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Monocam Drone Swarm Guard: A Real-Time Collision Detection and Avoidance System

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Abstract

Another technology which is becoming more popular in our skies is the unmanned aerial vehicles (UAVs or drones) particularly when they are operated in swarms. With the increased use of drones' concern over mid-air collisions has also become a natural issue particularly where visibility is low or when the drones are operating within a very close radius. This paper presents Monocam Drone Swarm Guard- a system that enables drones to navigate a shared airspace with one camera safely. Rather than implementing an intricate sensing system we decided to operate the system on a normal laptop with live video and discovered that it was able to follow through with drones even under vegetation and motion blur conditions. Our system can detect potential collisions before they happen by applying deep learning (YOLOv8) to detect and using a combination of a Kalman and Extended Kalman Filters to track and predict drone paths. Based on our experiment the findings indicate that the approach is effective in realtime tracking and ensuring safety of drone swarms when their operation occurs in adverse and realistic environments.

Keywords: Drone Swarm; Monocular Vision; YOLOv8; Kalman Filter; Extended Kalman Filter (EKF); Collision Avoidance; Real-Time Tracking; UAV Safety.

How to Cite This Article

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Introduction

Swarms consist of massive collections of drones that collaborate based on local interaction and shared objectives. Swarm robotics (SR) is a niche field of cooperative robotics that applies swarm intelligence ideas to facilitate coordination among a number of agents that do not have central control. Individual units relate to one another and to the surrounding environment in order to act in a complex and intelligent fashion in such systems. By doing so, it is possible to have a group of cheap, small-scale agents collaborate in areas previously needing an individual highly complex system or a small number of sophisticated units.

The most recent years saw the emergence of unmanned aerial vehicles (UAVs), also known as drones as one of the most popular platforms of swarm-based operations. Drones' swarms are becoming the research topic in surveillance, disaster management, environmental scanning, agriculture and defence. As the drones work as a coordinated group they can cover more space become more fault tolerant and do collective decisions to enhance the efficiency of the whole system. Nevertheless, the more drones are operated in shared airspace the more safety-related, coordination related and collision related issues develop.

Detecting, tracking and predicting the motion of individual drones in the swarm is one of the most difficult aspects in the deployment of the drone swarm. The drones are characterized by quick velocity and switching of the trajectory and frequent occlusions especially in the thick swarm structures. These aspects complicate the accurate tracking in the real world that involves vegetation, non-uniform light and motion blur. Besides, drones in a swarm tend to be extremely similar and travel parallel flight paths that may cause the detection algorithms to mix up and switch identities or they may lose track.

The growing application of drones in sensitive as well as civilian settings has resulted in grave apprehensions about the airspace security and unproven missions. When swarming, there is high likelihood of colliding with other mid-air and dynamic drones that are close to each other. Devoid of tracking and prediction methods like such collisions can jeopardize the safety of the people, ruin infrastructure and restrict the scaling nature of swarm-based systems. This results in an increase in the need to have an accurate, real-time and reliable swarm monitoring solutions.

The current drone tracking and collision avoidance systems in use are based on sensor intensive designs e.g. GPS, radar, LiDAR or stereovision cameras. Whereas these strategies raise the cost of a system, computational complexity and implementation limitations. Compensation In contrast monocular vision-based systems offer a lower priced and simpler to implement alternative yet need more complex computer vision and state estimation methods to offset a shortage of explicit depth data.

These difficulties inspired this study which suggests the solution named Monocam Drone Swarm Guard a real-time collision avoidance and detection system that is constructed on the foundation of one monocular camera. The proposed system relies on the YOLOv8 deep learning model to detect drones with high precision in a visually challenging setting such as vegetation and motion blurred scenes. Multi-object tracking is performed by a Kalman Filter to guarantee that constant tracking and strong motion estimation and non-linear trajectory prediction is conducted by an Extended Kalman Filter (EKF).

The system predicts future trajectories and determines the possible risks of collision and delivers an estimated collision point in a real-time user interface. The general purpose of the work is to come up with a camera-alone lightweight design that can identify, follow, and predict drone movement in real time hence able to identify the threat of collision early and have low hardware complexity and high scalability. The paper is also structured as follows: Section 2 conducts a literature review of related work in the areas of drone swarms and vision-based tracking. Section 3 explains the system architecture and the methodology being proposed. Section 4 shows the experiment structure and the outcome of the evaluation. Lastly, Section 5 summarizes the paper and gives the future directions of the research.

Background

The swarm concept is largely a term applied to denote a group of drones that can collaborate with each other by means of local interactions to accomplish a common goal. The swarm-based systems largely rely on decentralized decision making in which intricate global behaviour is developed through basic local rules. Swarm robotics is a domain of cooperative robotics inspired by natural flocks of birds, schools of fish and insect colonies and is specifically concerned with scalability, robustness and flexibility

which enable them to be especially appropriate to dynamic and uncertain environments. Drones or unmanned aerial vehicles (UAVs) have experienced an accelerated adoption in civilian and military sectors in the recent years. In addition to single drone-based solutions the concept of drone swarm has attracted much interest because it can improve coverage, redundancy and efficiency of the mission. A drone swarm is a group of smart UAVs that collaborate with each other and can act as one system with the capability to coordinate movement, communicate and react to changes in the environment. Consequently, drone swarms are currently regarded as a transformative technology in such fields as surveillance, reconnaissance, disaster management and defence. The rise in the popularity of the drone swarm technology is attributed to its strategic benefits that encompass cost reduction, fault-tolerance and the capability of performing tasks that are impractical to the individual drone. Drones swarms could be used to conduct coordinated situational monitoring, border monitoring and threat monitoring across vast geographic areas in defence and security applications. Likewise, swarms are being investigated more in the civilian world in search and rescue, environmental monitoring, smart farming and infrastructural investigations. The benefits notwithstanding drone swarms are posing serious technical setbacks especially with regard to safe operation and collision avoidance. The more drones are flying at a time, the more the chances of colliding in the air. The high speed of drones, the high inter-drone distances, the crisscross movement and high frequency of occlusions also contribute to this risk. Also, the drones in a swarm tend to resemble in visual appearance such that it is hard to differentiate and monitor each member at any given time

Drone Swarms and Sensing Technologies

Radar sensor: An instrument used to locate the position of an object on the road (Pile, 2008). The swarms of drones will rely on precise perception to identify, track and locate other drones and environmental obstacles around them. Various sensing technology has been considered to detect and track a drone like radio frequency (RF) analysis, radar, acoustic sensing and optical cameras. RF based methods keep track of communication between drones and controllers but cannot be utilized in the case of autonomous operation or when drones are following a pre-programmed trajectory. The acoustic sensing technologies strive to detect the drones by the sound of rotors but they lack the range and are unable to operate in the noisy environment. The cameras have come out as an awesome substitute in terms of long-range capability and high spatial resolution in optical sensing. Drone could be seen visually by vision methods with abundant data about their movement and the spatial relations. Traditional camera-based systems, however, generally rely on setting up stereo-vision or a multi-synchronized camera in order to determine depth correctly. Although these methods make the system more complex, expensive and laborious to calibrate. Systems that can be used to monitor the movements of an object using a single camera are known as Monocular vision-based systems that are lightweight and very inexpensive at a price, however have other issues. Monocular systems, provided that no explicit depth information is given, have to depend on sophisticated algorithms to estimate and predict motion. These limitations are more pronounced in the outdoors environment that has vegetation, different illumination and motion blur in which detection reliability may significantly drop. In this paper we present a drone swarm multi-object tracking model as an additional result of iconic application.

Multi-Object Tracking with drone swarms

It is a basic computer vision issue, which entails the detection of multiple objects in a video stream, keeping track of their identity throughout the video and estimating their motion. Multi Object Tracking is significant in drone swarms to facilitate collision avoidance and coordinated behaviour in the context of drone swarms. The uses of MOT are spread into various areas such as pedestrian tracking, traffic tracking, autonomous navigation and aerial surveillance. It is difficult to track drones in a swarm due to abrupt changes in their appearance, sudden acceleration, crossed paths and repetitive blocking. These issues are further compounded in high density swarm arrangements in which drones travel at close ranges and share identical visual properties. Traditional tracking techniques usually do not perform well in such situations resulting to identity change and tracking failure. Kalman Filter a probabilistic state estimation algorithm have been popular in measuring moving objects with noisy measurements. The Kalman Filter gives the most effective calculation of the position and velocity of the object in the case when the motion of the drone can be considered to be linear. Drone motion hardly ever takes the linear pattern especially when unexpected environmental factors are involved. In order to overcome this shortcoming, the Extended Kalman Framework (EKF) compounds the Kalman model with non-linear transitions in the state that are more appropriate in predicting drone paths in real world setup. The available research on drone swarm tracking is mostly based on the detection or tracking of swarms without paying much attention to the joint issues of dense structure, active movement and real time collision prediction. In addition, many of these techniques rely on specialized hardware or controlled conditions restricting their application in practice. Summarily as stated in the current literature is the increasing importance of drone swarm technologies and a major gap in terms of lightweight, vision allied collision detection and avoidance systems that are able to function within dense and dynamic environment. To address this gap, we have come up with a monocular vision-based framework that unites deep learning-based detection with Kalman-based tracking and prediction. The solution is intended to offer real time drone swarm monitoring and collision avoidance with a pragmatic and scalable solution.

A Swarm Drone Tracking Framework

Multi-Object Tracking (MOT) is generally regarded as one of the more problematic tasks of computer vision and especially dense and dynamic scenes. MOT is also more complicated in drone swarm conditions due to the presence of several high-speed bodies per frame, high levels of occlusion and high visual similarity of drones. Due to the ongoing growth in the use of drone technology, particularly in surveillance and autonomous environment, reliable real time tracking systems are needed nowadays. Situation awareness and avoidance of mid-air collisions in swarm of drones requires accurate detection and tracking of the swarm. The loss of identity or wrong trajectory estimation or delayed collisions due to loss of track could occur.

Within the framework of the safety of drone swarms, accurate detection and tracking of drone swarms are fundamental in ensuring situational awareness and avoiding mid-air collisions. Loss of identity or inaccurate estimation of trajectory or slow alert notifying collisions may occur due to a tracking failure. Hence, effective and powerful tracking system is demanded which was to work in real time with lightweight sensing equipment. It is in this section that the proposed Monocam Drone Swarm Guard framework is presented which combines both probabilistic tracking and probabilistic prediction with deep learning-based detection achieve collision detection and avoidance with only a single monocular camera.

Drone Swarm Tracking Pipeline:
The proposed framework entirely aims at identifying, monitoring and forecasting the movement of drones within a common airspace as they fly in a coordinated manner with real time video footage of a monocular camera. We rely on motion modelling and trajectory prediction as opposed to explicit depth estimation in stereo vision or additional sensor readings in order to detect possible collisions. The pipeline comprises of sequential modules such as detection, refining of bounding boxes, identity association, tracking, trajectory prediction and estimation of collision risks. The system constantly works with live video input and processes updates on the status of drones' frame by frame.

Algorithm 1: Monocam Drone Swarm Tracking and Collision Prediction

Input: Live video frames from monocular camera
Output: Collision alerts with predicted coordinates
    Initialize YOLOv8 detector
    Initialize Kalman Filter and EKF for detected drones
    While video stream is active do
    Capture current frame
    Detect drones using YOLOv8
    Apply Non-Maximum Suppression (NMS)
    Assign unique IDs to detected drones
    Predict next state using Kalman Filter
    Update state using current detections
    Predict future trajectories using EKF
    Estimate inter-drone distances
    If predicted distance < safety threshold then
    Generate collision alert
    Output predicted collision coordinates
    End while

System Architecture

YOLOv8-Based Drone Detection:
YOLOv8 deep learning model is used to perform drone detection and it has high detection accuracy and minimal inference latency that makes it befit the application of drone detection in real-time. YOLOv8 breaks down the input frame into a grid and estimates bounding boxes and scores in one forward pass. This one stage detection architecture enables the system to identify a number of drones in a single frame. In training, we employed the drone pictures which were captured in the vegetation-filled and motion-blurred spaces in order to make the model more responsive to the visual complexities. YOLOv8 is capable of recognising even small-scale drones, with partial occlusions or high motion. Nonetheless, since swarm scenes are densely packed, the overlapping bounding boxes of the same drone can be formed.

Bounding Box Refinement and Identity Assignment:
In order to remove redundant detections, NonMaximum Suppression (NMS) is utilized on each frame. NMS duplicates the overlapping bounding box and retains the most certain detection of a drone. Practically this step has a significant effect of minimizing false detection and increasing accuracy in localization. After refining, each drone that is identified is given a distinct identity (ID) that is maintained across frames. Persistence of identity association enables the system to track individual drones at any time in cases where there are more number of similar looking drones.

Multi-Object Tracking with Kalman filter:
After the establishment of the drone identities, Kalman Filters are utilized in multiobject tracking. The Kalman Filter of each drone is independent, and it estimates the position and the velocity of the drone using a constant-velocity motion model. Kalman Filter works in two phases: Prediction, an approximation of future state based on past movement. Update which corrects the estimate with YOLOv8 detection measurements. Practically this probabilistic formulation enables tracking to stay constant even in instances where the detections are subjected to noise or temporary occlusions.

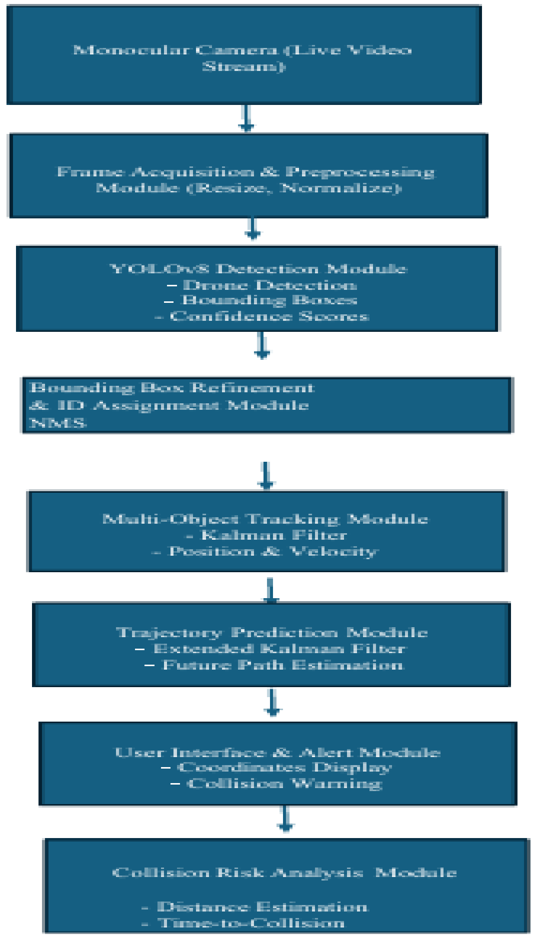

Fig. 1. *System Architecture*

Prediction of Non-Linear Trajectory with Extended Kalman Prediction:

The non-linear movement of drones in the real world is usually caused by abrupt turns, acceleration and environmental interference. The proposed framework based on an Extended Kalman Filter (EKF) to predict future trajectories will address this issue. The EKF is a variation of the Kalman Filter which linearizes non-linear equations of motion around the current state estimate. The system is used to make short term predictions of the position of each drone over a given period of time using EKF. The basis of collision risk assessment is based on these projected paths**.**

Collision Risk Estimation and Coordinate Output

The collision detection is done by examining the projected paths of all the drones being tracked. The prediction horizon is computed on the Euclidean distance of predicted positions of drone pairs. When the estimated distance is less than the set allowable level the system detects a possible collision. When a risk of collision is detected by the framework, it produces: Drone IDs involved Anticipated collision coordinates.

Estimated time-to-collision These findings are presented on a real-time user interface that allows taking early warning measures and collision prevention measures.

Conclusion on the Proposed Framework

The Monocam Drone Swarm Guard framework suggested combines YOLOv8 detection, tracking with the Kalman filter and prediction with the EKF in a single real-time pipeline. The utilization of monocular video as the only source of input rendered the system efficient and hardware needs easy, as well as allowed keeping good accuracy. The solution will offer a viable method of monitoring drone swarms and preventing the risks of collisions in real world conditions.

Evaluation

This section outlines the evaluation plan, experimental research and observations of the proposed Monocam Drone Swarm Guard system. At this level of development, the assessment is to acquire knowledge of feasibility and system behaviour under controlled conditions with quantitative benchmarking. These tests help us to determine the level of effectiveness of the proposed pipeline in terms of detection, tracking, and prediction of drone motion and detection of swarm collision risks. The assessment system is aimed at real-time functionality ability to work within visually demanding settings and in swarm density. The camera-based setup combined with a laptop- based processing unit is used to carry out all experiments.

Experimental Platform and Configuration

The platform and configuration of the experiment were as follows: The suggested system is applied to a laptop-based platform, which is attached to a real-time monocular RGB camera. The pipeline is created in Python and OpenCV and includes the drone detection with the use of YOLOv8 and the tracking and prediction stage with the help of the Kalman filters. The system works in real time, it is not needed to have any external sensors like LiDAR, radar or stereo cameras.

Table 1 summarizes the experimental platform configuration used for the preliminary evaluation.

Table 1. *Experimental Platform Configuration*

Component	**Specification**
Detection Model	YOLOv8
Tracking	Kalman Filter
Prediction	Extended Kalman Filter
Camera	Monocular RGB Camera
Processing Unit	Laptop
Operating System	64-bit System
Programming Tools	Python, OpenCV

Implementation Overview

Implementation of the architecture is based on architecture described above in Section 3. Frames of the live video camera are obtained at the monocular camera and sent to the YOLOv8 detector module. The identified bounding boxes are optimized by Non Maximum Suppression (NMS) and then identity assignment is done to each drone. Kalman Filters are applied in cases when tracking the object over time should be constant and Extended Kalman Filters are applied in cases when one wants to predict the future trajectory. Practically the system processes one frame at a time, but continuity in time is enforced by estimating the state. The anticipated tracks are monitored in order to identify the possible collision hazards that are then represented by coordinate based notifications on the user interface. The system has so far been tested against controlled video input, recorded drone footage and small amounts of real time camera testing to confirm that the system is functionally correct and stable with regard to the pipeline.

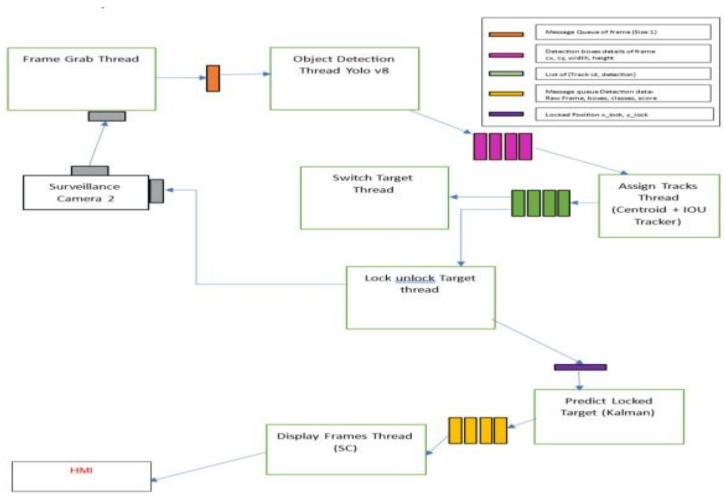

Fig. 2. *Implementation Overview*

Data Preparation and Training plan:

The detection model is trained since the existing drone swarm datasets in the real world are scarce the combinations of existing drone images that are accessible on the internet and the custom images that are taken to reflect the presence of drones in vegetation laden and motion blurred environments. The data set comprises the variation in the orientation of the drone, scale, complexity of the background and the light conditions. Standard bounding box labelling tools are used to annotate images in a standard format, and these are converted into

YOLO format. The data is separated into training and validation samples that allow to monitor the performance in the process of training. To speed up convergence and enhance generalization, YOLOv8 is loaded with pretrained weights. The training is to be carried out to enhance small object detection and resistance to blur that are severe in drone swarm conditions.

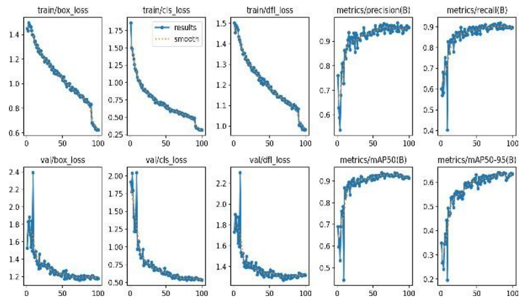

Fig. 3. *Result of Training of Yolo*

Fig. 4. *Validation Result*

Preliminary Drone Detection Evaluation

This evaluation is conducted to determine the initial possible steps in creating a drone detection device. The initial assessment phase is primarily aimed at the determination of the possibility of the system to identify several drones in one frame. Our initial test is on video sequences containing a small number of drones and then proceeds to the case of denser swarm formations. It is observed that YOLOv8 is able to detect drones in moderate visual clutter and changing background environments. Non-Maximum Suppression successfully provides better results by cutting down redundant detections which causes a cleaner and more accurate bounding box output. We qualitatively assess the performance of detection using visual inspection of the performance of bounding boxes, detection consistency over time and stability of confidence during motion and partial occlusions. The results during different environmental conditions were tested and noted down in tabular format.

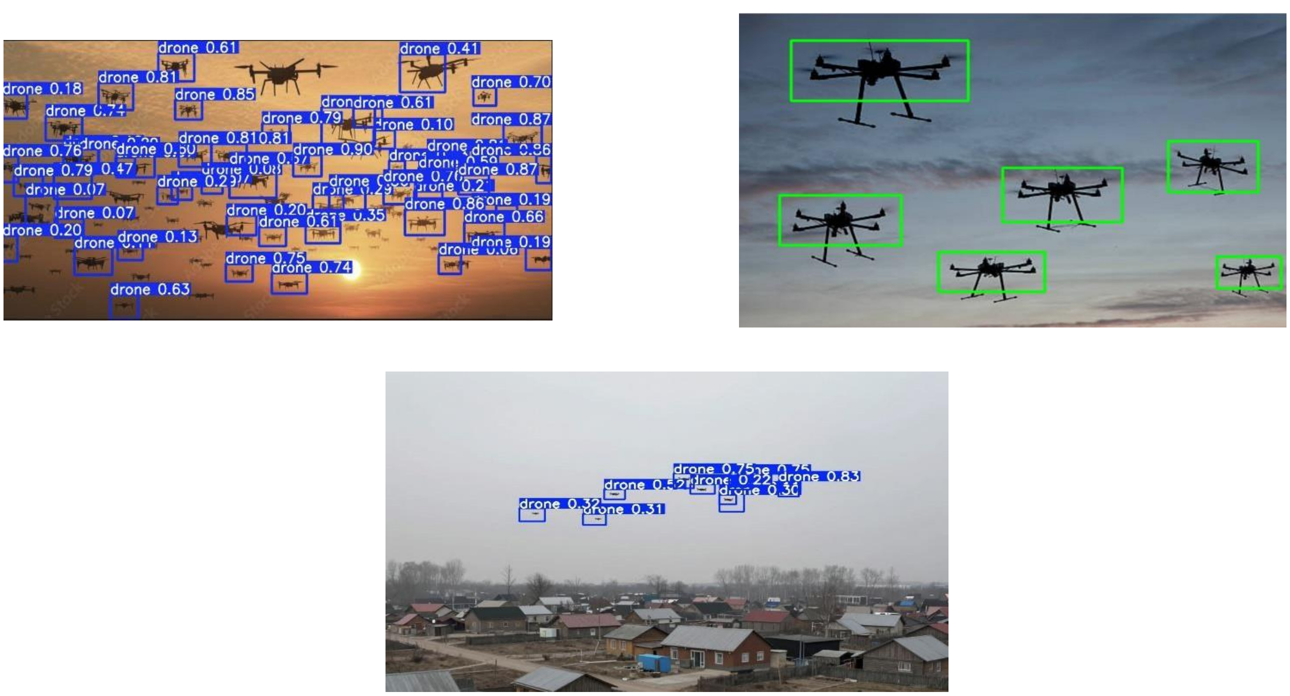

Fig. 5. *Detection Images of Drone Swarm*

Initial Tracking and Forecasting Assessment

The second step of assessment will assess tracking and prediction of the proposed framework. The Kalman Filters are employed to determine the positions and velocities of drones and allow following the trajectory smoothly in the cases when the detection is lost because of the occlusions or motion blurs. The long- term Kalman Filters are applied to predict short-term future locations of drones. The patterns of relative motion are analysed using these predictions in an effort to estimate possible collision scenarios. The reason is that the logic is very complex due to numerous factors needing to be clarified.

Fig. 6. *Tracking Result in Vegetation*

Collision Risk Analysis (Conceptual Validation)

This is because the reasoning is extremely complicated since many variables have to be explained. The estimation of the collision risk is confirmed in the context of interaction-based simulations in which drone paths are planned to cross. The system is able to detect predicted cross over points of the trajectory and issue warning of a collision before the drones hit the critical proximity. That output consists of the predicted coordinates of the collision and the drone identity that is reflected on the user interface. The initial findings support the ability of the collision detection logic and its implementation into the real-time pipeline.

Scalability Account

Scalability is tested by running experiments with more and more drones with recorded or simulated video flow inputs. The higher the swarm density, the more complex will be the detection and tracking as a result of overlapping bounding boxes and the like visual features. Initial experiments with the modular design seem to be able to support growing numbers of swarms quite well, but larger systems are going to demand additional refinements in their performance and optimization.

Discussion of Limitations

Given that the project is still being developed the evaluation here is only restricted to initial and qualitative evaluation. A large-scale quantitative study using measures of accuracy, distribution of errors, and comparison values will be carried out in further research when full scale experiments are accomplished. Also, real world testing in highly dynamic swarm conditions is yet to be evaluated.

Summary

This assessment part describes the experimental procedure and the initial testing of the Monocam Drone Swarm Guard system. Based on our experiments, it can be stated that monocular camera with deep learning and probabilistic filtering could be effectively employed in the drone swarm monitoring in real time and collision prediction. The next generation of experiments will be aimed at massive quantitative testing, real-world implementation, and most efficient performance.

Discussion

Drones Unmanned Aerial Vehicles (UAVs) have become very common due to their ability to provide flexibility in operation, high mobility and low cost of deployment. Nevertheless, with the fast development in the application of drones, especially swarm like formations there are concerns that involve airspace safety, privacy and protection of infrastructures. The unauthorized drone swarms that are flying in the areas of mass events, sensitive areas or other infrastructure, can present a serious threat. These issues point at the need of a system that would be able to identify, monitor and forecast the movement of drones in real time. In the current work a monocular-based vision frame Monocam Drone Swarm Guard is introduced, which is capable of identifying and tracking multiple drones, maintaining the real-time performance. Based on the analysis provided above we have discovered that just one camera is needed in order to identify and follow several drones. A discussion which follows examines the behaviour, strengths and limitations of the proposed framework according to initial observations of experiments. Swarm density influences performance of the system. At distance enough, the YOLOv8-based detection module provides stabilized and uniformity in bounding boxes that allow the Kalman filter to track the individual drones successfully. However, in more dense swarm operation, visual overlap of the drones is more common. The collision to give uncertainty in both detection and identity association resulting into lower tracking accuracy. This behaviour is desired in dense swarm cases, and is a fundamental problem in vision based multiobject tracking. Non-Maximum Suppression (NMS) has been integrated and is useful in minimizing false positives produced by the detection model. YOLOv8 though exceptionally good at detecting small objects can create various overlapping bounding boxes of the same drone in congested scenes. NMS addresses this problem by giving the highest certainty in the detection hence enhancing localization and minimizing tracking artifacts. Practically, Kalman Filter-based tracker averages motion estimates and assists continuous trajectories even in short intervals of loss to view in detection due to occlusions or motion blur. This is a critical property especially in swarm environments where the drones can just vanish out of sight. Nevertheless, the common Kalman Filters model linear dynamics that might not quite represent the non-linear dynamics of an agile drone. In order to overcome this weakness, the proposed framework uses an Extended Kalman filter (EKF) to predict future trajectory. EKF allows the non-linear motion patterns to be modelled and offers more realistic future position predictions. It is observed that the EKF based prediction will enhance prediction capability of the system in anticipating possible collisions particularly in situations where the direction changes suddenly. The fact that the EKF is included is also a considerable strength of the offered approach and is in line with the goal of early detection of collision risks. In a real-time deployment frame rate performance of the camera, processing frame rate, swarm size and computational resources are all practical considerations to system performance. Processing time naturally just grows as more tracked drones are in use as more drones are detected and filters processed. Balancing frame rate and workload is thus crucial in order to provide real time functionality. Practical ranges of frame rates between 15 and 30 frames per second (FPS) have been found to be adequate to provide smooth tracking and collision warnings in time in most drone swarm situations. The other critical factor is parametric uncertainty that occurs due to changes in the environmental factors, camera positioning, lighting and drone look. Under the current implementation, the detection and tracking of all the experiments is done using a fixed set of parameters. Although this will guarantee consistency it can restrict flexibility in situations that are extremely dynamic. Future directions It can be further studied how to tune parameters in an adaptive manner to achieve a greater level of robustness in the face of environmental variability. Nevertheless, despite these issues the proposed Monocam Drone Swarm Guard structure has a high potential as a lightweight and scalable system of monitoring a drone swarm. Its capability to work with a single camera and with normal computing devices renders it appropriate when used in resource constrained settings. Besides, the modular structure of the system enables future upgrades such as more accurate prediction models, adaptable filtering approaches and combination with autonomous avoiding systems. To conclude the discussion, it is important to note that dense swarm arrangements are still a difficult situation to track with a vision-based system but the suggested framework is still effective at moderate swarm densities and can be used as a base to make further improvements. The Kalman and Extended Kalman Filters with YOLOv8 give a balance between the accuracy, efficiency and simplicity of the system.

Conclusion and Future Work

The current paper introduced Monocam Drone Swarm Guard as a real-time drone swarm detection, tracking and collision risk estimation framework that has been developed based on a monocular camera. The suggested system will be seeking to comprehend and observe the behaviour of individual drones in a swarm by integrating both deep learning-based detection and probabilistic tracking and prediction. The monocular vision arrangement of the framework also lowers the complexity of the hardware used without losing its real-life applicability. The suggested pipeline will use YOLOv8 to detect the drone in real-time and Non-Maximum Suppression (NMS) to remove overlapping detections. A Kalman Filter is used to track each detected drone and so offer a smooth and stable state estimate between frames. An Extended Kalman Filter (EKF) is added to predict the position in the future to deal with nonlinear drone motion. According to the calculated path that the system takes into account collision risk and gives the anticipated positions based on the predefined paths using a user interface that allows early warning and avoidance. When combined, the presence of these components will enable the proposed framework to identify and monitor several drones at once with a high level of time consistency. YOLOv8 allows the effective search of small and fast-moving drones in the conditions with low visibility like vegetation backgrounds and motion blur. The Kalman Filter allows the tracking system to be more robust in the face of noise and failure to make an observation whereas the EKF-based prediction allows the system to predict the possible occurrence of a collision before it happens. Initial verification and high-level testing prove that the suggested framework can run in real time on a laptop-based processing unit with a live camera stream connected to it. The findings imply that the system is effective when the swarm densities are moderate to ensure the system has stable tracking and meaningful trajectory prediction. Nevertheless, with a higher swarm density and drones starting to overlap considerably performance is likely to decay because of the natural bounds of monocular eyesight and visual blockages. Regardless of these issues, the Monocam Drone Swarm Guard framework proposed still provides a robust base of lightweight, vision only drone swarm surveillance. The system can be extended and optimized over time and hence it is modular, which enables it to be used in applications like airspace safety, surveillance, infrastructure protection and swarm behaviour analysis.

Future Work

There are a number of directions of future research and development identified as promising:

1. Better Non-Linear Prediction Models: Future research will focus on improving the accuracy of trajectory prediction by enhancing the Extended Kalman Filter and investigating other non-linear estimation methods that can address sharp manoeuvres and

complex swarm dynamics.

2. Minimization of Adaptive Parameters: In the existing implementation, detection and tracking use a fixed set of parameters. The system can be further enhanced by introducing adaptive parameter tuning based on swarm density, motion patterns, and environmental conditions.
3. High-Level Occlusion Management: Overlap of drones in dense swarms remains a significant challenge. Future studies will explore identity reassociation strategies, motion-based reidentification, and learning-aided tracking methods to overcome failures caused by occlusions.
4. Self-Driving Collision Avoidance Embedding: Although this project focuses on collision detection and risk estimation, future developments will integrate control mechanisms to enable automatic evasive actions based on calculated collision points.
5. Defence and Security Applications: The proposed framework can be extended to defence-related scenarios such as hostile swarm surveillance, airspace intrusion detection, and swarm resiliency assessment. Additionally, the system can be used to study natural collective phenomena such as bird flocks and fish schools.

To conclude, Monocam Drone Swarm Guard demonstrates that efficient drone swarm recognition, tracking, and collision prediction can be achieved using a single camera enhanced by intelligent vision and state estimation algorithms. As the proposed framework is further refined and validated on a larger scale, it has the potential to contribute significantly to safe, autonomous, and scalable drone swarm operations in both civilian and defence sectors.

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