IMPLEMENTATION OF OBSTACLES AVOIDANCE AND DISTANCE MEASUREMENT WITH MONOCULAR VISION FOR UNMANNED AERIAL VEHICLES

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Abstract - Drones, also referred to as uncontrolled airborne objects, are more appropriate as "dull, dirty, or dangerous" tasks than are piloted aircraft. The drone can be operated remotely or alternatively it might follow a predetermined route by use of an intricate automation program. The most difficult issue for UAVs to solve in order to become fully autonomous is avoiding obstacles. This research uses monocular vision to detect frontal obstacles by employing machine vision to extract characteristics techniques such as Scale Invariant Feature Transform and Accelerated Robust Feature (SURF, SIFT). By calculating the pixel fluctuation in a series of successive video frames, the separation in length between the obstruction and The lens is determined. The designed method is evaluated using independently produced films shot with a Phantom 4 Pro DJI in order to achieve the established goals.

Key words- Speeded up robust features (SURF), scale invariant feature transformation (SIFT), obstacle avoidance and distance measurement Unmanned aerial system

I. INTRODUCTION

Drones, often known as unmanned aerial vehicles are becoming increasingly ubiquitous for both military and non-military purposes. The use of UAVs has grown significantly over time. with a broad variety of uses from military surveillance to commercial uses including delivery of products, extinguishing fires, and accuracy farming, etc. Their potential is boundless. UAV use has dramatically increased, and they will be very successful in the upcoming years. Figure 1 illustrates the range of uses about drones and the projected increase in demand for them in the future. Similar to [1], Ten are present. degrees completely autonomous systems (UAVs without a human operator) are examples of mission control transitioning from fully autonomous to partially autonomous (UAV outfitted with failure adaption algorithms). Mission control automatically is the highest level. Mini UAVs must fly at lower altitudes or operate inside buildings for commercial purposes, exposing them to several risks and barriers. In contrast to unmanned aerial vehicles, manned aerial (UAV) technology is still in its infancy when it comes to automatically sensing, recognizing, and avoiding permanent impediments like power lines, buildings, towers, and trees, as well as moving obstacles like birds and other aircraft. Therefore, there's a lot of room for study into Sense- Avert Detection algorithm embedding on UAVs. Upon obtaining the method of sensing, the best UAV routing as. One interesting approach for more straightforward obstacle identification in real-time video processing is the application in computer vision algorithms. Performance and object tracking are key elements of navigating using vision accuracy. Faster Up Robust Features (SURF) [3] and Scale Invariant Feature Transform (SIFT) [4] are two examples of feature descriptor techniques. While SIFT has demonstrated remarkable efficacy in object identification applications, its substantial computational complexity poses a significant disadvantage, particularly in real-time applications. The SIFT-approximating Accelerate Robust Feature (SURF) method outperforms SIFT without sacrificing The standard of the identified points. Both of these resilient feature descriptors remain constant in the face of affine transformation, blur, rotation, scale, and illumination variations. Different techniques for extracting features and, consequently, detection of This implementation of Using monocular vision, obstacle avoidance and distance measuring for UAVs provides an essential capability for autonomous navigation. By combining computer vision algorithms, distance estimation techniques, and a well-designed control system, the UAV can navigate through environments with obstacles, making it suitable for a variety of of applications. Monocular vision, which involves using a single camera, is a cost-effective and lightweight solution for implementing these functionalities. This implementation aims to create a system that enables UAVs to navigate autonomously by avoiding obstacles and measuring distances using monocular vision.

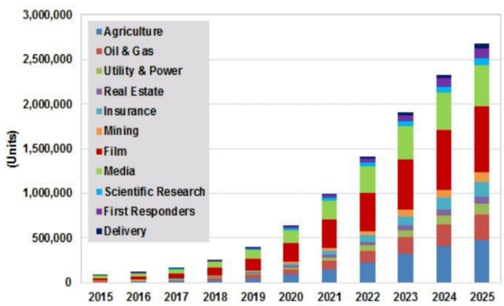

Fig.1 bar chart

II. LITERATURE SURVEY

Real-time object identification and collision avoidance technique for UAVs was summarized by **Abdulla Al-Kaff et al. [5]**. To take the picture, a single one-eye camera is fixed to the car. The algorithms Brute Force and SIFT are used to create and match key points. With a 62-degree area of view, 52.4 m s of processing time is needed (FOV). They are able to detect items in the 90–120 cm range with their approach.

As summarized by **Levente Kovacs et al. [6**], a deconvolution technique is used to identify the object region, extract features from that object, and generate a feature map, also known as a D-map. A monocular camera is commonly used in numerous contexts to catch obstacles with a low collision ratio. They will eventually need to combine the map function with additional image features. The methodology employed in this paper is useful for odometry, mapping, military applications, surveillance, and navigation systems.

An aerial drone, or quadrotor collision avoidance strategy was summarized by **Omid Esrafilian et al. [7].** Via a wireless network connection, frontal camera-captured video streams and aerial quadrotor-measured navigation data are delivered to the base station. Orientation and charting both benefit from simultaneous localization and mapping, or SLAM. With the navigation data obtained, Oriented Fast and Rotated Brief (ORB) and SLAM compute the robot's three-dimensional position and create 3D maps. Linear filtering is employed to ascertain the monocular SLAM scaling parameter. The sensor of the aerial quadrotor one-eye camera is fused using the Kalman Filter (KF). An integral derivative that is proportional (PID) controller has been devised to control the three- location in dimensions of an obstacle. A controller with PID design for AR drones is provided in [8].

An Unmanned Helicopter (UAV) navigation technique in GPS-enabled environments was written by **Jakob Engel et al. [9].** The Kalman Filter Extended (EKF) for sensor fusion and the SLAM algorithm are included in the quadrocopter-based system. PID provides steering commands for precise control and direction. If the worth is true, EKF computes the scale diagram as much as ± 1.7%. This system can be used in environments with average location precision of 18.0 cm in outdoor settings and 4.9 cm in indoor settings, with a 400 ms tolerable latency. This method delivers precise navigation estimation, removes odometry flow caused by SLAM, and is resilient counteract the loss of visual tracking.

Summarized SURF and SIFT busing object detection and tracking systems approaches were reported by **Sakai Yuki et al. [10].** When comparing this approach to SIFT, the precision discovered for correlated critical points utilizing The algorithm known as SURF is higher. It is anticipated that Eventually, a variety of applications, including automobile detection features for ITS and other systems, this will be advantageous technology for identifying specific objects in photos or videos.

To ensure that identify the focal point of attention for automobiles on the road, **Hsieh Jun Wei et al. [11]** invented the symmetrical SURF detector. The algorithm known as SURF is utilized in this car extraction technique attributes. SURF is effective for apps in real time and does away with background subtraction. One significant obstacle was the misunderstanding caused by cars with similar shapes. The provided image is divided into multiple grids to be able to handle the ambiguity issues. Numerical characteristics are taken out. from the sectored grid by applying SURF and Histogram of Gradient (HOG). Lastly, the vehicle category is classified using SVM stands for Support Vector Machine. classifier.

A system for object identification and stabilization of videos was summarized by **Walha Ahlem et al.[12].** Because the camera moves, the data that The system of aerial surveillance provides varies. Using SIFT and Kalman filtering are utilized in order to maintain the airborne surveillance footage and identify the moving item. For the purpose of feature matching, an algorithm for matching is employed. Consensus from Random Samples (RANSAC) provides a corresponding outlier important points and estimates the movement of the dominant object. A flexible grouping approach is applied for object detection. The application of Kalman filtering to follow moving objects and smooth their motions as they're recognized. Median filtering is used to maintain desired motion.

In UAV videos, **Hailing Zhou et al. [13]** demonstrate a vehicle tracking system. The designated road is extracted within the ROI (Region of Interest) using a graph cut technique. The numerical features are gathered using the fast feature approach, and the motion is estimated using the Kanade-Lucas-Tomasi (KLT) feature tracker. To list the characteristics of the valid key point, the RANSAC estimator is recommended. The zigzag contour and drift error problems are used to examine the preferred system performance. As stated by the findings of the experiments, this method effectively addresses two issues with UAVs: low altitude and high speed video capturing.

An independent model for object tracking based on template matching has been created by **Pouria Sadeghi-Tehran et al. [14].** AR Drone footage that had been pre-recorded was used to test this strategy. FAST detector is accustomed to identify important feature spots. In this case, Template correspondence is carried out by comparing the search frame's features with those of the reference frame. Important things are first feature matched using the brute force approach. The basic H matrix is computed by the RANSAC estimator. RANSAC detects inliers, and the H matrix calculation removes the outliers.

Chen Tao al. [15] developed An conscious of context Motion Characteristic (CMD) for use with moving cameras to identify object level motion. The contextual data, such as the movement of light of the visual background encircling the object of interest, is calculated. Measured is the histograms' discrepancy between the object and its surrounds.

A real-time micro aerial-based system for object identification and It has been suggested to avoid collisions. by **Wilbert G. Aguilar et al. [16].** The obstacle The extraction of feature points is done using the SURF descriptor in this manner. The retrieved characteristics are contrasted between the database photographs without increasing the computational expense. A law of control is put into place to prevent an impediment. Real-time testing of this technique on a cheap UAV demonstrates its effectiveness in detecting and averting collisions.

To get over **Trung Nguyen et al. [17]** have proposed three-dimensional visual navigation as a solution to the KLT feature's limitations. algorithms based on the quadrotor funnel lane hypothesis vehicles. Utilizing the SURF feature, funnel lane theory navigating on a four rotors is developed, and system resilience is increased. Compared to the KLT feature, it is less computational and more resilient. Feature matching is employed to monitor characteristics. The Robot Operating System and Gazebo simulator are used for simulation. used. Future route following will benefit from this method since it tackles the problem of visual obstacle avoidance and enhancing the self-localization problem.

A moving objects identification module and video stabilization have been put forth have been put forth by **Jagdeep Kaur et al. [18].** As descriptors, SURF and SIFT are employed. This approach uses Kalman filtering to locate moving objects while predicting camera settings. The object is identified by the referenced module, which then reconfigures the object's motion to place it in a stable position. In this case, SIFT is utilized to identify moving objects and stabilize video. Camera motion estimation makes use of feature extraction and the descriptor matching algorithm. This approach aims to apply strategies for stabilizing videos in subsequent projects that require a substantial amount of frames or a very fast processing speed in addition to a very large video size

III. METHODOLOGY

The "DJI Phantom 4 pro" [19] drone, which has a 1920x1080 frame resolution, created the database. The drone's designed flight altitude is six feet, and its speed is one meter per second. Multiple movies are documented, considering the varying states of the object. are recorded, taking into account the was created by employing both stationary and moving cars within the quadcopter's field of vision. The angle that vision is 700 and The distance traveled is roughly 30 meters for each database. The unmanned aerial vehicle and the stationary or moving item must maintain a minimum distance of around between three and four meters. To expedite the pace of analysis, the frame rate, and image resolution must be reduced or converted because the recorded videos have very high resolution for a single frame analysis.

Algorithm 1: Identification and Assessment of Obstacles

Video input is being received.

Output: An obstacle has been found.

First, create the frames from a video.

Step 2: To eliminate extraneous noise, apply median filtering and histogram equalization.

Step 3: Use SIFT and SURF descriptors to identify the salient features of each frame. (Done independently to compare results)

Step 4: Use the Algorithm for Matching Features Metrics to match the important spots in each frame.

Step 5: To generate a section of interest, Applying the convex hull around matching key points.

Step 6: An obstacle is identified if the current frame's convex hull size is larger than that of the preceding frame.

Step 7: Use Euclidean distance to calculate the change in pixels in location between the previous and current frames.

Step 8: Adjust the distance between the camera and the item.

Algorithm Termination

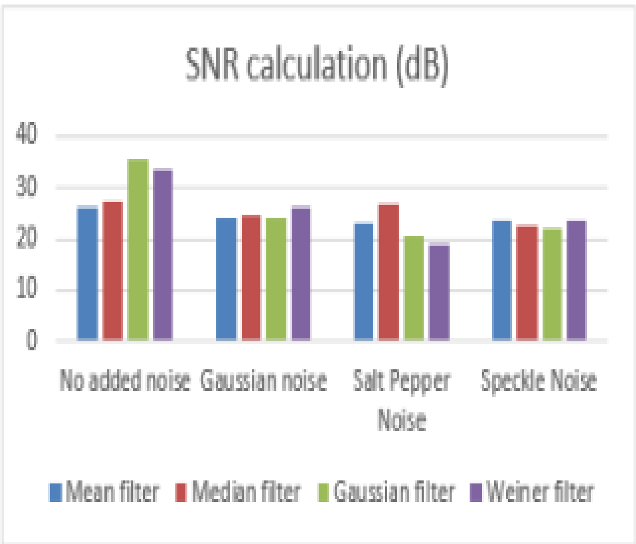

Fig.2 computed signal-to-noise ratios with and without additional noise

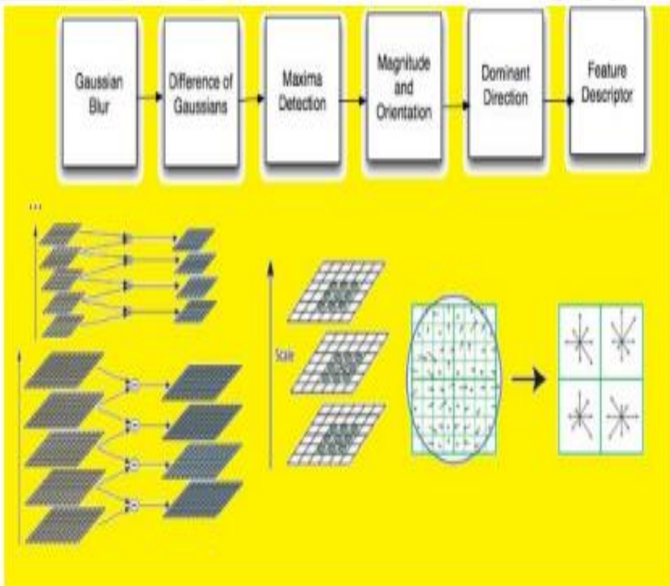

Fig.3 Steps in the SIFT algorithm

We have attempted to take features out from successive frames using both the SURF and SIFT methods. Figure 3 and lists the several procedures employed in the SURF and SIFT descriptor algorithms for the purpose of identifying important locations.

IV. RESULT AND ANALYSIS

Table 1 provides the duration of feature extraction for both SURF and SIFT. Using the SURF descriptor, Figure 6 displays the key points that were retrieved for consecutive frames. According to the Table, SURF extracted features a little bit faster than SIFT, however in support of SIFT, the ratio of matched critical points in the ith and ith+15 frames was greatest. Because the strongest pixel is extracted, it is possible to determine the pixel difference between the current and prior video frames with greater precision. important points from both frames.

Tabel 1. SIFT and SURF performance comparison

Algorithm	Time Taken for Feature Extraction in i^{th} Frame	Time Taken for Feature Extraction i^{th}+15 Frame	Extracted Key Points for i^{th} Frame	Extracted Key Points for i^{th} +15 Frame	Matched Key points between i^{th} and i^{th}+5 frame
SIFT	0.014834 Sec	0.013015 Sec	1792	1664	5
SURF	0.010106Sec	0.013177 Sec	40	37	14

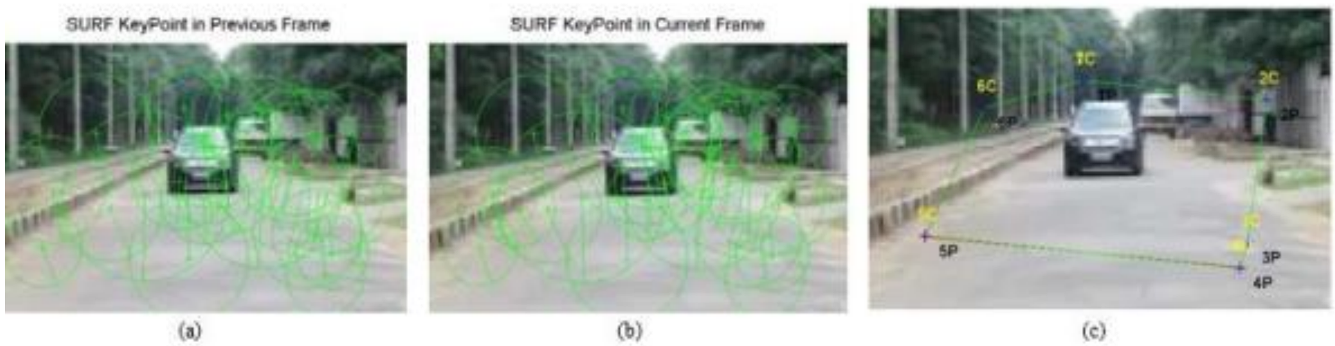

Fig. 4 (a) the before and present frames
(b) matched important details.
(c) the measured separation between the UAV and the dynamic object

V. CONCLUSIONS

The SURF descriptor algorithm in the suggested work calculates the important points of interest more quickly and effectively than SIFT. The separation between the lens and the obstruction is measured using pixel difference computation and camera calibration methods. From the perspective of real-time obstacle avoidance, The complete process takes under a second, making it extremely efficient. The following action is to use CNNs, or convolutional neural networks to identify impediments coming from the side and adjust the drone's trajectory accordingly.

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