# Cooperative Vision-Based Collision Avoidance for Unmanned Aircraft

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## I. Introduction

AOVIDING collisions between aircraft is a fundamental air transportation safety goal. That goal is achieved through the application of common airspace procedures and the provision of centralized strategic and tactical separation services by air traffic control. These routine separation methods are augmented by backup, onboard collision avoidance algorithms designed to provide safety in the rare event that regular separation processes fail. The efficacy of such algorithms and systems can make the difference between a close encounter and a mid-air collision.

Small unmanned aircraft systems (UAS) may not have the ability to carry or power existing cooperative surveillance sensors that are used by manned aircraft, including Autamotic Depenent Surveillance – Broadcast (ADS-B) or a Mode C or S transponder. Insead, non-cooperative sensors, those that do not rely on other aircraft to transmit their locations, or new types of cooperative sensors may fill this important surveillance system gap. A promising sensor solution is the use of cameras to detect intruding aircraft and obstacles because video cameras are small, lightweight, use little power and are already onboard most small UAS. The drawback to this approach is that sophisticated and computationally intensive algorithms are required to process the video information, however flight tests demonstrating the ability detect fixed obstacles visually in real time have shown that it is feasible.[1]

A majority of prior work considers static obstacles, limiting the applicability of such approaches in multi-UAV scenarios. Magree et. al. proposed a monocular visual mapping framework for estimation of potential obstacles in the surrounding environment, avoiding them with vertical maneuvers.[2] Fu et al. also employed monocular simultaneous localization and mapping (SLAM) to estimate states in a static obstacle avoidance setting using fuzzy logic controllers.[3] Watanabe et. al. used a vision-based navigation framework is used to avoid obstacles, employing a collision cone approach.[4] Holz et. al. address the problem of obstacle avoidance in domestic environments for ground robots, exploiting a pitching 2D laser scanner for the generation of a 3D map.[5] An insightful comparison into the performance of 2D versus 3D based obstacle avoidance is presented.The next step in visual collision avoidance will be to use SLAM to not only avoid obstacles but also determine the location of the ownship vehicle and a cooperative vehicle within a known environment. If a team of UAS all posses the same capability and can share their locations within the commonly developed map then collision avoidance between each aircraft can be done without access to GPS information or any active surveillance sensors (e.g. radar, lidar). This capability could provide the primary separation function in places where other sensor information is unavailable, for example indoors or in a GPS-denied environment environment, or as a redundant system that provides continuity of navigation information during temporary GPS outages.

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This paper describes progress in the effort to develop and flight test a SLAM capability integrated with a collision avoidance (CA) algorithm. The CA algorithm is formulated as a partially observable Markov decision process (POMDP) and the optimal policy is generated offline via dynamic programming so that it is computationally inexpensive to use in real time. The vision-based SLAM system is the adapted from the real-time appearance-based mapping (RTAB-Map) package that is distributed with the robot operating system (ROS) used on many small UAS. The state estimates provided by the SLAM system are combined with the onboard inertial measurement unit (IMU) estimates via an extended Kalman filter (EKF). The remaining uncertainty is compensated for in the algorithm by using a QMDP approach to make CA actions more robust, an approach that has been successfully applied to large aircraft collision avoidance in the past.[6]

## II. Collision Avoidance Algorithm

The development and evaluation of the partially observable Markov decision process (POMDP)-based collision avaidance algorithm is described in detail in a separate paper.[7] The algorithm is shown to perform on par with other collision avoidance approaches in terms of the separation achieved against the intruder aircraft and the mean deviation from the desired trajectory, and to have benefits in terms of robustness to intruder maneuvering and consistency with aircraft operator expectations.[8] Other algorithms outperformed the POMDP algorithm in other areas, including uniformity of achieved separation and worst-case trajectory deviation distance.

Policies that result from approximating the optimal solution to the POMDP are shown in Figure 1. In those policy plots, the ownship is shown as a quadrotor aircraft at the origin and the colors surrounding it represent the optimal actions to take based on the location of the intruder. In the left diagram, both the intruder and ownship velocities are zero and the ownship has no error from the desired trajectory. In the right diagram, the ownship is moving in the positive y-axis direction at 1 m/s with zero trajectory error. The intruder is stationary. The colors indicate, for example, that in the stationary case on the left if the intruder position lies in the black region centered around a relative range of (0,-10) that the optimal action is to move in the positive y-axis direction.

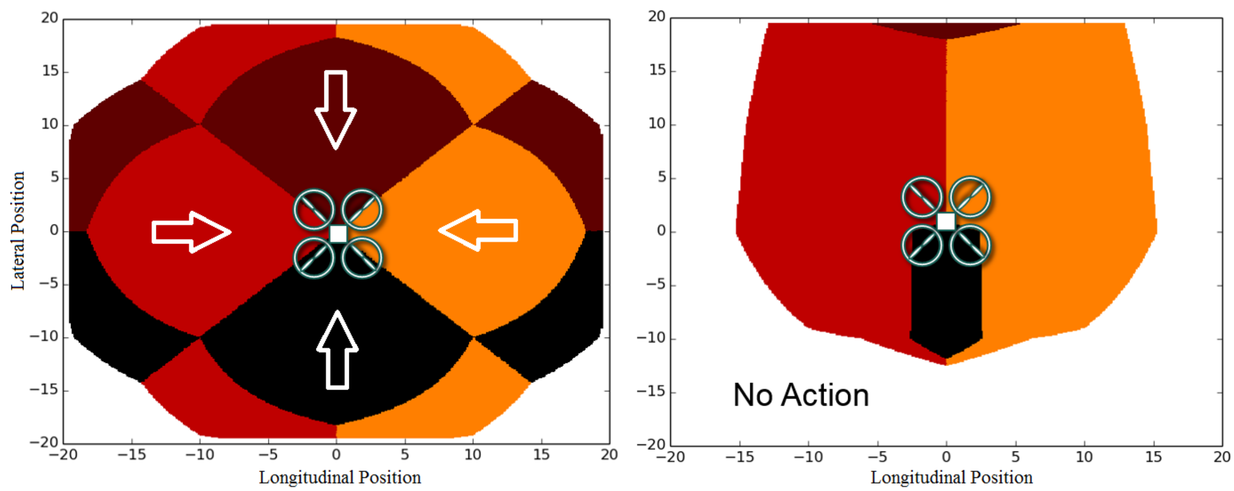


*Figure 1. Collision avoidance policies representing approximately optimal solutions to the POMDP.*

Flight testing the collision avoidance algorithm required several changes with respect to the simulation evaluations reported in separate papers.[7,8] The software was ported from the Julia computing language to C++ for consistency with key hardware's ARM architecture. This change required rewriting several libraries, including key multi-linear interpolation functions, in C++. Methods were created to read the current states from the ownship's and/or intruder's sensor measurements, and filters developed to make those surveillance system outputs robust to real-world uncertainties. Finally, avoidance system mode switching and trajectory tracking algorithms were added to make the aircraft capable of conducting a collision avoidance flight test in real-world conditions.

## III. Vision-Based Surveillance

In order to retrieve a robust state estimate for the UAS in GPS-denied environments we propose the use of a stereo video camera system. This setup was selected because video cameras are passive sensors, the operate well outdoors, are light weight, draw little power and are inexpensive. The proposed method makes use of visual odometry (VO) and SLAM to provide an estimate of the position and velocity of the UAS. Incremental VO alone would not be sufficient for a collision avoidance application because it provides position updates relative only to an initialization point. Two UAS will have no ability to measure their relative distances. Such a system would provide state estimates for each UAS in a different reference frame with no robust method for transforming between them.

The novelty of our approach lies in running a SLAM system across both UAS that facilitates the co-localization of the ownship and the other aircraft. The ownship generates a map while the intruder simply localizes itself in this map, without attempting to build its own map or augment the ownship's map. This approach of co-localization within a single map frame reduces the problem to running the same data correspondence on two parallel sets of camera feeds with regard to the same map. It also solves the problem of determining the initial pose (position and attitude) estimates for each UAS. The resulting system operates significantly faster than two parallel SLAM systems would by eliminating the need for map building on the intruder side. Such an approach is naturally independent of which UAS is the ownship—defined as the aircraft performing the collision avoidance maneuver—and which is the intruder.

We use RTABMap, an RGB-D graph SLAM package, to generate the 3D map of the environment. RTABMap is particularly suitable for this application because it has distinct "mapping" and "localization" modes.

### A. Sensors

Two Mobium C2 stereo cameras are mounted on a 2D (pitch and roll) gimbal to maintain the stereo rig in a horizontal position and provide stability of the RGB-D input feed. This setup reduces the rotational and vibrational modes experienced by the cameras supplying the VO and SLAM algorithms, making position lock more robust. A depth point cloud is retrieved from the stereo camera rig based on triangulation of the image disparities, which is then fed to the SLAM algorithm. Both UAS involved in the flight tests have this stereo camera system.

### B. Resetting Odometry and Extended Kalman Filter

The visual odometry module of RTABMap uses random sample consensus (RANSAC)[9] to determine the transformation between successive camera images of the stereo rig. The position and velocity estimates provided by the VO and SLAM algorithms are fused with dead-reckoning estimates from the IMU using an extended Kalman filter (EKF). Because odometry is based on visual features, when the images lack sufficient texture the algorithm may lose position hold. To solve this problem, we set a maximum temporal threshold for loss of tracking duration. When this threshold is reached we use the estimate from dead reckoning alone to actively reset the odometry from the last known pose estimate and then continue with a new mapping "session."

### C. System Architecture

The architecture of the visual SLAM system that will perform vision-based collision avoidance is depicted in Figure 2. In addition to the PikHawk autopilot and tablet ground station, eEach UAS has an auxiliary on-board microprocessor, an oDroid-XU4, that performs three tasks:

1. Retrieves the camera feed and throttles it to a slower effective framerate for efficient network transmission.
2. Communicates with the UAS autopilot/controller regarding the behavior to be executed. In this case, we make use of the mavlink protocol designed for the Pixhawk autopilot.
3. Communicates with other UAS and a common groundstation. The network communication is achieved using the common broadcast-message passing system of ROS over a WiFi channel.

The architecture across the groundstation and each UAS is set up to facilitate inclusion of any 6 DOF VO and SLAM system running on any of the aircraft or ground stations. This framework also distributes computing by allowing the running of nodes over multiple devices. The collision avoidance algorithm may be run on any or all of the UAS, and the actions commanded by it may be sent to any of the other aircraft. This setup could allow decentralization of the collision avoidance problem, enabling the current algorithm to be extended to small groups of UAS outside range of communication of the groundstation. The setup also allows the SLAM algorithm to run on the more computationally powerful groundstation, reducing latency and improving performance.

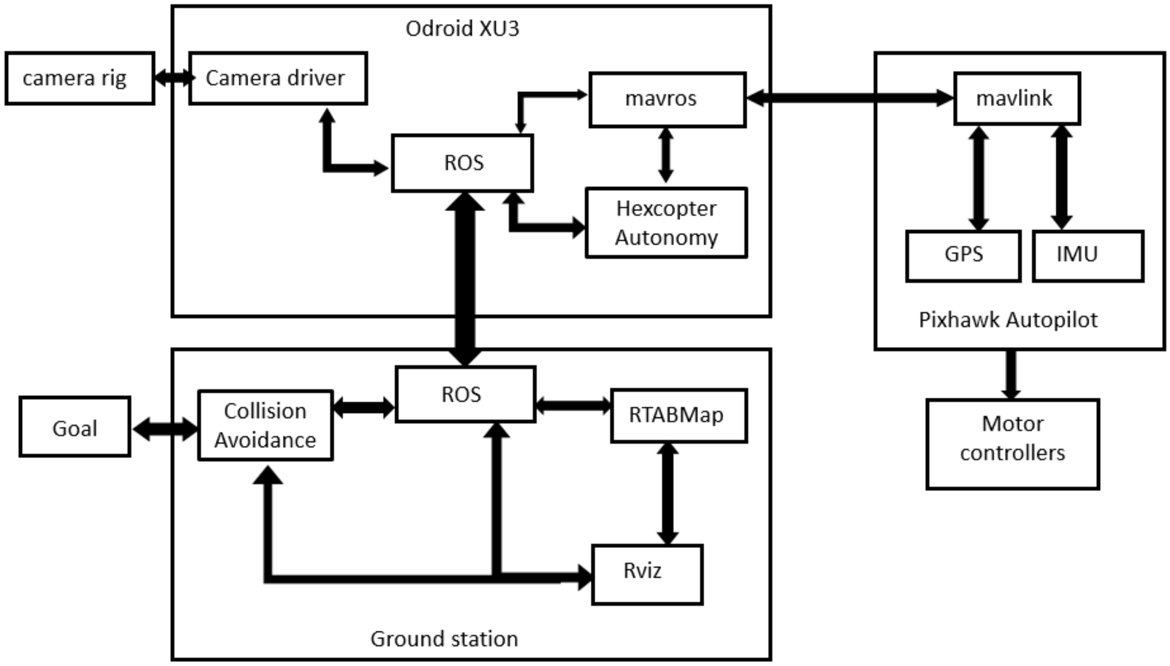


*Figure 2. Visual SLAM system architecture.*

## IV. Flight Tests

Flight testing of the collision avoidance algorithm with a fleet of hexacopters based on the DJI Flamewheel F550 aircraft have demonstrated the feasibility of the algorithm when state estimates were provided by GPS and the inertial measurement unit (IMU) on the 3DR Pixhawk 4 Autopilot. A diagram of the components involved in those flight tests is shown in Figure 3.

The next step in the flight tests is to replicate in the field the capability already demonstrated in the laboratory for the RTAB-Map package and stereo video cameras to generate a map of their surroundings and perform visual odometry relative to that map. Once that step is completed, the state estimates from the SLAM system, rather than GPS, will be passed to the collision avoidance algorithm. These flight tests are expected to be complete by January 2016 and will be incorporated into the full version of this paper.

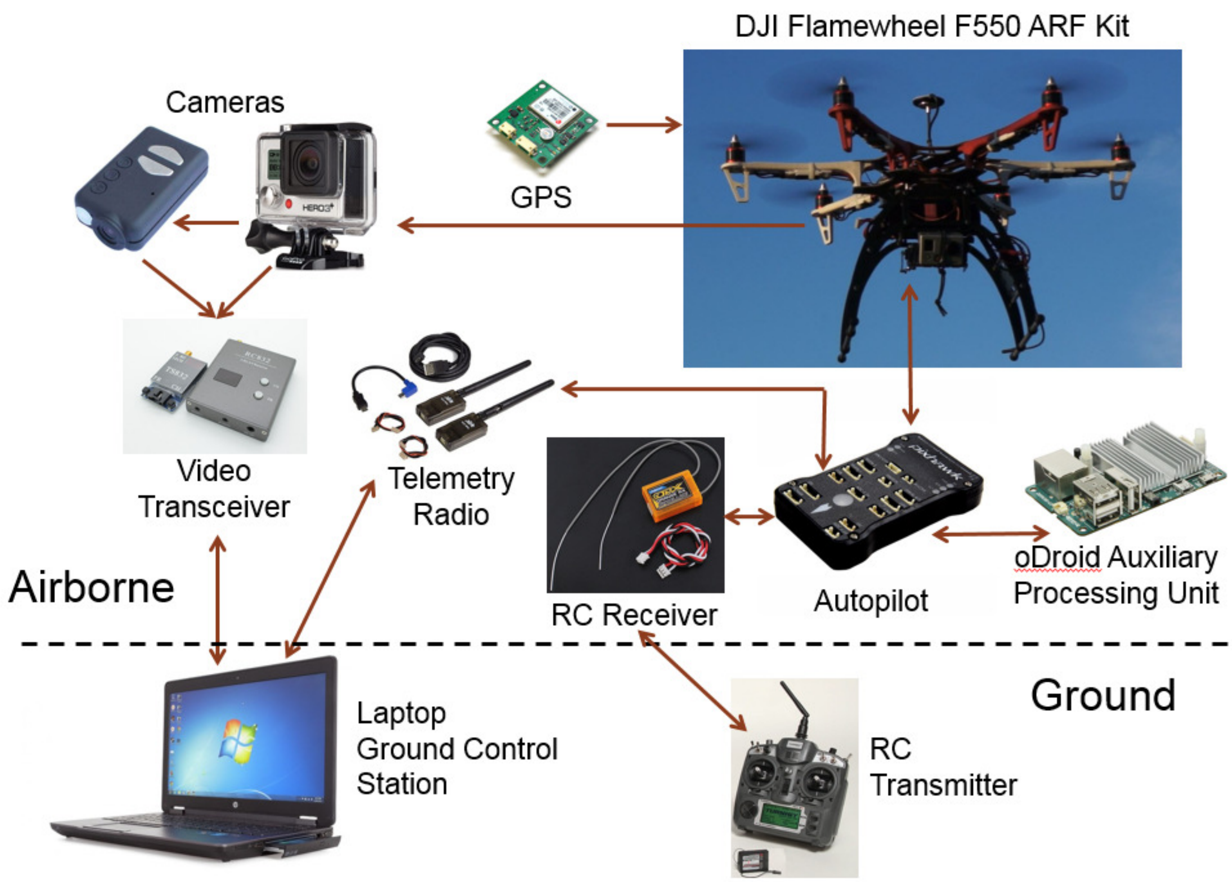


*Figure 3. Flight test components.*

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