

POTENTIAL ACTIVE-VISION CONTROL SYSTEMS FOR UNMANNED AIRCRAFT

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Abstract

This paper discusses the generalized visual tracking problem, or tracking of objects/features based on real-time imagery for pursuit, evasion, or maintaining formation flight. Estimating target range is challenging – and a number of approaches are discussed. Flight tests of vision-based formation flight between two aircraft are described.

1 Introduction

This article contains a summary of several methods to enable vision-based tracking of aircraft. Successful tracking allows for the utilization of visual information of an airborne target in the feedback loop for the purposes of pursuit, evasion, or formation flight.

However, when 2-D vision sensors are used, estimating target range is challenging – and a number of approaches have been studied, including utilization of target size/shape in the image, optimal guidance policies, and use of adaptation in the estimation process. This represents a challenging combined image processing, estimation, and guidance problem, and so the methods fall into all of these categories, Figure 1. References are included for additional details on the methods described.



Figure 1: Generalized vision-based tracking problem: Based on camera imagery, perform image processing to provide inputs to a 3D target state estimation algorithm – guidance inputs to autopilot are then based on these estimates for pursuit, evasion, or perhaps to maintain formation flight with leader/target.

The following sections cover image processing methods, estimation methods, and guidance methods. This is followed by more detail on flight test results.

2 Image Processing

2.1 Geometric Active Contours and Particle Filters

A visual tracking methodology based on particle filtering in the framework of the Chan-Vese active contour model [1] has been developed. This technique has been combined with particle filtering, and has been shown to robustly track a maneuvering aerial target under varied conditions, Figures 1 and 2, including with minimal contrast and extensive background clutter. The computational speed of the algorithm has allowed it to be employed for formation flight. It has also been used to demonstrate multiple target tracking in the presence of occlusions.



Figure 1: Tracking aerial targets against clutter using particle filtering, horizontal and vertical distributions of target location probability density (from particle filter) shown on edges.



Figure 2: Tracking aerial targets against clutter using particle filtering, horizontal and vertical distributions of target location probability density (from particle filter) shown on edges.

3 Target State Estimation

3.1 Unscented Kalman Filter (UKF) and Extended Marginalized Particle Filter (EMPF)

An Unscented Kalman Filter (UKF) approach to the highly nonlinear vision-based estimation problem has been developed [2]. Particle filtering has also been explored for this purpose, resulting in the Extended Marginalized Kalman Filter (EMPF) [3].

While particle filters have many attractive features, including their applicability to general nonlinear non-Gaussian problems without approximations of probability distributions, they often suffer from high computational cost. One technique to surmount this problem without reducing the efficiency of sampling techniques is to reduce the dimension of the state space model by marginalizing out some of the state variable components. Since the vision-based tracking problem can only be completely described by a relatively high-dimensional statespace model, direct employment of the particle filtering on this problem is prohibative because an enormous number of samples are required to properly approximate the posterior distributions.

Hence, the idea of marginalization (or Rao-Blackwellization) is extended to solve this problem in the framework of the EMPF. In this approach, while part of the state components are represented by nonlinear dynamics with Gaussian process noise, those state components can be effectively marginalized out by employing the UKF to deal with those state components. The method utilizes the reasoning that the UKF can more accurately and effectively solve the nonlinear estimation problems with Gaussian noise characteristics compared to the EKF. Since vision sensor measurements can better be represented by the non-Gaussian noise characteristics and the vision information itself directly provides the position information only (and not directly but indirectly the velocity and acceleration information over the progression of time), only the position state components with measurements of vision information are solved in the particle filtering framework. The other state components represented by nonlinear equations with Gaussian noise are handled by the UKF, Figure 3.



Figure 3: Target position estimation (top 3) and target velocity estimation (bottom 3) using the image processing results obtained during flight testing. GPS/INS results were independently recorded from onboard during the flight test for comparison.

3.1 Adaptive Estimation

Here, an artificial neural network (NN) is utilized to estimate the unmodeled leader acceleration in the target state estimation filter [4]. Effectively the NN is curve fitting the guidance policy of the target/leader, enhancing the accuracy of the estimation over time.

4 Guidance Policies

It is well-known that vision-based estimation performance highly depends on the relative motion of the vehicle to the target. The stochastically optimized guidance design for vision-based control applications has been investigated [5]. For the case of an extended Kalman filter (EKF) applied to the relative state estimation problem, the guidance policy is derived by minimizing the expected value of a sum of guidance error and control effort subject to the EKF procedures.

Furthermore, a one-step-ahead suboptimal optimization technique has been developed and implemented to avoid iterative computation. The approach is applied to vision-based target tracking and obstacle avoidance. Simulation results verify that the suggested guidance law significantly improves the estimation performance, and hence improves the overall guidance performance, Figure 4 [6].



Figure 4: (Top) Vehicle trajectories comparing suggested suboptimal guidance and conventional guidance for vision-based target tracking, terminal miss distance is significantly reduced; (Bottom) Estimation error converges to zero when using the suboptimal guidance (Conventional green dashed lines, Suboptimal solid blue)

5 Flight Test Results

On June 15, 2006, a research aircraft held formation for an extended period with another aircraft, utilizing a vision sensor as its only indication of the state of the other aircraft. The Leader/target aircraft was a 1/3 scale Edge 540T with a GPS/INS based autopilot, flying in a large circular pattern over our test range at slow speed, Figure 5. The Follower aircraft was the GTMax (based on the Yamaha RMAX) research helicopter, utilizing onboard image processing, lead aircraft state estimation, guidance, and control, Figure 6.



Figure 5: Leader/target aircraft for flight tests, at 9 ft wing span airplane



Figure 6: Follower aircraft #1 for flight tests, a 10 ft rotor diameter helicopter, includes onboard cameras and image processing, estimation, and guidance computer

On engagement, the follower held formation for approximately two full "orbits" of the test range in a shallow turn - encountering a variety of lighting and wind/gust conditions. This may have been the first time automated formation flight based on vision has been done. Segmentation and estimation data are shown in Figures 7.



Figure 7: Estimation performance during closed-loop formation flight using vision

For the next phase, the leader aircraft was replaced with an airplane capable of maneuvering as aggressively as the leader, Figure 7. Both are capable of similar speeds, turns, climbs, and descents. Figure 8 shows a typical output of the estimation process for a series of turns and straight segments.



Figure 7: Follower aircraft #2 for flight test, able to maneuver similar to leader, includes onboard cameras and image processing, estimation, and guidance computer





Figure 8: Estimation process for a series of turns and straight segments. Blue 'x' on the plot indicates that the image processing step failed, usually due to the leader leaving the camera field of view

6 Conclusions

Efforts to date have resulted in demonstration of basic capabilities for vision-based formation flight and pursuit problems at close range. New methods of image processing and estimation greatly facilitated these tests. Even with these advancements, practical/effective automatic see/sense and avoid based on vision sensors alone has not been achieved. That said, the capabilities demonstrated have immediate potential use for formation flight maintenance, in-air-refueling, and some pursuit/engagement problems.

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