the state of the platform on which the testing is performed. However, several open questions remain on our path that require additional attention.

The first area for improvement is working with dynamic environments. Most of the algorithms tested are focused mainly on interaction with static objects, while methods for dynamic environments use comparisons with databases, machine learning, etc. Future work will be aimed at finding optimal real-time data fusion algorithms with low computational requirements and performance characteristics in dynamic conditions (moving, layering, and rotating landmarks).

The next steps will be integration with visual odometry and SLAM methods, which can significantly increase positioning accuracy, especially in the absence of navigation signals or in situations with a limited number of landmarks.

In addition, we plan to expand the available APIs for DJI Tello EDU, which will allow for more flexible settings based on user-defined conditions. We also plan to consider combining the capabilities of small quadcopters with the involvement of machine learning in positioning tasks and scenario determination, which takes into account modeling of uncertainty situations in which the system can operate autonomously, minimizing manual intervention and independently predicting the effectiveness of the system based on error calculations.

The general advantages of the improvement are increased accuracy in localizing the current location of small drones in an unknown space, as well as flexibility in system configuration and availability.

7. Conclusions

The proposed cascade approach allows to significantly reduce computational costs and energy consumption when localizing a drone without losing accuracy. Unlike approaches based on Fingerprinting, the implementation does not require prior training or the creation of a complex database, which greatly simplifies the implementation of the system in a new environment.

The algorithm demonstrates the ability to adapt to different levels of complexity of conditions: more complex positioning methods are activated only when simple ones are not accurate enough. The transition to cartographic positioning is initiated in cases when its necessary, which optimizes the use of resources.

The obtained experimental results prove the effectiveness of the approach for tasks of autonomous UAV navigation in closed rooms and open up prospects for further integration with other sensor channels and flight stabilization algorithms.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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