# The ONERA ReSSAC Unmanned Autonomous Helicopter : Visual Air-to-Ground Target Tracking in an Urban Environment

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This paper outlines an autonomous flight system developed onboard the ONERA ReSSAC unmanned helicopter for an air-to-ground target tracking mission in an unkown urban environment. The system consists of the following three components: i) an image processor which detects the target and estimates ground motion around the detected target position, ii) an integrated vision/inertial navigation filter which simultaneously localizes the target and the own-ship UAV with an occasional loss of GPS, and iii) a guidance law which achieves target tracking as well as obstacle avoidance. Those algorithms are implemented in the Orocos robotic architecture, integrated with the auto-pilot system of the ReSSAC helicopter, and tested in closed-loop flight of vision-based target tracking.

# 1 Introduction

Unmanned aerial vehicles, or UAVs, have great potential not only in military operations but also in civil missions such as search and rescue in a disaster site. Towards a practical use of UAVs in such missions, their autonomous flight system has been progressively developed (Ref. 1). In particular, vision-based navigation, guidance and control is one of the most studied research topics in automation of UAVs in recent years. This is because a 2D vision sensor is suitable to be mounted onboard, since it is information-rich, low-cost, light-weight and compact.

This paper addresses a vision-based air-to-ground target search and tracking problem in an unkonwn urban environment. Figure 1 summarizes a mission scenario. First, the UAV explores the operation site at a sufficiently high altitude to gather information which is post-processed to construct a 3D obstacle map ( $\phi$ 1). Then, the UAV searches a target at a lower altitude along a search path pre-planned based on the obstacle map ( $\phi$ 2). Once the target is detected,

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<sup>||</sup>Research Engineer, Email: Guy.Le\_Besnerais@onera.fr Presented at the American Helicopter Society 66th Annual Forum, Phoenix, Arizona, May 11-13, 2010. Copyright©2010 by the American Helicopter Society International, Inc. All rights reserved. the UAV starts localizing and pursuing it while avoiding obstacles ( $\phi$ 3). The first task can be achieved by using the vision-based mapping system developed in (Ref. 2). This paper focuses on developing an autonomous visual target search and tracking system.



Fig. 1. Air-to-Ground Target Search & Tracking Mission Scenario

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Model	YAMAHA RMax	
Length	3.63 (m)	
Weight	60 (kg)	100
Payload	20 (kg)	TEMP
Sensors	GPS/INS, compass,	
	barometer, vision	

Fig. 2. The ONERA ReSSAC Helicopter

One of the challenges in this system is to enable an accurate global localization of both the target and the UAV while operating in a GPS degraded/denied environment. There is a large body of research on visual SLAM for UAV selfnavigation without GPS (Ref. 3). By combining ideas of visual SLAM and visual target tracking, the authors have suggested an integrated vision/inertial navigation system for simultaneous target and self localizations by utilizing sparse optical flow to complement the velocity information (Ref. 4). A guidance objective of the UAV is to achieve a target tracking or search mission while avoiding obstacles with a knowledge of the 3D environmental map obtained in the first operation phase. Since the vision-based navigation performance significantly depends on the camera motion relative to objects of interest (such as target and the ground surface), the guidance law is designed based on the concept of observer trajectory optimization (Ref. 5). This paper adopts the one-step-ahead optimization approach proposed in (Ref. 6) so that the resulting guidance law creates motions which enhance accuracies of the target and the UAV localizations.

The visual target search and tracking system proposed in this paper is implemented in the Orocos (Open RObot COntrol Software (Ref. 7))-based architecture, and its performance is firstly tested through closed-loop simulations by connecting Orocos with the OpenRobots simulator developed collaboratively at CNRS-LAAS and ONERA (Ref. 8). After evaluated in simulation, the target tracking system is implemented onboard the ONERA ReSSAC unmanned helicopter (Figure 2) and integrated with the auto-pilot system which has already been developed in (Ref. 9). Finally, the system performance is validated by achieving a closed-loop flight of purely vision-based target tracking.

This paper is organized in the following manner: Section 2 proposes the visual air-to-ground target tracking system. Section 3 describes the onboard system of the ON-ERA ReSSAC helicopter and presents the flight experiment results. Section 4 includes concluding remarks.

#### 2 Visual Target Search & Tracking System

Figure 3 depicts the entire UAV onboard system of the visual air-to-ground target tracking. The system includes i) image processor, ii) navigation filter, and iii) guidance and control system. The following subsections detail each of these components.



Fig. 3. Visual Target Search & Tracking System



a) Target Detection and Image Masking

b) Optical Flow Estimation

## Fig. 4. Example of Image Processing Result

#### 2.1 Image Processor

Two tasks are devoted to the embedded image processor: ground motion estimation and target detection and tracking. Both tasks lead to problems of very different difficulty depending on the imaged scene: typically the urban environment is quite challenging. Ground motion estimation from aerial imagery sequence uses sparse optical flow estimation (Ref. 10), but it is necessary to reject image regions which belong to superstructures (buildings, trees, etc.) and to moving objects.

In this paper, the target detection and tracking problem is made simpler by assuming a-priori knowledge of the target color and size. An example of the image processing outputs is illustrated in Figure 4. The automatic detection in this example is performed based on the fact that the target's graylevel is significantly higher than the background. Given the detected target position, the ground motion can be more easily estimated in its neighborhood by making the hypothesis that ground surface around the target is flat. After a step of sparse optical flow estimation, an affine model is robustly fit to approximate the flow field. This fast process is used in the flight experiment described in Section 3.

#### 2.2 Integrated Vision/Inertial Navigation

The navigation filter is designed based on an extended Kalman filter (EKF), to simultaneously estimate the global position and velocity of the UAV and those of the target by



a) INS-Only Navigation b) Vision/Inertial Navigation

Fig. 5. Navigation Results with and without Optical Flow Measurement

fusing the onboard inertial sensor data with the image processing outputs. The GPS/INS navigation in general gives a very accurate estimate of the UAV state (Ref. 11), while the INS-only navigation solution diverges very quickly due to an accumulation of the measurement bias. In order to prevent such a navigation divergence in case of occasional GPS loss, the ground motion estimation result of the image processor is utilized as a complementary velocity measurement of the UAV. See (Ref. 4) for details of this integrated vision/inertial navigation filter design. Its estimation performance has been verified through offline simulations using the actual vehicle state data synchronically recorded with the onboard camera images in open-loop flight of the ON-ERA ReSSAC helicopter. Figure 5 compares the self- and target-localization results of the INS-only navigation and the suggested vision/inertial navigation when assuming an absence of GPS measurements. It is clear from the result that the optical flow measurement effectively complements the GPS information and eliminates the divergence in the INS-only navigation solution.

#### 2.3 Guidance Design for Tracking

A UAV guidance objective of the target search operational phase is to follow a pre-planned search path (say  $X_{ref}$ ), and that of the target tracking phase is to track the target while avoiding obstacles. In this paper, for simplicity, obstacle avoidance is performed by maintaining a positiondependent safety altitude  $h_d(X,Y)$  that is determined from the 3D obstacle map obtained during the first operational phase. Then, the UAV guidance problem becomes a position tracking problem where the desired position is given by

$$X_d(t) = \begin{cases} X_{ref}(t), & \text{during target search} \\ \begin{bmatrix} X_t(t) \\ Y_t(t) \\ -h_d \left( X_v(t), Y_v(t) \right) \end{bmatrix}, & \text{during target tracking} \end{cases}$$

 $(X_t, Y_t)$  and  $(X_v, Y_v)$  are global horizontal position of the target and the UAV respectively. As shown in Figure 3, the guidance input is calculated by using the estimated state of the UAV and the target. The following linear feedback



a) Nominal Linear Guidance b) OSA Optimal Guidance

Fig. 6. Target Localization with and without Optimal Guidance



# Fig. 7. Obstacle Avoidance with and without Optimal Guidance

law for the UAV acceleration input is the simplest and most commonly used approach to determine the UAV acceleration input for position tracking.

$$a_d(t) = -K_p(\hat{X}_v(t) - \hat{X}_d(t)) - K_d(\hat{V}_v(t) - \hat{X}_d(t)) + \hat{X}_d(t)$$

However, this linear guidance can cause a large tracking error when the estimation error is large.

In vision-based navigation and control problems in general, the separation principal does not hold between estimation and control. It means that the navigation performance significantly depends on relative motion of a camera with respect to objects of interest (such as target and ground surface). Particularly in bearing-only relative navigation, the depth information becomes unobservable when there is no lateral relative motion (Ref. 12). Therefore, this paper suggests introducing an extra input  $\Delta a_d$  to create motions that enhance the estimation performance and minimize the expected position tracking error. In order to reduce the computational load, the one-step-ahead (OSA) optimization approach proposed in (Ref. 6) is applied to obtain this extra input. The OSA optimization technique performs the optimization under an assumption that there will be only one more measurement at the one time step ahead.

Figure 6 compares simulation results of vision-based target localization when using the nominal linear guidance law and the OSA optimal guidance law. Similarly as seen in related work by others, the optimal guidance law creates a small sinusoidal motion to improve the depth observability and a large drift in the target height estimation error is eliminated. Figure 7 shows simulation results in which an absence of GPS signals during the target tracking is assumed. In this situation, the optimal guidance law takes into account the effect of the camera motion both on the optical flow-based self localization and on the vision-based target localization. Figure 7 plots the resulting UAV trajectories when using the nominal and the optimal guidance laws, compared with the desired path. When using the nominal guidance, the UAV fails to avoid the obstacle due to the error in its self localization. The UAV horizontal position is overestimated, and hence it decends to the commanded altitude before flying over the obstacle. This collision is prevented by enhancing the UAV self localization accuracy by creating the additional camera motion relative to the ground surface on which optical flow is calculated.

#### 3 UAV Onboard System and Flight Experiment

This section explains a real-time implementation of the visual target tracking system designed in the previous section onboard the ONERA ReSSAC unmanned helicopter, and presents some flight experiment results.

#### 3.1 The ONERA ReSSAC Unmanned Helicopter

The ONERA ReSSAC helicopter is an experimental platform that has been developed based on an industrial unmanned helicopter YAMAHA RMax. Figure 2 summarizes its specifications. The onboard system of the ReSSAC helicopter is composed of two main processors. The first one (the primary processor) is dedicated to a basic flight controller including the GPS/INS navigation filter and autopilot system that have been described in previous publications (Ref. 9). The second one is for the decision architecture which is in charge of mission management, decisionmaking and supervision. The system proposed in this paper is implemented on this second processor. These two processors interact and communicate through a serial connection. This connection allows the decision architecture to obtain the UAV estimated state from the GPS/INS navigation filter and also to send a guidance command to the auto-pilot.

### 3.2 Orocos-Based Decision Architecture

The decision architecture is executed on a Linux Debian system and is based on Orocos middleware (Ref. 7). Orocos is an open source robotic framework, which offers a real-time toolkit (RTT) that manages interactions and execution of components that are defined and developed by a user. An Orocos component interface is shown in Figure 8. Such a component may be connected to hardware devices or it may integrate processes. All the algorithms of the visual target tracking system including the image processor, the navigation filter and the guidance law are implemented as a single Orocos component in C++ based on the Orocos RTT library. Besides this main 'Target Tracking' component, there are components which connect to the onboard camera and to the primary processor, and also components



Fig. 8. Orocos Component Interface



Fig. 9. Orocos-Based Decision Architecture

which perform data recording. The entire system is built by connecting and activating these components as illustrated in Figure 9. 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.

### 3.3 Closed-Loop Simulation with OpenRobots Simulator

After implemented in the Orocos architecture, the entire target tracking system is first verified through the software-inthe-loop (SITL) simulation. The SITL simulation uses the OpenRobots simulator that has been collaboratively developed at CNRS-LAAS and ONERA (Ref. 8). The Open-Robots simulator is built based on Blender and Python script language, and it is able to simulate multiple mobile robots in a 3D dynamic environment. It can also emmulate onboard sensor measurements (such as GPS, inertial sensors and camera) and communication link between the robots. Figure 10 shows the interface of the OpenRobots simulator while performing the closed-loop target tracking simulation. In this simulation, motion of the ground 'target'



Fig. 10. OpenRobots Simulator Interface

robot was given manually via keyboard. The left-top window appeared in Figure 10 is the emmulated camera image. The Orocos-based architecture is connected to the Open-Robots simulator using Yarp. It receives the simulated UAV onboard sensor measurements and camera images from the simulator, processes those data, and sends back the UAV velocity command to the simulator. The SITL simulation is very beneficial in debugging the implemented system before conducting flight experiments using the actual vehicles.

#### 3.4 Flight Experiment

First, a simplified version of the target tracking system (assuming no obstacles and no loss of GPS signal, and hence without the optical flow estimation algorithm) has been developed and implemented in the Orocos architecture onboard the ReSSAC helicopter. An entire process including the image processor (automatic detection and target tracker), the relative navigation filter and the guidance law runs at 10 Hz. The guidance law outputs a set of the UAV horizontal velocity, height and heading angle commands based on the visually estimated relative state, and sends these commands to the flight controller which calcultes actuator inputs of the helicoter to realize the command while stabilizing the vehicle. Flight experiments of air-to-ground target tracking have been conducted using a manually-driven car as a moving ground target, and purely vision-based closed-loop flights have been successfully achieved. Figure 11 presents the flight test results of the UAV tracking trajectory and the target GPS-measured and vision-based estimated trajectories. To ensure flight safety, constant height and heading angle commands were used in this experiment. The results prove that the target position is accurately estimated by using its image pixel coordinate information and hence the UAV pursues the target with a good precision. By using the same system, the closed-loop target tracking was also achieved in a combat training village, a more complex environment. Figure 12 depicts the resulting target and UAV trajectories from this experiment.

Then, the OSA optimal guidance policy was augmented



a) Experiment Scene b) UAV and Target Trajectories

Fig. 11. Closed-Loop Target Tracking Results



Fig. 12. Closed-Loop Target Tracking Results in the Combat Village

to improve the vision-based relative navigation performance, and tested for the first time in actual flight. Figure 13-a) shows the UAV horizontal trajectory compared with the GPS-measured target trajectory. 13-b) is the relative position estimation result. As seen in the simulation result presented in Section 2.3, the OSA optimal guidance law creates some lateral motions relative to the target in order to improve the depth observability.

Now the embedded system will be completed by the optical flow estimation, the optical flow-based self-navigation and the obstacle avoidance algorithms. The optical flow estilmation algorithm has been already implemented in the Orocos architecture, and tested in flight by running it with the target detection and tracking algorithm. It is observed that the optical flow estimation takes about 150 (msec) on the onboard processor and the target tracking system can no longer run at 10 Hz. We will try to reduce this processing time before implementing the optical flow-based self navigation filter. The ultimate goal is to perform closed-loop target tracking in the presence of obstacles and occasional loss of GPS signals. This will be the first attempt of a GPSfree automatic flight of the ReSSAC helicopter.



a) Horizontal Trajectories

b) Relative Position Estimate

# Fig. 13. Closed-Loop Target Tracking with Optimal Guidance

#### 4 Conclusion and Future Work

This paper proposed the UAV navigation and guidance system for vision-based ground target search and tracking in a GPS-denied urban environment. It is suggested to utilize sparse optical flow to aide UAV self-navigation when GPS information is not available. Moreover, the optimal guidance law is applied to improve navigation accuracy by taking into account the inseparability between control and vision-based estimation. The embedded software architecture is developed based on Orocos in order to implement the suggested system into the onboard processor of the ONERA ReSSAC helicopter. The implemented system was first verified through the software-in-the-loop simulation by using the 3D robotic simulator. Then, closed-loop purely visionbased target tracking have successfully been achieved in flight with this architecture. The optical flow-based self localization algorithm is expected to be implemented and tested in flight shortly. For future work, we aim to augment the system with mission planning and decision making algorithms so that it can be applied to a more complex mission scenario.

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