TOWARDS A UAV VISUAL AIR-TO-GROUND TARGET TRACKING IN AN URBAN ENVIRONMENT

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Abstract

This paper proposes a UAV navigation and guidance system for air-to-ground target search and tracking mission in an unknown urban environment. The mission is divided into three operation phases: i) cartography, ii) target search, and iii) target tracking. In particular, the paper focuses on development of the visual target tracking system. The integrated vision/inertial navigation filter is designed to simultaneously localize the target and the own-ship UAV in case of disruption in GPS signals. The guidance law which achieves target tracking and obstacle avoidance while enhancing the navigation accuracy is proposed. The entire system is implemented onboard the ONERA ReSSAC UAV experimental platform and evaluated in its actual flights.

1 Introduction

Uninhabited aerial vehicles (UAVs) have great potentials to carry out both military and civil missions, as they have advantages over manned aircraft of being cost-effective and of having no risk in human pilot life. Towards a need of UAVs performing a complex task such as reconnaissance & surveillance in an adversarial environment and search & rescue operation in a disaster site, tremendous work has been devoted to UAV flight automation since early 1990's. In recent years, the broader concept of unmanned aircraft system (UAS) including UAVs, ground control station, communication link and other equipments was introduced, and the research interest in the UAV community has widened from vehicle automation to system autonomy[1].

This paper outlines the UAS development and its in-flight evaluation for visual air-to-ground target search and tracking in an unknown urban environment. Vision sensors are widely used in UAV navigation, guidance and control, since they are information-rich, small-sized, and light-weighed. Especially, a monocular vision-based target localization and tracking problem has been well-studied with various applications including aerial refueling[2], formation flight[3] and ground target observation[4]. However, most assume a UAV operation in an open space but not in an congested area like an urban city. Two main challenges associated with an urban environment are; i) an access to GPS signals can be denied, and ii) there are obstacles to be avoided. Those two conditions are seldom incorporated in the UAV visual target tracking problem.

This paper supposes a mission scenario in which a UAV first explores the operation site at a high and safe altitude and collects environmental data to construct a 3D obstacle map, and then performs visual target search and tracking at a lower altitude while avoiding obstacles based on this a-priori obtained map. The cartography can be realized by using a vision sensor[5], a laser range finder (LRF) or by fusing measurements of the two[6]. For obstacle avoidance based on the cartography result, a UAV needs to be accurately localized even in case of GPS loss. Visual SLAM (simultaneous localization and mapping) approach has been intensively investigated for in-door robot navigation, and some studies apply it to UAV navigation in a GPS-denied environment [7][8]. By combining techniques of visual SLAM and visual target tracking, the authors have developed an integrated vision/inertial navigation system to simultaneously localize an own-ship UAV and a ground moving target without using GPS[9]. This system utilizes optical flow field measurements to complement the UAV velocity information. The navigation results are used in a guidance law to calculate a UAV acceleration input in order to achieve target tracking and obstacle avoidance. Since the vision-based navigation performance significantly depends on a relative motion between a camera and objects of interest, the guidance law is designed by taking account into evolution of uncertainties in the target and UAV localization errors. Such an idea is called dual control and was firstly treated in [10]. Since then, similar studies have been done for a bearing-only target interception problem[11][12]. This paper applies the one-step-ahead suboptimal guidance design developed in [13] to enhance the navigation accuracy while achieving the target tracking mission.

The entire system of visual target search and tracking system including the image processor, the navigation filter and the guidance law is evaluated through simulations and then in actual flights of the ONERA ReSSAC VTOL UAV experimental platform. The onboard system of the ReSSAC UAV consists of the basic flight control system[14] and the decision architecture where the system developed in this paper is implemented. The system performance is validated by achieving a closed-loop flight of purely vision-based target tracking.

This paper is organized as follows: Section 2 presents the mission scenario, Section 3 describes the visual air-to-ground target tracking system. Section 4 explains the real-time implementation of the suggested system. Section 5 shows flight experiment results, and Section 6 include concluding remarks.

2 Mission Scenario

As stated in the introduction, the mission scenario considered in this paper can be divided into three different operation phases: i) cartography, ii) target search, and iii) target tracking. This section briefly describes each of them.

2.1 Cartography

This paper supposes a cartography from distance measurements from a LRF. Given an operation site, UAV maneuverability constraints, specifications of the LRF (such as field of view and resolution), the UAV trajectory for laser scanning is generated offline. The trajectory is planned at a sufficiently high altitude so that no collision with obstacles nor GPS signal disruption occurs during the scanning. The UAV flies over the operation site by following this pre-planned path, while storing the laser scanning data time-synchronically with the GPS/INS-based UAV state estimates. During or after the flight, the LRF distance measurements are projected to a 3D inertial space by using the corresponding UAV position and attitude estimates. Then, an elevation map of the operation site is constructed by gridizing the resulting 3D position data.

2.2 Target Search

The target search and tracking is performed visually by using a single camera mounted on the UAV. First, the UAV trajectory for target search is generated offline based on the 3D obstacle map obtained from the cartography. Unlike the laser scanning path, the target search path is planned at a low altitude to take a closer look at the operation site, and hence the path planning has to manage obstacle avoidance. While the UAV flies along this search path, the onboard camera images are processed to detect the target automatically based on a-priori knowledge of its characteristics such as color and size.

2.3 Target Tracking

Once the target is detected, the operation phase is switched from target search to tracking. In this tracking phase, the UAV is required to localize and pursue the target by using its pixel position detected on each image from the onboard camera. At the same time, the UAV performs obstacle avoiding knowing its position and height from the map. The visual target tracking system proposed in this paper is discussed in detail in the following section. The tracking mission is terminated either by a mission supervision algorithm or by a human operator.

3 Visual Target Tracking System

This paper focuses on development of the visual target tracking system, and all the other algorithms required in realization of the missions scenario described in Section 2, such as trajectory planning, are assumed to be available. Fig.1 summarizes the UAV onboard system for visual target tracking. The system is composed of the image processor, the navigation filter and the guidance law.

3.1 Image Processor

Two tasks are devoted to image processing: target tracking and ground motion estimation. The algorithms used in this paper have been developed based on basic image processing routines that can be found on the Kovesi's website[16]. Target de-

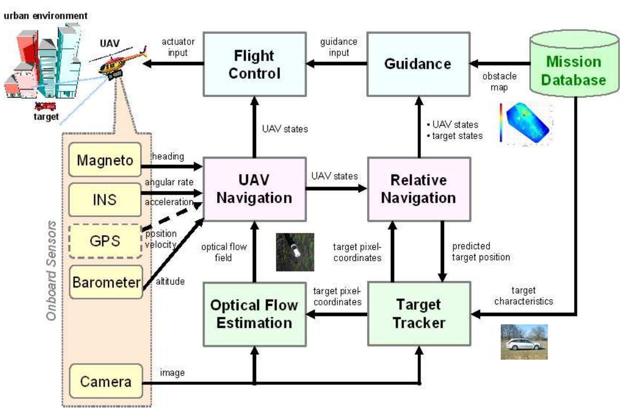


Fig. 1 Visual Target Tracking System

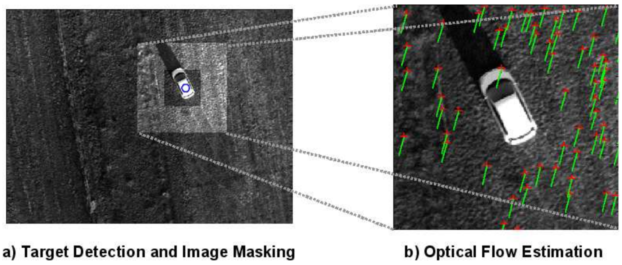


Fig. 2 Image Processing Results

tection and tracking problem is made simpler by assuming a-priori knowledge of the target color and size. For example, the target detection illustrated in Fig.2-a) uses the fact that the target's gray-level is significantly higher (e.g. whiter) than the background. Then the target tracker simply consists in convolving the current image by a Gaussian kernel, and in selecting a position attaining the maximum. Ground motion estimation applies optical flow estimation[17], however in urban environment, it is necessary to reject image regions which belong to superstructures (buildings, trees, etc.) and to moving objects. In this air-to-ground target tracking problem, we can assume that the surroundings of the target on the image correspond to the locally flat ground surface. Hence, given the detected target position, the optical flow estimation focuses on its neighborhood (Fig.2). First, the feature points are detected by Harris-Stephen operator on the current and previous images. Then feature matching between the two images is performed based on a back and forth correlation. Finally, an affine motion model is robustly fitted to the estimated flow vectors. Fig.2-b) shows an example of the ground motion estimation results.

3.2 Navigation Filter

As shown in Fig.1, the navigation system includes two different filters. One is to estimate the global position and velocity of the UAV (UAV navigation), and the other is to estimate the position and velocity of the target relative to the UAV (relative navigation). The UAV can be localized very accurately by GPS/INS integration[18]. However, its accuracy highly relies on GPS signals, and an INS-only navigation solution diverges quickly due to an accumulation of measurement biases. Therefore, the authors have proposed the vision-aided inertial navigation which uses the optical flow field measurement to obtain the UAV velocity information in the absence of GPS[9]. The target relative state is estimated from its pixel-coordinates measurement and the UAV state estimate. Since those 2D vision-based measurements are nonlinear to the 3D estimation state, an extended Kalman filter (EKF) is applied to both the UAV and relative navigation. In the filters, we assume that well-estimated attitude of the UAV (i.e., of the onboard camera) is available from INS. Also, the unknown target motion is modeled as non-accelerating in the relative navigation design. See [9] for more details of the navigation filter design.

3.3 Guidance Law

A UAV guidance objective during the target tracking mission is to pursue the target while avoiding obstacles by using the estimated states of the UAV and the target as well as the 3D obstacle map. In this paper, for simplicity, a guidance law is designed to make a UAV achieve target tracking by its horizontal motion and obstacle avoidance by its vertical motion. A position-dependent safety altitude $h_d(X,Y)$ is defined based on the obstacle map, and the UAV is required to follow its profile along the target trajectory. Hence, the UAV guidance problem becomes a position tracking problem in which the desired position is given by

$$X_d = \begin{bmatrix} X_t & Y_t & -h_d(X_v, Y_v) \end{bmatrix}^T$$

where (X_t, Y_t) and (X_v, Y_v) be global horizontal positions of the target and the UAV, respectively. Define the tracking error vector $x(t)$ by

$$x = \begin{bmatrix} X_v - X_d \\ V_v - \dot{X}_d \end{bmatrix}$$

Then, at time t_k, the guidance law for the UAV acceleration input $a_v(t)$ can be derived by solving the following optimization problem.

$$\min_{a_v(t)} J_k = \frac{1}{2}\int_{t_k}^{\infty} \left\{ x^T(t)Ax(t) + a_v^T(t)Ba_v(t) \right\} dt \tag{1}$$

subject to the tracking error dynamics with an initial condition $x(t_k) = x_k$. Let $a_v^*(t, x_k)$ denote its optimal solution. This optimal guidance, however, is not realizable in the real-world since the true state x_k is unaccessible. A conventional way to derive the guidance input is to simply replace the true state in $a_v^*(t, x_k)$ by its estimate $\hat{x}_k$. This approach coincides with solving the optimization problem (1) under an assumption of zero estimation error, and hence it can cause a large tracking error when having a large estimation error.

It is the well-known fact that observability of 3D state estimation from 2D vision information is significantly influenced by a camera motion relative to objects of interest. That is, the performance of the navigation filter described in Section 3.2 depends on the UAV motion relative to the target and also to the ground surface. Therefore, in order to improve the navigation accuracy while achieving the guidance objective, this paper adopts the one-step-ahead (OSA) suboptimal guidance law developed in [13]. This OSA suboptimal guidance policy minimizes the expected value of J_k in (1) under an assumption that there will be only one more final measurement at one-time-step ahead. The resulting input at time t_k can be written as

$$a_v(t_k) = a_v^*(t_k, \hat{x}_k) + \Delta a \tag{2}$$

The additional input Δa in (2) creates some ex-

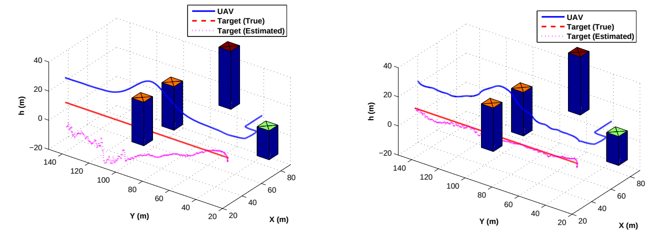


Fig. 3 UAV Trajectory, True and Estimated Target Trajectories : using the nominal guidance (left) and the OSA optimal guidance (right)

tra motions to enhance the UAV and target localization accuracies. Through preliminary simulation results, it has been discovered that an excitation in the horizontal motion enhances the target height estimation (as shown in Fig.3) while the vertical motion enhances the optical flow-based UAV localization. What is particularly interesting in our problem is that the altitude tracking performance depends also on the accuracy of the horizontal localization because of the position-dependent altitude command. More details on the guidance design can be found in the previous publication[19].

4 System Implementation

The visual target tracking system developed in Section 3 is implemented onboard the ONERA ReSSAC VTOL UAV and evaluated in its flight.

4.1 UAV Experimental Platform

The ONERA ReSSAC UAV is an experimental platform that has been developed based on an industrial unmanned helicopter YAMAHA RMax. Table 1 summarizes its specifications. Its onboard system is composed of two processors. The primary processor uses the PC/104 with Pentium 266 MHz, and it is dedicated to a basic auto-pilot system, described in [14], including the GPS/INS navigation filter and the flight controller. The secondary processor is for the decision architecture which is in charge of mission management, decision-making and supervision. The visual target tracking system proposed in this paper is implemented on this decision architecture. It uses the PIP11 (MPL) hardware unit which incorporates the embedded Pentium M 1.8 GHz. The PIP11 is connected to the onboard camera via FireWire, and to the ground control station via Ethernet/Wifi bridge. The two onboard processors interact and communicate through two RS-232 serial connections.

Table 1 Specifications of the ReSSAC UAV

Model	Yamaha RMax
Length	3.63 (m)
Weight	60 (kg)
Payload	20 (kg)
Onboard sensors	GPS, INS, Compass, Barometer, Camera, LRF

4.2 Embedded Decision Architecture

The decision architecture is executed on a Linux Debian system and is based on Orocos middleware[15]. Orocos is an open source robotic framework, which offers a real-time toolkit (RTT) that manages interactions and execution of user-defined components. All the algorithms in the visual target tracking are implemented in C++ as a single Orocos component. Besides this main component, there are components which connect to hardware and also ones for data recording. The entire system is built by connecting and activating these components as illustrated in Figure 4. Execution of each Orocos component is monitored and controlled by a special component, called *Deployer*. Deployer is considered as a central component in terms of control flow. The supervision algorithm which manages the mission can be implemented in a form of a finite state machine[20] and executed within this component.

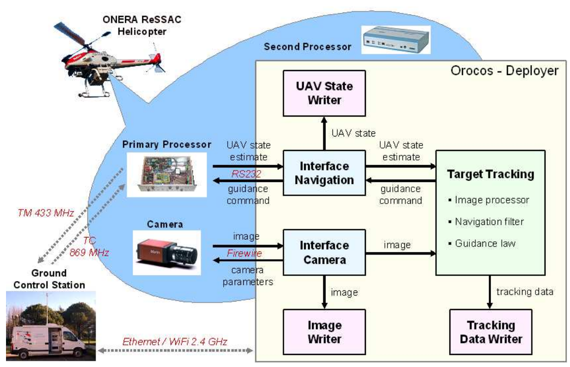


Fig. 4 The Embedded Decision Architecture

4.3 Software-in-the-Loop Simulation

After implemented in the Orocos architecture, the visual target tracking system is first tested in the software-in-the-loop (SITL) simulation. The SITL simulation uses the OpenRobots simulator that has been collaboratively developed at CNRS-LAAS and ONERA[21]. It is built based on Blender and Python script language, and is able to simulate multiple mobile robots in a 3D dynamic environment. It can also emulate onboard sensor measurements (such as GPS, inertial sensors and camera) and communication link between the robots. Figure 5 shows the interface of the OpenRobots simulator when running the closed-loop target tracking simulation. In this simulation, motion of the ground 'target' robot was given manually via keyboard. The left-top window appeared in Figure 5 is the emulated camera image. The Orocos architecture can be directly connected to the OpenRobots simulator by using Yarp. The SITL simulation is very beneficial in debugging the implemented system before flight experiments.

5 Flight Experiment Results

This section presents flight experiment results of the algorithms that have been developed so far. It is remarkable that all the results shown here were obtained either through an offline process using the actual sensor data recorded during flight or through a real-time process onboard in flight, and that nothing was simulated nor emulated.

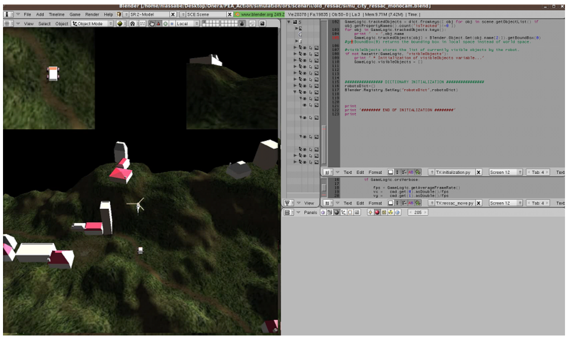


Fig. 5 OpenRobots Simulator Interface

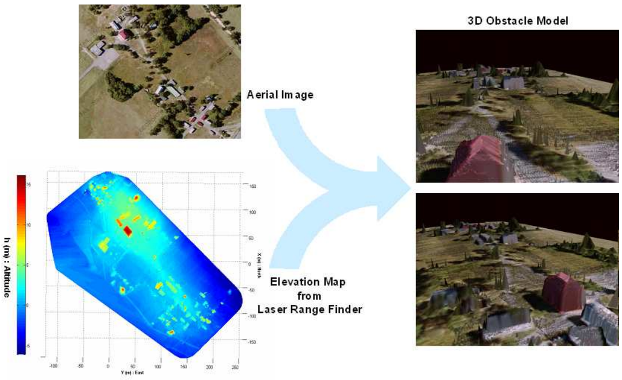


Fig. 6 3D Obstacle Model Construction from Laser Range Finder

5.1 Cartography

The flight experiment of cartography has been conducted in the military combat training village in Caylus, about a 100 km away from Toulouse, France. In this experiment, the ONERA ReSSAC UAV automatically flew over the village by following a manually pre-programmed sequence of waypoints. The UAV state estimate is calculated on the auto-pilot system, and sent to the Orocos decision architecture where the distance measurements from the LRF were recorded. The laser data were taken at 8Hz with the field of view of $72^\circ \times 2.4^\circ$ and the resolution of 144×4 scans. Fig.6 shows the elevation map obtained offline by using those LRF data, and the 3D village model constructed by fusing this elevation map with the aerial image. We can see that the buildings as well as the trees have been reconstructed in 3D with a good precision. This result will be used for target search path planning and also for obstacle avoidance during the target tracking.

5.2 Target Detection and Tracking

The simplest version of the visual target tracking system has been implemented onboard and its performance is validated by achieving a closed-loop flight of purely vision-based air-to-ground target tracking. The implemented system includes the image processing algorithms for target detection and tracking, the relative navigation filter for target localization, and the linear

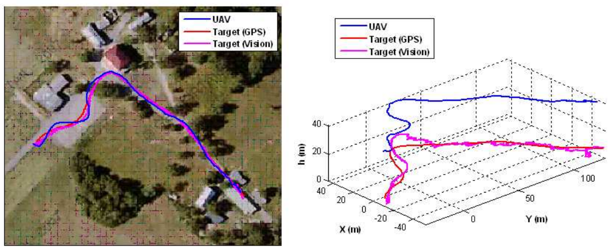


Fig. 7 Closed-Loop Visual Target Tracking : UAV trajectory (in blue), GPS-measured target trajectory (in red), and vision-estimated target trajectory (in magenta).

guidance law for tracking. This entire process runs at 10Hz. A manually driven white car was used as a moving ground target in this experiment. The Orocos deployer component is programmed to trigger the target tracking control mode as soon as the target is detected. Fig.7 compares the UAV trajectory, the GPS-measured and the vision-estimated target trajectories. The error in target height estimation due to its poor observability was observed in this result.

5.3 UAV Self-Localization without GPS

The optical flow estimation algorithm which estimates the ground surface motion in the image sequence was added to the onboard process. The closed-loop target tracking flight has successfully been achieved with this algorithm running onboard. However, the system performance was degraded from 10Hz to 8Hz due to its heavy computational load. Fig.8 compares the resulting optical flow vector measurements with those estimated from the GPS-measured UAV velocity and altitude, and the two results are well-matched. As stated in Section 3.2, the optical flow measurement can aid the UAV self-localization in case of GPS signal loss. Fig.9 shows the UAV localization results of the offline simulation using the optical flow and the inertial sensor measurements recorded in the actual flight. The figure presents that the GPS/INS navigation solution quickly diverges once the GPS signals become unaccessible. However, this divergence can be avoided by using the optical flow information.

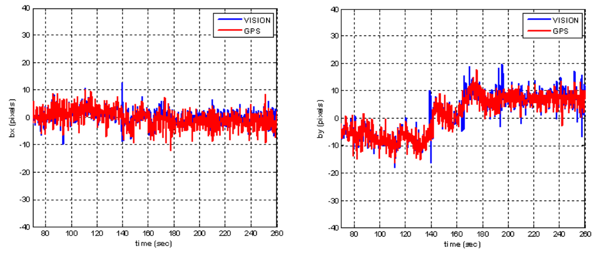


Fig. 8 Optical Flow Estimation : image processor outputs (in blue) and GPS-estimated optical flow (in red).

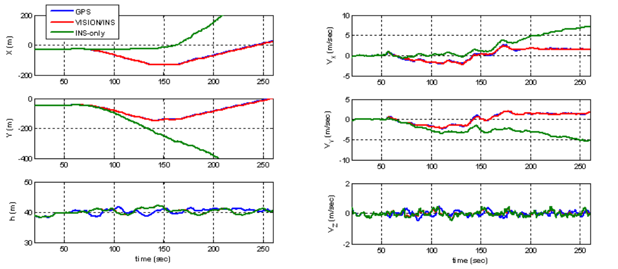
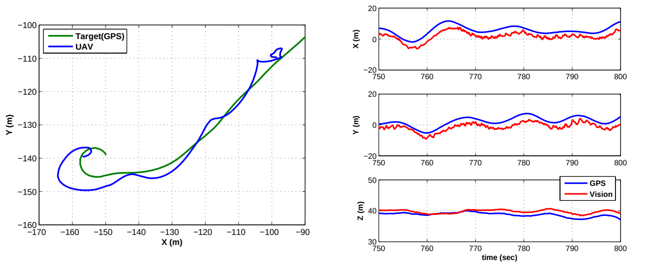


Fig. 9 Optical Flow-Based UAV Navigation without GPS : UAV position estimates by using GPS/INS (in blue), INS-only (in green), and vision/INS (in red).

5.4 OSA Suboptimal Guidance

The implemented target tracking system was augmented with the OSA suboptimal guidance policy developed in Section 3.3 to improve the relative navigation performance, and tested for the first time in actual flight. Fig.10-a) shows the UAV horizontal trajectory compared with the GPS-measured target trajectory. Fig.10-b) is the relative position estimation result. Similar to the simulation result presented in Fig.3, the OSA optimal guidance law creates some lateral motions relative to the target in order to improve the observability of target height. However, at the end of this flight, the UAV became unstable due to the additional input created by the OSA suboptimal guidance policy. It is necessary to perform stability analysis of the algorithm and also to add some flight safety criteria in the system before the next in-flight evaluation.



a) Horizontal Trajectories b) Relative Position Estimate

Fig. 10 Closed-Loop Target Tracking with Optimal Guidance

6 Conclusion

This paper outlines the UAV onboard system development towards a vision-based air-to-ground target tracking in a GPS-denied environment. Particularly, this paper focuses on the visual target tracking system. In the navigation design, it is suggested to utilize optical flow field information to aide UAV self-localization when GPS signals are disrupted. The UAV guidance law is designed to pursue the target's horizontal trajectory while vertically avoiding obstacles. Furthermore, the optimal guidance law is applied to enhance the vision-based navigation accuracy by creating some extra motions. An embedded software architecture is developed based on Orocos in order to implement the target tracking system into the onboard processor of the ONERA ReSSAC UAV. Closed-loop vision-based target tracking has successfully been achieved in flight with this architecture. Some preliminary flight experiment results were also shown to validate the suggested navigation and guidance algorithms.

The ultimate goal of this work is to demonstrate the whole mission scenario described in Section 2 in an autonomous flight. Towards this goal, first, the onboard target tracking system will be completed by implementing the optical flow-based UAV self-navigation and the guidance law for obstacle avoidance. Then, for future work, we aim to augment the system with mission planning and decision making algorithms which manage the mission.

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