Real-Time Optical Localization and Tracking of UAV using Ellipse Detection

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***Abstract*—A real-time three-dimensional (3D) spatial localization system to track a UAV (unmanned aerial vehicle) using a single off-board conventional camera and an onboard circle-shaped colored Light-Emitting Diode (LED) marker is presented. The image from the camera is color-segmented and then morphologically closed before being sent to the ellipse detector. The location of the drone is then estimated with geometric/optical calculations using the pixel coordinates provided by the real-time ellipse detector. The location data generated by this system was validated by a Motion-Capture System (MCS) that was simultaneously tracking the system in real-time. The average position error was of 6cm, while the processing speed achieved 15 locations/second, which are comparable with recent research references. The usage of a low-cost camera makes this method promising for most mobile UAV tracking applications.**

***Index Terms*—Optical Localization, Unmanned Aerial Vehicle, Ellipse Detection, Real-Time Image Processing.**

I. Introduction

Real-time localization and tracking of Unmanned Aerial Vehicles (UAVs) is expected in many applications where a precise location of the UAV is needed for a base station while GPS or Wi-Fi signals are not available [1]. Such tracking tasks are usually achieved using various types of sensors including radio sensors, inertial measurement units (IMUs), and image sensors [2]–[4]. In these systems, the target UAV should be identified and isolated from the environment by means of detecting of active markers such as optical markers, RF signals, or other identifiers that are unique to the particular UAV [5], [6]. The primary specification of the tracking task includes localization accuracy, processing time, and the cost of the localization system. Technical challenges of UAV localization come from the complexity of the environment and weather [7], [8].

A typical vision-based UAV localization system is the one that uses constellations of special markers onboard the UAV. This enables separating the UAV from the background using segmentation and filtering methods [9], [10]. Markers may have a special color or a pre-defined blinking pattern, which can be identified using color segmentation or temporal filters during image processing. The markers detected from the image are then processed with geometric methods using prior measured physical dimensions of the constellation to obtain the spatial localization information of the UAV. An optical localization system can also be implemented with the assistance of a combination of other sensors or prior knowledge of the flight area from the UAV's perspective [11]. However, such methods may require data fusion from complementary sensors, or machine learning to process depth maps, especially when relying on techniques like Monocular-Simultaneous Localization and Mapping (SLAM) [5], [12], which has a high computing overhead that reduces the power efficiency. Other challenges in current optical localization systems include the cost of special sensors, high latency from communication and processing systems, and the complexity of system implementation.

To address the above-mentioned challenges, a monocular-vision-based localization system is proposed and tested in our prior work using a circle-shaped marker [13], [14]. The marker is blinking at a fixed frequency to allow an event-based image sensor to identify it using a temporal difference filter in image processing. The circle-shaped marker on the UAV can be identified as an ellipse in the image, which is more friendly for image processing algorithms compared to a constellation. However, the system in [14] requires an expensive event-based camera, and its performance suffers from random background noise due to reflections of the blinking LED marker and long latency (100ms) of image processing due to the complicated event-based signal processing. Therefore, a system with higher noise immunity and a lower latency using a low-cost camera while keeping the advantage of using the circle-shaped marker would be more desirable.

This work proposes a low-cost high-speed real-time optical spatial localization system for UAV utilizing ellipse detection algorithm. A real-time ellipse detection method is used for the initial detection of the UAV in combination with pre-processing image segmentation for improvement of detection in noisier and less stable environments. A triangulation-based algorithm is implemented after properly finding the target UAV, utilizing the known knowledge of the camera's FOV (field of view) and the diameter of the markers on the UAV. The primary advantages of the proposed method include that the localization task is achieved using a regular read-green-blue (RGB) camera instead of an expensive event-driven dynamic vision image sensor. Moreover, compared to our prior work [14] the processing latency has been improved by 30% from 100ms to 66.7ms while keeping the same localization accuracy thanks to the proposed color-segmentation filter before ellipse detection. The average error of the proposed method

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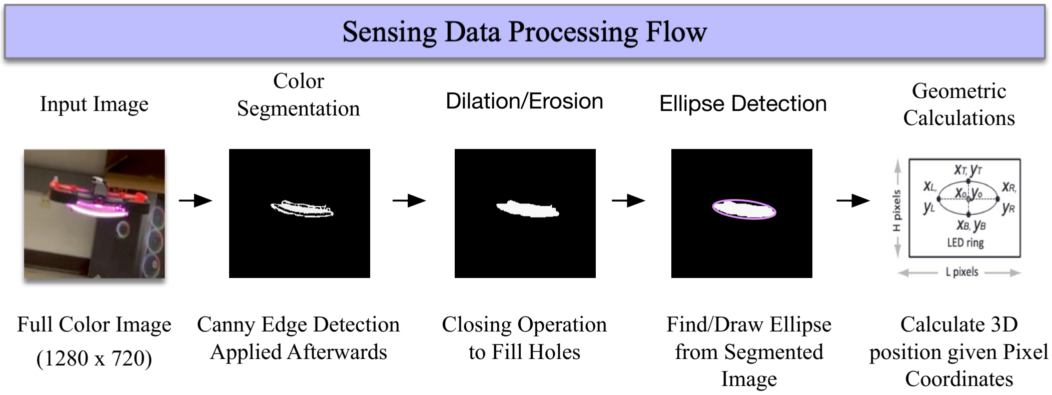

Fig. 1. Flow Diagram showing processing steps for the localization of the UAV in real-time, each step is done on every image retrieved from the video stream from the camera.

is comparable with other recently published references. These performance makes the proposed method attractive for low-cost mobile UAV tracking applications.

II. System Design

This section describes the proposed UAV optical localization system including the hardware sensors and the image processing methods.

A. System Overview

The optical localization system contains both hardware implementation and software algorithms. The hardware system consists of the camera, the processing unit, the UAV, and the marker installed onboard the UAV. The sensing system emphasizes a low-cost regular RGB camera instead of using an expensive dynamic vision image sensor [14]. In our experiment, a GoPro Hero 7 Black camera is applied for good color consistency since the system uses color to identify the circle-shaped marker. The processing unit in our system is a regular laptop with an Intel 8850H 2.6GHz CPU. The target in the experiment is a Parrot Bebop 1 UAV which is able to carry the LED ring. A moderately bright pink LED ring is the ellipse marker, which is supplied with a 9 V battery.

The localization task begins when the camera starts taking images of the UAV, and sending those images to the processing computer. The algorithm on the computer process the incoming images from the camera, which is expected to obtain the 3D location of the UAV in real-time. The signal processing flow chart is shown in Fig. 1. The first step is color segmentation, in which the image is converted into a hue-saturation-value (HSV) format. Then, a pre-defined HSV threshold is applied to identify the pixels with pink color from the image, which correspond to the leds of the ellipsoid marker. After this, the edges of the selected pixels are extracted using the Canny Edge Detection algorithm. Next, a morphological closing operation with erosion and dilation filters is applied to the edges to fill in any holes or gaps that are in the segmented contour. Finally, the ellipse detection algorithm is applied to the processed image to match the contour. The locations of the edge pixels of the detected ellipse are forwarded to the optical localization algorithm.

B. Real-Time Ellipse Detection

Elliptical shape detection is an active research area in image processing and have been applied in UAV localization

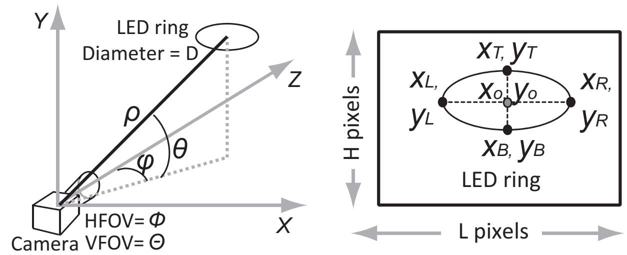

Fig. 2. Geometry for localization algorithm (left), Measurement setup of the target ring (right), retrieved from [13].

applications [15]. Ellipse detection can be accomplished by a variety of methods such as arc-adjacency matrix implementations matching with connected pairs of arcs, Mask R-CNN (Regional Convolutional Network) implementation matching elliptical regions, or arc pairing through elliptical primitives [16]–[18]. In this work, we choose an ellipse detection algorithm optimized for low-computing-overhead and low-latency by comparing the amount of overlap of every connected-contour with a predicted ellipse for that size of the bounding box [15]. The ellipse detection algorithm loops through each contour/edge in every incoming image. Pre-defined thresholds are applied to reject contours whose dimensions/properties are unreasonable, e.g., if the size or the aspect ratio of the ellipse is too samll.

Pixel overlap is compared to a fitted ellipse drawn by the fitEllipse function from the open computer-vision (OpenCV) toolbox, and then used as a metric for accepting/rejecting contours as a possible ellipse. When a contour has a low amount of overlapping pixels with the fitted ellipse, the contour is rejected. The ellipse-fitting is accomplished via a least-squares approximation method proposed by Fitzgibbon [19]. This method fits an ellipse to any contour that is left on the image after color-segmentation/filtering. One of the advantages of this proposed system is that the prior steps of color segmentation limit the number of potential contours that are sent to the ellipse detection algorithm, which greatly reduces the computing cost.

C. Optical Localization

Once an ellipse is detected, the parameters of the ellipse are sent to the optical localization algorithm for computing the spatial location of the target UAV. The triangulation-based algorithm has been proposed and tested in real-time before

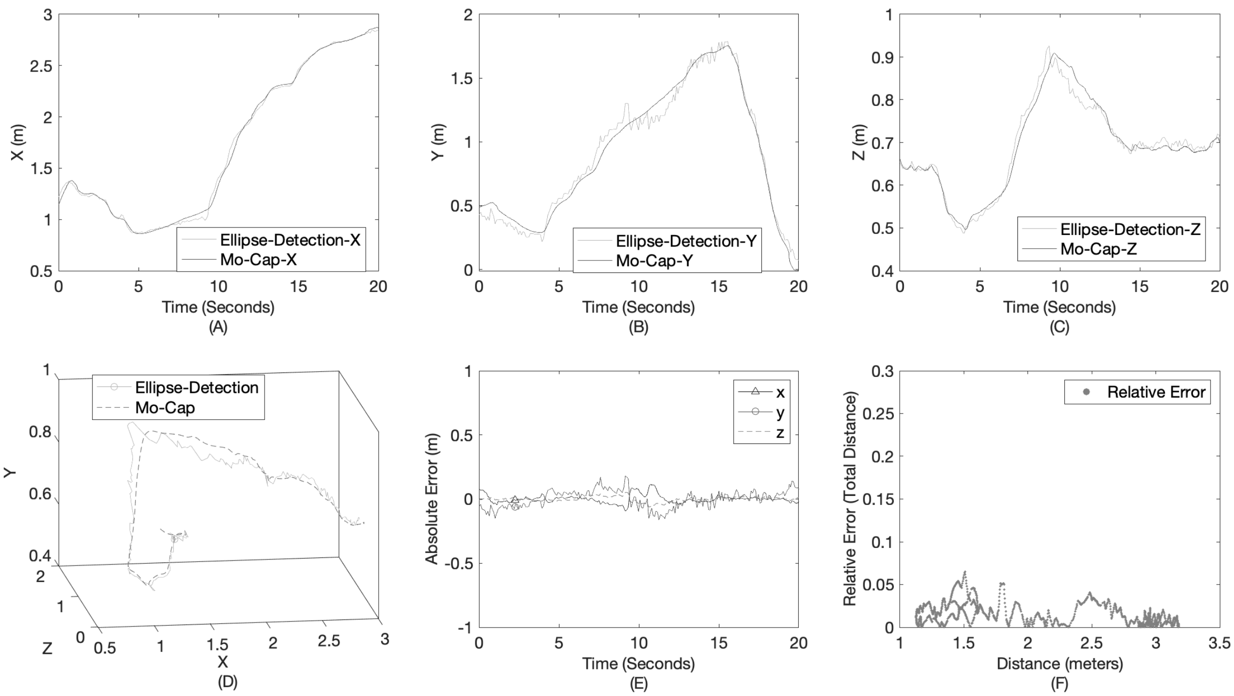

Fig. 3. Experimental results of the localization system (A)-(C) 2D plots of traces for the X,Y,Z axis, recorded by proposed Ellipse Detection system and the benchmark Optitrack Motion-Capture system (unit in meters). (D) 3D traces tracked by the proposed Ellipse Detection system and the benchmark Optitrack Motion-Capture system (unit in meters). (E) The relative error with respect to the coordinates. (F) The relative error over distance.

[13], [14]. As shown in Fig. 2, making use of the ellipse, the center of the target UAV in the image, (X_O, Y_O), can be calculated as:

$$X_O = (X_L + X_R)/2 \tag{1}$$

$$Y_O = (Y_L + Y_R)/2 \tag{2}$$

Then the tangent value of azimuth angle ϕ and elevation angle θ (shown in Fig. 2) are obtained as:

$$\tan\phi = 2 \cdot X_O \cdot \frac{\tan(\Phi/2)}{L} \tag{3}$$

$$\tan\theta = 2 \cdot Y_O \cdot \frac{\tan(\Theta/2)}{H} \tag{4}$$

Finally, the radial distance ρ, which is the distance between the centroid of the target ring and the lens of the camera is obtained as

$$\rho^2 = \Big(\frac{D}{2} \cdot \frac{X_O}{|X_O - X_R|}\Big)^2 \cdot \Big(1 + \frac{1}{\tan^2\phi}\Big) \tag{5}$$

The spherical coordinates are then converted to the Cartesian coordinates for displaying location data and further usage.

III. Experimental Setup and Results

The experimental setup is shown in Fig. 4. In the UAV flight testing, the proposed single-camera ellipse-detection-based optical tracking system is tested simultaneously with an OptiTrack Motion Capture System (MCS). The 3D location results obtained by both systems are compared. The data from the MCS are utilized as the benchmark result. The MCS makes use of eight cameras for tracking, and provides a sampling rate of 100Hz. The MCS is active over a volume of 5x3x3 meters. The camera for elliptical tracking was placed at the edge of the MCS area. A constellation of markers was added also to the camera, on top of it, for verification of its position with respect to the target UAV. Recording location data for each device (camera and UAV) was started after the UAV lift-off. During the experiment, the UAV was human-controlled making use of a flight control joystick.

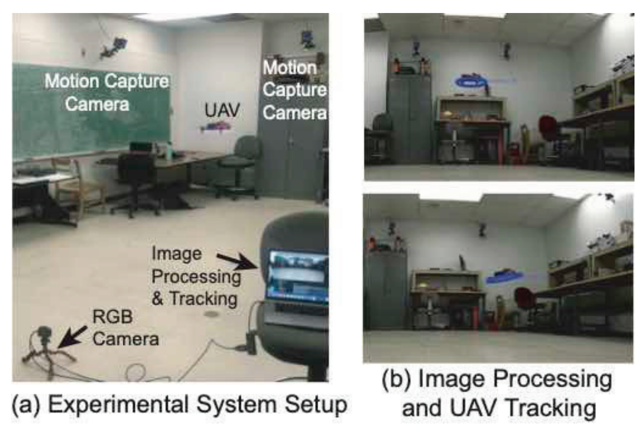

Fig. 4. Experimental setup. (a) The UAV localization system including the RGB camera, the processing computer, the UAV, and the MOCAP system for comparison. (b) UAV identified in screen view using ellipse detection algorithm in image processing.

In Fig. 3(A-C) the traces of the (x,y,z) Cartesian coordinates are plotted in order to compare the MCS ground truth data versus the ellipse-detection technique. In Fig. 3D the proposed tracking algorithm's 3D traces are plotted over the MCS 3D traces. The 3D traces from real-time testing are consistent with the traces from the MCS. The proposed system retrieves the UAV's 3D location relative to the position of the camera in real-time every 66.7ms. The data was recorded at a rate of

TABLE I
COMPARISONS OF RECENTLY PUBLISHED UAV LOCALIZATION METHODS USING MONOCULAR CAMERAS AND TRACKING MARKERS.

	RA-L 2018	RA-L 2019	IROS 2021	IROS 2021	This Work
Sensor Type	2xIMU + RGB Camera	Ultraviolet-Sensitive Camera with UV Filter	RGB Camera	Event Camera	RGB Camera
Marker	Five RGB LEDs & cross-constellation	Blinking UV LEDs & Hexagonal Constellation	Ellipse on white background	Blinking Circular Marker	Pink LED ring
Processing Algorithm	Particle Filter & Pose Estimation	Geometric Calculation	Ellipse Detection & State-Based Tracking	Temporal Filter & Optical Localization	Ellipse Detection & Optical Localization
Error	2-20cm	15m * 20% - 3m	Not Localizing Depth	2-6cm(Range 6m)	2-20cm
Processing Time	50ms (20Hz)	100ms (10Hz)	32.2 ms avg.	100ms	66.7ms (15 Hz)

15Hz and then interpolated to 100Hz for verification to plot against the MCS location data. There is jitter noise in the traces, which can be reduced with the addition of a Low-Pass filter.

Fig. 3E presents the position error over time for each one of the axis. The error peaks during a higher velocity turn in the trial, and remains fairly steady throughout the rest of the trial. The scatter plot in Fig. 3F shows the relative error over distance for the trial. The relative error is calculated by dividing the absolute error by the measured MCS-based value. The distance between the UAV and the camera (ρ) in this trial ranges between 1 and 3.5 meters, which is limited by the 3x3x5m space where the MCS can track objects. The error over distance for this trial does not correlate with distance, as the detection range is larger than the size of the testing area.

IV. DISCUSSION

The advantages of the proposed method include an easy implementation that uses a single regular camera and real-time ellipse detection, thanks to the color-segmentation pre-processing filter. A comparison of the proposed method with other recently published methods is summarized in Table I. Compared to other similar technologies, the proposed ellipse tracking method achieves localization with a regular RGB camera with no additional sensors. The primary limitations of the proposed system include the finite resolution of the image sensor and the system processing time, mostly due to pre-processing/segmentation of the image. This method can be improved upon in the future by using optical filters combined with UV/IR markers instead of using resource-heavy color segmentation in the image.

V. CONCLUSION

This letter presented a novel method of tracking the 3D location of a UAV utilizing an off-the-shelf camera pointing toward a UAV equipped with elliptical markers. The algorithm is implemented with color-segmentation, real-time ellipse detection, and a triangulation-based method for localization estimation. Since the proposed system uses a simple regular camera, it has the potential to be applied to low-power mobile applications for tracking the UAV in a low-cost implementation. The proposed work reduces the cost by using the single camera, thus, also reduces the system complexity. The system achieved acceptable accuracy and latency for real-time UAV tracking applications.

REFERENCES

[1] H. Shakhatreh, A. H. Sawalmeh, A. Al-Fuqaha, Z. Dou, E. Almaita, I. Khalil, N. S. Othman, A. Khreishah, and M. Guizani, "Unmanned Aerial Vehicles (UAVs): A Survey on Civil Applications and Key Research Challenges," *IEEE Access*, vol. 7, pp. 48 572–48 634, 2019.

[2] I. Guvenc, F. Koohifar, S. Singh, M. L. Sichitiu, and D. Matolak, "Detection, Tracking, and Interdiction for Amateur Drones," *IEEE Communications Magazine*, vol. 56, no. 4, pp. 75–81, 2018.

[3] K. Shamaei, J. Khalife, and Z. M. Kassas, "Exploiting LTE Signals for Navigation: Theory to Implementation," *IEEE Transactions on Wireless Communications*, vol. 17, no. 4, pp. 2173–2189, 2018.

[4] Y. Shao, X. Tang, H. Chu, Y. Mei, Z. Chang, X. Zhang, H. Zhan, and Y. Rao, "Research on Target Tracking System of Quadrotor UAV Based on Monocular Vision," in *2019 Chinese Automation Congress (CAC)*, 2019, pp. 4772–4775.

[5] W. Wei, L. Tan, G. Jin, L. Lu, and C. Sun, "A Survey of UAV Visual Navigation Based on Monocular SLAM," in *2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC)*, 2018, pp. 1849–1853.

[6] Z. Kaleem and M. H. Rehmani, "Amateur Drone Monitoring: State-of-the-Art Architectures, Key Enabling Technologies, and Future Research Directions," *IEEE Wireless Communications*, vol. 25, no. 2, pp. 150–159, 2018.

[7] F. Mohammed, A. Idries, N. Mohamed, J. Al-Jaroodi, and I. Jawhar, "UAVs for smart cities: Opportunities and challenges," in *2014 International Conference on Unmanned Aircraft Systems (ICUAS)*, 2014, pp. 267–273.

[8] M. Erdelj, E. Natalizio, K. R. Chowdhury, and I. F. Akyildiz, "Help from the Sky: Leveraging UAVs for Disaster Management," *IEEE Pervasive Computing*, vol. 16, no. 1, pp. 24–32, 2017.

[9] L. Teixeira, F. Maffra, M. Moos, and M. Chli, "VI-RPE: Visual-Inertial Relative Pose Estimation for Aerial Vehicles," *IEEE Robotics and Automation Letters*, vol. 3, no. 4, pp. 2770–2777, 2018.

[10] V. Walter, N. Staub, A. Franchi, and M. Saska, "UVDAR System for Visual Relative Localization With Application to LeaderÃŘFollower Formations of Multirotor UAVs," *IEEE Robotics and Automation Letters*, vol. 4, no. 3, pp. 2637–2644, 2019.

[11] C. Campos, R. Elvira, J. J. G. Rodriguez, J. M. M. Montiel, and J. D. Tardos, "ORB-SLAM3: An Accurate Open-Source Library for Visual, VisualÐInertial, and Multimap SLAM," *IEEE Transactions on Robotics*, vol. 37, no. 6, pp. 1874–1890, 2021.

[12] S. Yang and S. Scherer, "CubeSLAM: Monocular 3-D Object SLAM," *IEEE Transactions on Robotics*, vol. 35, no. 4, pp. 925–938, 2019.

[13] I. White, E. Curry, D. K. Borah, S. J. Stochaj, and W. Tang, "An Optical Spatial Localization Algorithm Using Single Temporal Difference Image Sensor," *IEEE Sensors Letters*, vol. 3, no. 3, pp. 1–4, March 2019.

[14] H. Stuckey, A. Al-Radaideh, L. Escamilla, L. Sun, L. G. Carrillo, and W. Tang, "An Optical Spatial Localization System for Tracking Unmanned Aerial Vehicles Using a Single Dynamic Vision Sensor," in *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2021, pp. 3093–3100.

[15] A. Keipour, G. A. S. Pereira, and S. A. Scherer, "Real-Time Ellipse Detection for Robotics Applications," *CoRR*, vol. abs/2102.12670, 2021. [Online]. Available: https://arxiv.org/abs/2102.12670

[16] C. Meng, Z. Li, X. Bai, and F. Zhou, "Arc Adjacency Matrix-Based Fast Ellipse Detection," *IEEE Transactions on Image Processing*, vol. 29, pp. 4406–4420, 2020.

[17] W. Dong, P. Roy, C. Peng, and V. Isler, "Ellipse R-CNN: Learning to Infer Elliptical Object From Clustering and Occlusion," *IEEE Transactions on Image Processing*, vol. 30, pp. 2193–2206, 2021.

[18] H. Dong, E. Asadi, G. Sun, D. K. Prasad, and I.-M. Chen, "Real-Time Robotic Manipulation of Cylindrical Objects in Dynamic Scenarios Through Elliptic Shape Primitives," *IEEE Transactions on Robotics*, vol. 35, no. 1, pp. 95–113, 2019.

[19] A. Fitzgibbon, M. Pilu, and R. Fisher, "Direct least square fitting of ellipses," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 21, no. 5, pp. 476–480, 1999.