Ground-Based Vision Tracker for Advanced Air Mobility and Urban Air Mobility

Evan Kawamura *[1], Keerthana Kannan †[1], Thomas Lombaerts ‡[1], Vahram Stepanyan§[1], Chester Dolph ¶[2], and Corey Ippolito ‖[1]

[1]*NASA Ames Research Center, Moffett Field, Mountain View, CA 94035*

[2]*NASA Langley Research Center, 1 Nasa Dr, Hampton, VA 23666*

Advanced Air Mobility (AAM) Air Mobility and Urban Air Mobility (UAM) require aircraft surveillance and monitoring for safety and security. Persistent tracking of flying objects provides Air Traffic Control (ATC) and Air Traffic Management (ATM) continuous coverage and knowledge of the national airspace system (NAS). Given the significant disparity in the number of AAM and UAM aircraft compared to commercial aircraft in the NAS, coupled with the dense AAM/UAM operations in urban environments, employing the existing ATC/ATM architectures poses considerable challenges. A first step in creating a similar ATC/ATM architecture for AAM/UAM will require ground-based and airborne-based sensors to provide monitoring, which will be difficult in urban environments due to GPS degradation. This paper proposes a vision-based tracking method with static cameras by utilizing image subtraction and blob detection, which avoids adding additional electromagnetic interferences in the environment with sensors such as radar. The ground-based vision tracker (GBVT) outputs the detected objects' azimuth and elevation angles from unmanned aerial system (UAS) flight tests. Future and ongoing work includes sending the detected objects' azimuth and elevation angles as inputs for an extended Kalman filter (EKF) to estimate the position and velocity of the detected object.

I. Introduction

Advanced Air Mobility (AAM) and Urban Air Mobility (UAM) require aircraft surveillance and monitoring for safety and security purposes. Since there will be numerous more AAM/UAM aircraft than commercial airplanes flying in the airspace, it will be difficult to scale conventional Air Traffic Control (ATC) and Air Traffic Management (ATM) procedures and protocol for AAM/UAM concepts of operation. One way to reduce scaling complexities and increase efficiency is to implement distributed sensors in the enivronment for passively monitoring the airspace. Then, the distributed sensors can provide aircraft tracking information to the modified ATC/ATM architectures by leverging automatic and passive tracking capabilities. Therefore, these modified ATC/ATM architectures will have an efficient and scalable solution for monitoring the airspace by having increased awareness, path planning, and contingency management. This paper focuses on vision-based tracking with ground-based distributed sensors in the envrironment.

There are research efforts for vision-based tracking. A real-time, adaptive visual algorithm with Multiple-Instance (MI) learning approach, Multiple-Classifier (MC) voting mechanism, and Multiple-Resolution (MR) representation strategy solves online learning and tracking arbitrary aircraft and intruders in the air with experimental results [1]. Combining a vision-based target tracker with a neural network and a Kalman filter creates an adaptive target state estimator [2]. A survey of on-road vision-based vehicle detectors shows a wide variety of monocular and stereo vision-based trackers [3]. An Incremental Focus of Attention (IFA) hierarchical architecture provides robust, adaptive, and real-time vision-based tracking [4]. Combining onboard inertial navigation system (INS) telemetry data and a ground-based monocular camera running optical flow into an Extended Kalman Filter (EKF) leads to robust and accurate state estimation of the tracked unmanned aerial vehicle (UAV) [5].

*Computer/GNC Engineer, Intelligent Systems Division, NASA Ames Research Center, Moffett Field, Mountain View, CA 94035, USA.

†Software Engineer, KBR Wyle Services, Intelligent Systems Division, NASA Ames Research Center, Moffett Field, Mountain View, CA 94035, USA.

‡Aerospace Research Engineer, KBR Wyle Services, Intelligent Systems Division, NASA Ames Research Center, Moffett Field, Mountain View, CA 94035, USA.

§Aerospace Research Engineer, KBR Wyle Services, Intelligent Systems Division, NASA Ames Research Center, Moffett Field, Mountain View, CA 94035, USA.

¶Aerospace Engineer, Aeronautics Systems Engineering Branch, NASA Langley Research Center, 1 Nasa Dr, Hampton, VA 23666.

‖Aerospace Scientist, Intelligent Systems Division, NASA Ames Research Center, Moffett Field, Mountain View, CA 94035, USA

The proposed research in this paper demonstrates a ground-based vision tracker for distributed cameras in an urban environment to simulate future AAM/UAM operations for monitoring the airspace. Post-processing a ground-based camera's video of a UAV flight shows preliminary image subtraction results of capturing a moving UAV across the camera's field of view. This extended abstract provides the preliminary results and next steps for the ground-based vision tracker (GBVT).

II. Proposed Solution

There are two proposed methods for GBVT: MATLAB and OpenCV (C++), and both utilize image subtraction and blob detection. Figure 1 shows the MATLAB image subtraction flowchart, while Figure 2 shows the OpenCV image subtraction flowchart. There are similar steps in the procedure but with differences due to programming language and data storage.

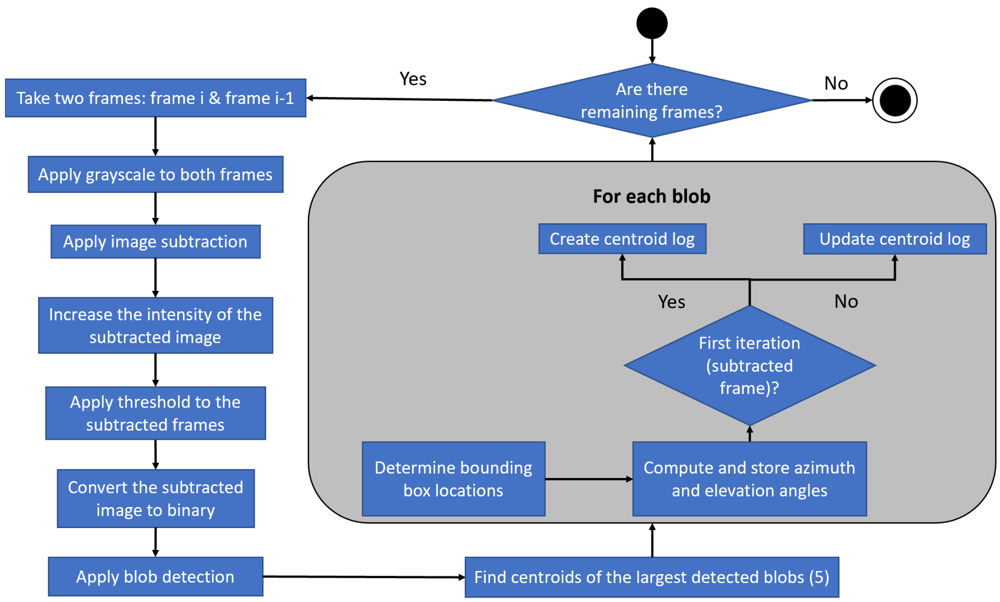


Fig. 1 MATLAB Image Subtraction Flowchart

III. Preliminary Results

A preliminary distributed sensing test involved one ground-based and fixed-angle camera to obtain flight test data for testing the GBVT. The UAS flew horizontally from left to right across the camera's field of view, and the camera specs for this preliminary flight test are given in Table 1. Figure 3 shows the sensor locations (yellow circles), and their locations are given in Table 2 [6, 7]. Here are the tentative UAS flight test plans with the same trajectories but with different distributed sensing hardware and software:

Table 1 Camera Specs for Preliminary Flight Test

Spec	Value
Horizontal Field of View (°)	110
Vertical Field of View (°)	57.6
Aspect Ratio	1.91
px	1920
py	1080
FPS	60

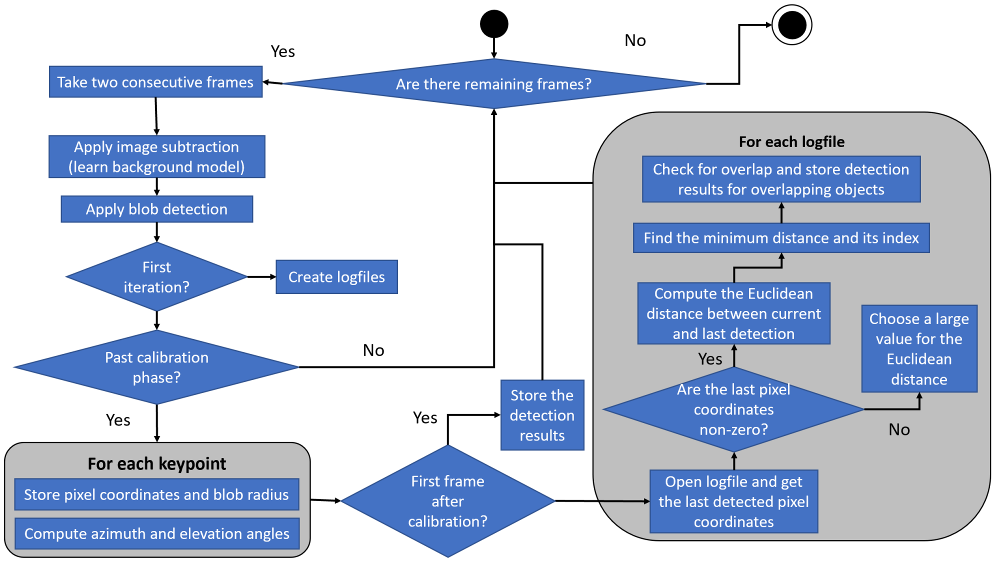


Fig. 2 OpenCV Image Subtraction Flowchart

1) May 2023: GoPro Hero10 Black cameras at each ground-based sensor node
2) June 2023: FLIR BlackFly cameras with Fujinon lens at each ground-based sensor node
3) July 2023: obtain real-time image tracker and connect to Ref. [8]'s vision-based EKF tracker for real-time estimation
4) August 2023: run image tracker in the larger DS system

Table 2 NASA Ames Build 1 Scenario Sensor Locations

Location	Latitude (°)	Longitude (°)
1	37.429540	-122.067712
2	37.425155	-122.059832
3	37.423476	-122.061238
4	37.426551	-122.067970
O	37.426861	-122.066015

Different GoPro Hero10 Black camera lens and modes will be selected and optimized to have the UAV within at least two camera fields of view throughout most of the UAV's flight path (see Figure 3), and the estimated horizontal field of view per camera is 40°. *

Table 3 shows the FLIR BlackFly camera specs. † Ideally, the BlackFly camera fields of view will resemble the GoPro Hero10 Black fields of view to keep the experimental setup as consistent as possible. Since lens selection and procurement for the FLIR BlackFly cameras are ongoing, the first UAS flight test will use the GoPro Hero10 Black cameras as mentioned earlier.

Figure 4 shows the architecture diagram for the four image trackers for the Ames Build 1 scenario. Each image tracker will run at some TBD frequency and receive RGB images. Then, each image tracker will compute the azimuth and elevation angles for detected and tracked objects within their fields of view, which feeds into the data assocation problem of keeping track of many objects [9]. Finally, the associated object's azimuth and elevation angles from multiple views will be sent to the vision-based tracker EKF presented in Ref. [8].

Figure 5 shows the intermediate steps during image subtraction with the original and masked image after applying image subtraction. Figure 5a shows the current image, and Figure 5b shows the subtracted image after applying the

*https://community.gopro.com/s/article/HERO10-Black-Digital-Lenses-FOV-Informations?language=en_US
†https://www.flir.com/products/blackfly-s-usb3/?model=BFS-U3-123S6C-C&vertical=machine+vision&segment=iis

Fig. 3 Ames Research Center Flight Test - Build 1: sensor stations (yellow)

Table 3 BlackFly Camera Specs

Name	Value
FLIR BlackFly	Part number: BFS-U3-123S6C-C
Pixel width	4096
Pixel height	3000
Aspect ratio	1.365
FPS	30
Megapixels	12.3
Pixel size	3.45
Dimensions in mm (W x H x L)	29 x 29 x 30

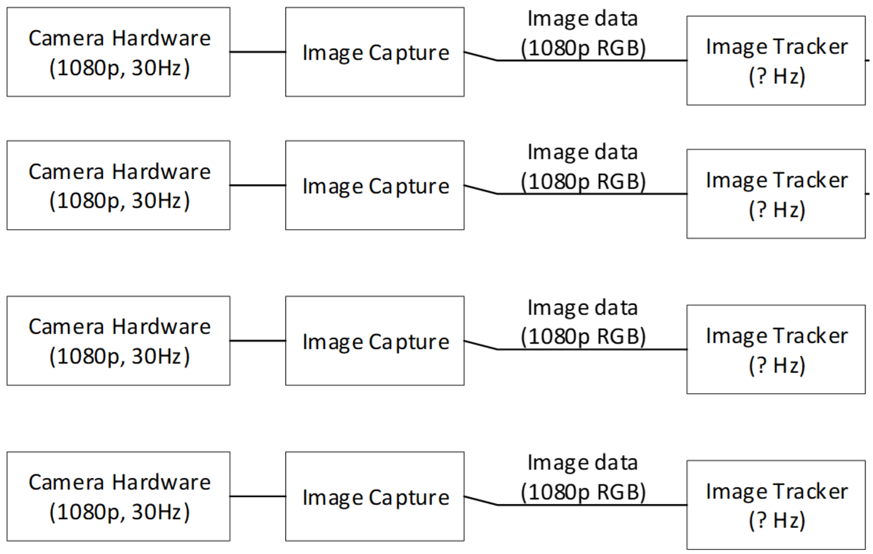
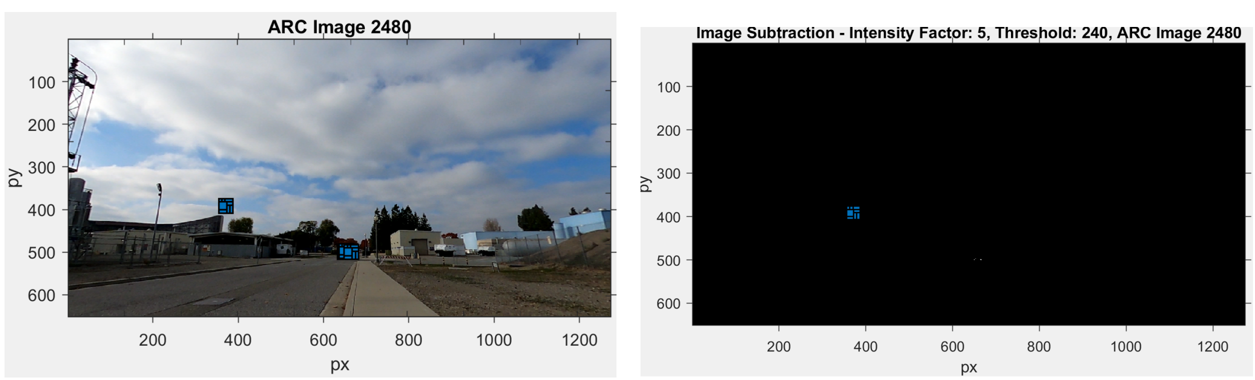


Fig. 4 Ames Research Center Flight Test - Build 1: sensor stations (yellow) and computing units (green)

steps shown earlier in Figure 1: the intensity factor is 5, and the threshold pixel value is 240 such that all pixels below 240 will be eliminated.



(a) Original Image

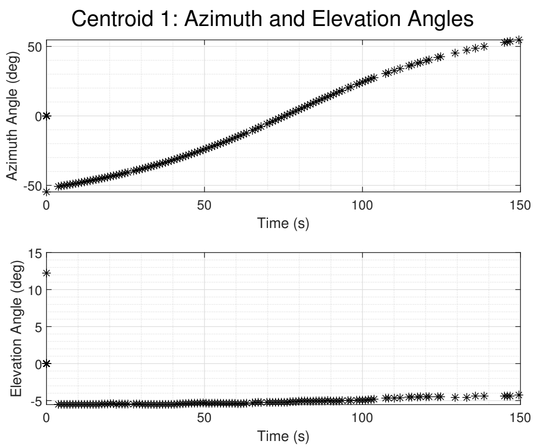
(b) Mask after Image Subtraction

Fig. 5 Image Subtraction Results: Frame 2480

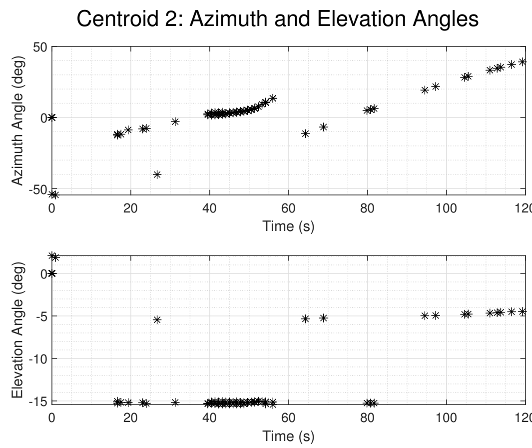
Preliminary tests in MATLAB include tracking five objects with image subtraction and blob detection (bwareafilt) [‡]. Objects (centroids) 2-4 might be cars since they have relatively low and flat elevation angles between approximately 40 and 55 seconds, which corresponds to cars in the video (see Figure 6). The fifth detection has random outliers and not shown for brevity. The average runtime per iteration is 0.2675 seconds, which demonstrates near real-time capabilities. The video was recorded at 60 frames per second, and the frame subtraction step is 55 frames to provide sufficient time and difference to detect the UAV motion. Preliminary tuning shows that the frame subtraction can be reduced down to 30 frames (0.5 seconds for a 60 fps camera), but there are multiple non-UAV detections, i.e., false positives.

The OpenCV C++ image tracker also utilizes image subtraction [§] and blob detection [¶]. It currently has a calibration phase where it takes the first 150 frames to learn the background model and uses the OpenCV MOG2 Background Subtractor. For rendering and tracking, none of the detections, matching, or plotting occur until after the calibration phase. Two drawbacks for the current implementation of the OpenCV image tracker are: 1) the image tracker does

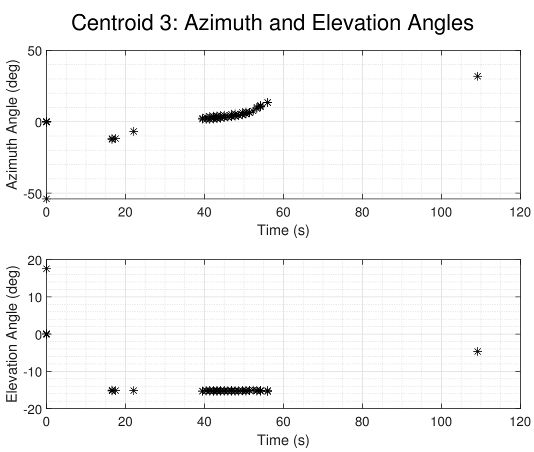
[‡]https://www.mathworks.com/help/images/ref/bwareafilt.html
[§]https://docs.opencv.org/3.4/d1/dc5/tutorial_background_subtraction.html
[¶]https://learnopencv.com/blob-detection-using-opencv-python-c/



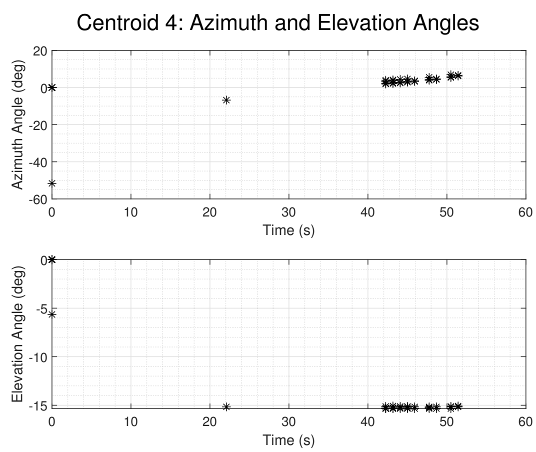
(a) Object 1 (UAV)



(b) Object 2 (car)



(c) Object 3 (car)



(d) Object 4 (car)

Fig. 6 MATLAB Image Tracker Azimuth and Elevation Angles per Detection

not track the UAV for the frames during the calibration phase, and 2) it must find the UAV in the first frame after the calibration phase, i.e., frame 151 in this preliminary test. The number of frames during the calibration phase is arbitrary, and future work may consider a more robust and flexible image tracker framework to avoid needing to detect the UAV in the first frame immediately after the calibration phase. For simplicity, the tracker currently detects the UAV and only considers future detections that are within an overlap distance of:

$$\text{overlap} = d - 2 \cdot \text{overlap radius} \tag{1}$$

Figure 7 shows a diagram of the distance between two detections and the overlap radius. Future work for the OpenCV

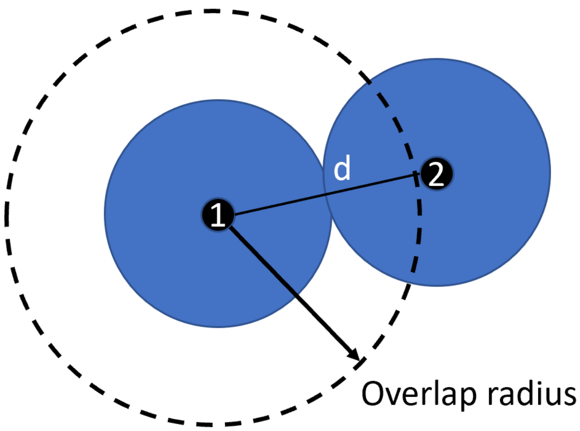
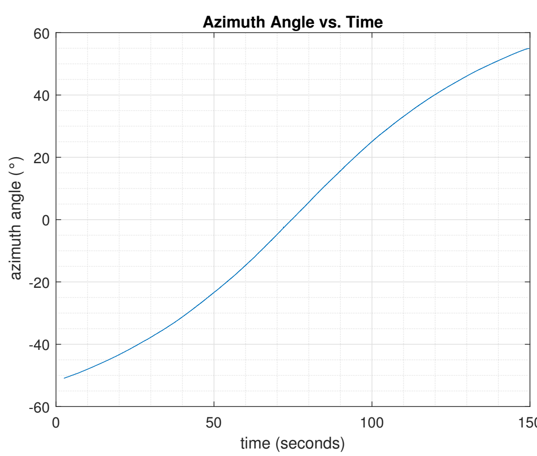
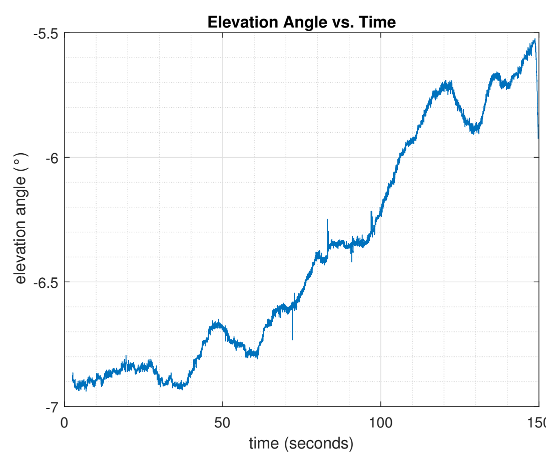


Fig. 7 Overlap Radius Diagram

image tracker may include new detections such as cars, birds, etc. like the MATLAB version. Figure 8 shows the azimuth and elevation angles of the tracked UAV for the OpenCV C++ implementation shown earlier in Figure 2. The goal is to run GBVT in real-time, so whatever method works accurately and quickly will be selected for implementation during the July and August 2023 flight tests.



(a) Azimuth Angle



(b) Elevation Angle

Fig. 8 Tracked UAV Azimuth and Elevation Angles

IV. Significance

The UAV flight test video shows promising results for ground-based distributed sensing of the airspace for tracking and monitoring AAM/UAM aircraft in scenarios such as corridor surveillance. Future AAM/UAM operations will require ground-based and airborne-based sensors for monitoring the airspace, and it will be complex in urban environments due to GPS degradation. Ultimately, experiments with UAS flight tests and real-time GBVT will lead towards initial attempts in creating AAM/UAM distributed sensing architecture that resembles ATC/ATM.

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