AFRL-SA-AR-TR-10-0338

[ACTIVE-VISION CONTROL SYSTEMS FOR COMPLEX ADVERSARIAL 3-D ENVIRONMENTS]

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MARCH 2009
Final Report

DISTRIBUTION A: Distribution approved for public release.

AIR FORCE RESEARCH LABORATORY
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20101202163

REPORT DOCUMENTATION PAGE

AFRL-SR-AR-TR-10-0338

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1. REPORT DATE (DD-MM-YYYY)	2. REPORT TYPE	3. DATES COVERED (From - To)
31-03-2009	Final Report	01-07-2003 to 31-12-2008

4. TITLE AND SUBTITLE
ACTIVE-VISION CONTROL SYSTEMS FOR
COMPLEX ADVERSARIAL 3-D ENVIRONMENTS

5a. CONTRACT NUMBER
F49620-03-1-0401

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
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5d. PROJECT NUMBER
E-16-V91

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
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8. PERFORMING ORGANIZATION REPORT NUMBER

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10. SPONSOR/MONITOR'S ACRONYM(S)
AFOSR/NM

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Unlimited

13. SUPPLEMENTARY NOTES

14. ABSTRACT
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15. SUBJECT TERMS
Vision, Control, Tracking

16. SECURITY CLASSIFICATION OF: a. REPORT	b. ABSTRACT	c. THIS PAGE	17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
U	U	U	none	40	Eric Johnson
					19b. TELEPHONE NUMBER (Include area code) 404-385-2519

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Final Report

AFOSR F49620-03-1-0401

For the period July 1, 2003 to December 31, 2008

March 31, 2009

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Abstract

This project has included development of methods that utilize 2-D and 3-D imagery (e.g., from visual, FLIR, LADAR, acoustic) to enable aerial vehicles to autonomously detect and prosecute targets in uncertain complex 3-D adversarial environments, including capabilities and approaches inspired by those found in nature, and without relying upon highly accurate 3-D models of the environment. The new capabilities of autonomous sensing and control enable UAV/munition operations: in a clandestine/covert manner; in close proximity to hazards, structures, and/or terrain; and in uncertain/adversarial 3-D environments. This project is a Multidisciplinary University Research Initiative (MURI). The critical technical innovations we are bringing to bear on the problem include:

1. Knowledge-based segmentation;
2. Adaptation and estimation in geometric active contours;
3. Adaptive control frameworks for active vision systems;
4. Multigrid and polygonal methods for optical flow;
5. Imaging sensors designed to produce sensor information for control.

Furthermore, the team performed a productive flying testbed activity as part of the program. This ensures that the methods are sound in the sense that they are: (1) implementable in real-time, (2) capable of practical use in the field, and (3) based on realistic/achievable sensor capabilities.

Final Status of Effort

Our team has completed the five years of this MURI along with a small part of the effort that continued on a contract extension for an additional six months. During that time, our first major focus was the *generalized visual tracking problem*, that is, the tracking of objects/features based on real-time imagery. 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. Utilization for a ground target, our second focus, enables automated pursuit/surveillance. 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 third year, vision-based formation flight between two aircraft was successfully accomplished. Subsequently, experimental work moved to more complex formation flight scenarios with the objective of vision-based pursuit utilizing vision sensors only. In addition, several results involving *visual tracking of a ground target* have been produced – our second major focus. In addition, progress was made on a third (related) focus, the *fixed object detection problem*. The issues are similar (e.g. the difficulty of estimating range), as are the methods we are exploring to tackle the problem. There have been extensive interactions with AFRL/MNGN in support of related activities there. This report covers the entire project. The section that immediately follows covers background material. This is followed by a description of the methods developed under the project and then flight testing results.

To summarize what was accomplished in terms of major flight testing events, with links to videos:

1. Vision-only formation flight and pursuit
   1.1. Helicopter maintaining formation with an airplane, vision-data only
   http://uav.ae.gatech.edu/videos/ef060615d1_firstVisionBasedFormation.mpg
   http://uav.ae.gatech.edu/videos/ef060615d1ob_firstVisionBasedFormation.mpg
   1.2. Airplane maintaining formation with an airplane, vision-data only
   http://uav.ae.gatech.edu/videos/ey070730b2_visionBasedFormation.wmv
   http://uav.ae.gatech.edu/videos/ey070730b2ob_visionBasedFormation.wmv

2. Vision-based ground vehicle tracking/following
   2.1. Following a truck based on camera image only
   http://uav.ae.gatech.edu/videos/f061113b1_goodCarTrack.wmv
   http://uav.ae.gatech.edu/videos/f061113b1ob_goodCarTrack.wmv

3. Vision-based obstacle avoidance
   3.1. Vision-data only to avoid a fixed obstacle
   http://uav.ae.gatech.edu/videos/f071030a2_autoAvoid1.wmv
   http://uav.ae.gatech.edu/videos/f071030a2ob_autoAvoid1.wmv

It is worth noting that these flight testing activities utilized the advanced methods developed under this effort, including geometric active contours, particle filtering, neural network augmentation of an extended Kalman filter, and others as noted in this report.

Note: References to other work are given numerically, and listed in the references section. References listed by Author and year are publications derived from this effort, listed in the Publications list. The publications list also includes publications not directly referred to in this report.

Background

Vision and Control

Prior to the effort, we had been working on problems in image processing and computer vision using geometry-based differential equations, invariant theory, and statistical methods for various purposes including segmentation, edge detection, image enhancement, de-noising, registration, surface warping, morphology, stereo, optical flow, shape representation and object recognition [1].

Boundary Based Tracking Using PDEs and Active Contours

Tracking by active contours (also known as snakes) was an established method in controlled active vision. In 2-D images, virtual forces derived from the images drive a parametrically defined line with constraints on how it can deform. Such a virtual force can, for example, be derived from the local edge strength. The parametric line, or the so-called snake, is then attracted to the edges of the images, forming an outline of the object at hand. The modern approach to active contours is based on a more rigorous mathematical framework. Snake-based tracking using mean curvature evolution schemes can be a powerful tool in real-time tracking, segmentation and target recognition [2].

Active contours, or snakes, are autonomous processes that employ image coherence in order to track features of interest over time. In the past few years, a number of approaches have been proposed. The underlying principle in these approaches are based upon the utilization of deformable contours that conform to various object shapes and motions. Snakes have been used for edge and curve detection, segmentation, shape modeling, and especially for visual tracking. We have developed and extended a deformable contour model that is derived from a generalization of the curve shortening evolution. It is based on the geometric intuition of multiplying the Euclidean arc-length by a function tailored to the features of interest to which we want to flow, and then computing the resulting gradient flow equations. This leads to interesting new models that efficiently attract the given active contour to the desired feature. The methods generalize naturally to 3-D or 4-D. The resulting active contour models have the ability to change topology (automatic merging and breaking of contours), essential to tracking multiple objects and tracking in clutter. Figure 1 illustrates the process of "bubbles" (expanding deformable contours) finding a truck in an image.

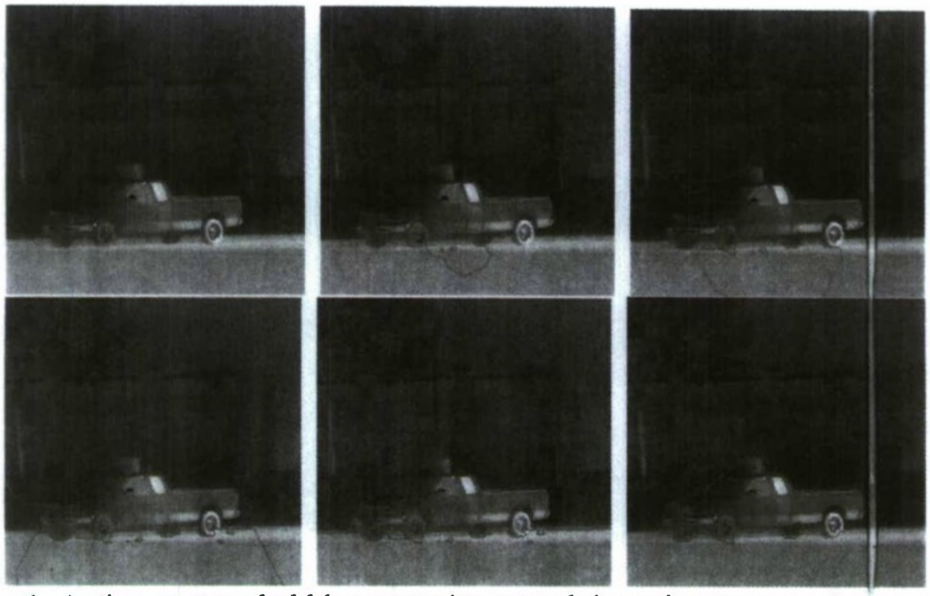


Figure 1: Active contour bubbles capturing a truck in an image; note the automatic merging and topological changes involved in finding the image.

Knowledge-Based Segmentation

In knowledge-based segmentation, these tracking approaches are augmented with knowledge of object shape to guide segmentation in uncertain regions. A natural way of doing this which combines the statistical and curvature driven approaches is to smooth the posterior probabilities and then extract a maximal a posteriori (MAP) classification in segmenting the given image. More precisely in the Bayesian framework, we can calculate the posteriors $P^c{}_i = Pr(C_i = c|V_i = v)$ (the C's are the possible classes and the V's the intensities) and smooth by evolving P^c according to the affine geometric heat flow equation, under which the level sets of P^c undergo affine curve shortening whilst preserving edges [3,4]. Shape information may be introduced into the image segmentation process using this geometric variational framework. The idea is to introduce a representation for shapes and define a probability distribution over the variances of a set of "training images". Then, in order to segment a structure from an image, one can evolve a geometric active contour using local information and globally to a maximum *a posterior* estimate of shape.

Adaptive Learning, Noise Models, and Geometric Active Contours

A key element in our approach is to advance our algorithmic research on PDEs and active contours. At the same time, we want to supplement the statistical methods discussed above with techniques that leverage anatomical knowledge, primarily the PDE and level set methods. So far, we have only considered simple prior distributions and adaptation techniques. At present, the weighting factor is derived locally, based on edge computations. A more flexible conformal metric will be obtained if the metric is learned from the data and if the model incorporates non-local information. For this purpose, we will explore the use of adaptive filtering. We also plan to incorporate Bayesian statistics into the stopping (conformal weighting) rule in the geometric active contour model. The classical snake cost-function is based on the minimization of length in the plane or of surface area in space. We will implement alternative cost terms that will be based on the minimization of other natural geometric quantities (such as area in the plane or volume in space) [5]. We also consider methods for explicitly coupling boundary and region data within the geometric active contour framework [6-9]. We plan to extend the techniques based on the concept of minimum description length (MDL). The idea is to consider the segmentation problem as a partitioning problem, where the criterion for choosing one partition instead of another is the *description length.* The measure of the description length must be accomplished according to some *a priori* language. Thus, it is essentially equivalent to the *maximum a posteriori* (MAP) estimate from the Bayesian paradigm. It may be regarded as an information interpretation of this classical method.

Robust Tracking of Deforming Targets

Earlier [10], we proposed a framework that allows us to *separate the overall motion from the more general deformation.* We have also extended this framework to handle occlusions, as a particular type of deformation [11]. The key idea underlying our framework is that the notion of *motion* throughout a deformation is very tightly coupled with the notion of *shape average.* In particular, if a deforming object is recognized as moving, there must be an underlying object (which will turn out to be the shape average) moving with the same motion, from which the original object can be obtained with minimum deformations. Therefore, we will model a general deformation as the composition of a group action g on a particular object, on top of which a local deformation is applied. The shape average is defined as the one that minimizes such deformations. The goal is, given a collection of images that contain a given target, to estimate both its motion (a finite-dimensional group) and its average shape. Some of our prior work was used as a starting point for studying these issues; see in particular [10-12].

Adaptive Estimation and Control

Nonlinear Estimation and Adaptive Control: Existing methods for nonlinear state estimation impose assumptions that severely limit their domain of applicability, such as to systems that are linear with respect to unknown parameters, or systems that can be transformed to output feedback form. Neural network (NN) based adaptive observers have relaxed some of these assumptions; however robustness to unmodeled dynamics and disturbances has not been addressed. We have recently developed a methodology for adaptive state estimation of bounded nonlinear processes. The approach augments an existing linear observer with two NNs that model the uncertainties from a finite history of available measurements [13]. *This approach is adaptive to both unmodeled nonlinearities and unmodeled dynamics,* precisely the situation commonly encountered in image processing applications.

Adaptive Guidance and Flight Control: Here, we explore direct utilization of vision data in guidance and flight control. We are approaching this topic from the perspective of using *only* vision data to analyze the environment in which the vehicle must be flown, and to pursue targets within this environment. The use of NN based adaptive control for flight control has been extensively developed and applied by our group [14-16]. We have also initiated several collaborative efforts at Eglin AFB in the area of cooperative flight control and adaptive missile autopilot design. The research aspects particular to guidance and flight control that are new to this effort will involve those aspects associated with pursuing a target in a highly congested/adversarial environment. We envision a space in which a vehicle must be flown so as to detect and pursue a target while avoiding both fixed obstacles and moving threats. Adaptation is required in order to capture the unknown and unmodeled dynamics associated with moving targets and threats in the presence of wind/gust disturbances [17].

Sensor Design

We believe that real-time control of autonomous airborne vehicles can be enhanced by image sensor information that is at the same time *rich* and *selective*. "Richness" quantifies the amount of information (in the Shannon sense) transferred through the sensor. "Selectivity" refers to the ability to discriminate the information that is most relevant to the mission (e.g., the location and distribution of targets on the ground) from irrelevant information (e.g., the grass on the ground). To meet this challenge, we will develop novel types of optical imaging sensors uniquely meeting two objectives: (i) the sensors will be optimized in terms of information quantity and quality (ii) the sensor outputs will be optimized to serve as input to the active vision control algorithms.

Accomplishments

Dynamic Active Contours

Active contours (also known as snakes) are autonomous processes employing image coherence in order to track features of interest over time. They are capable of conforming to objects in the image plane, making them ideal for segmentation, edge detection, shape modeling, and visual tracking. To overcome the local nature of active contours, statistical and adaptive based pre-processing can be integrated into the stopping criterion, the inflation mapping, and/or the gains to more effectively drive the contour to the desired minima. The ability of the snakes to change topology and quickly capture desired features makes them an indispensable tool for our visual tracking algorithms. In knowledge-based segmentation, the ability to track targets is enhanced through knowledge of image content for simplification and noise removal. Object shape can also be incorporated to improve targeting of desired objects and reduce false-positives. A natural way to incorporate knowledge-based techniques in an adaptive framework is to use *maximum a posteriori* (MAP) classification for segmentation of an image. An example of how the MAP algorithm can reduce irrelevant image content for improved segmentation and, in the process, provide an unambiguous minima to the active contour is shown in Figure 2.

(a) Original (b) Segmented (c) Active contour encircling object

Figure 2: Sample image processing with background clutter

The generalized tracking problem necessarily involves acquiring visual feedback from a dynamically changing external world. Although the algorithms discussed above perform well, they were initially developed for solve static problems. We seek to implement the dynamic version of geometric active contours for improved robustness to background noise and obstacles within the tracking context. Also, the MAP classification technique for knowledge-based segmentation of imagery relies on certain fixed assumptions, such as a static number of classes to segment the image into. However, as the nature of the terrain and the sky vary, so can the number of classes. We have also investigated methods to dynamically adjust the number of classes. Doing so reduces the probability of losing a tracked target in the segmentation process.

Particle Filtering for Geometric Active Contours

Although the algorithms discussed above perform well, they were initially developed for solve static problems. We have implemented the dynamic versions of geometric active contours for improved robustness to background noise and obstacles within the tracking context. Tracking algorithms using Kalman filters or particle filters have been proposed for finite dimensional representations of shape, but these are dependent on the chosen parameterization and cannot handle changes in curve topology. Geometric active contours provide a framework which is parameterization independent and allow for changes in topology. We formulated a particle filtering algorithm in the geometric active contour framework that can be used for tracking moving and deforming objects [Ha, Johnson, Tannenbaum 2008]. To the best of our knowledge, this is the first attempt to implement an approximate particle filtering algorithm for tracking on a (theoretically) infinite dimensional state space.

In Figure 2, we track a van moving amid clutter in the background. There is sudden and large motion of the van (in some cases, the van moves more than 20 pixels between consecutive frames) due to jitter in the camera motion. Furthermore, it gets largely occluded (only a small fraction of the van is visible) many times by buildings or trees. Tracking such a sequence using active contours alone is bound to fail since the van may lie outside the basin of attraction of the starting contour. As shown in Figure 2, the proposed method tracks the van successfully despite large motion and occlusion. For this test sequence, no motion model was adapted, i.e., the state transition assumed known with Gaussian noise. The figure shows tracking results with 50 particles.

Figure 2: Tracking van sequence through occlusions by adding a particle filter, note van going partially behind tree. Segmentation shown with red curve.

The video sequence sampled in Figure 3 has a very low contrast and in general, it is very difficult to locate the boundary of the airborne target. The motion of the airplane from one frame to the other is also quite large, hence traditional active contour based methods fail to track the plane. In this experiment, only translational motion was assumed for the moving airplane. Figure 3 shows a few frames of the tracking results. Even though, no scale parameter was included in the motion model, the contour deformation part of the algorithm adjusts for this change in size of the plane (see the first and last frame). Other types of affine changes in the shape are also taken care of within the proposed framework without having to explicitly model them. Tracking results were obtained with just 30 particles.

Figure 3: Tracking low-contrast rapid airplane motion. Segmentation shown with black curve.

We described a fast implementation of the algorithm which greatly improves the computational time of the segmentation process [Ha, Johnson, Tannenbaum 2008]. We have tested particle filtering using this fast active contour model, and the filtering algorithm has shown the ability to robustly track an aerial target under varied conditions, Figures 4, 5, and 6. The computational speed of the algorithm has allowed us to employ it for formation flight among several unmanned aircraft, described further below in the flight test results section. We have also demonstrated the utility of the filtering algorithm for multiple target tracking in the presence of occlusions.

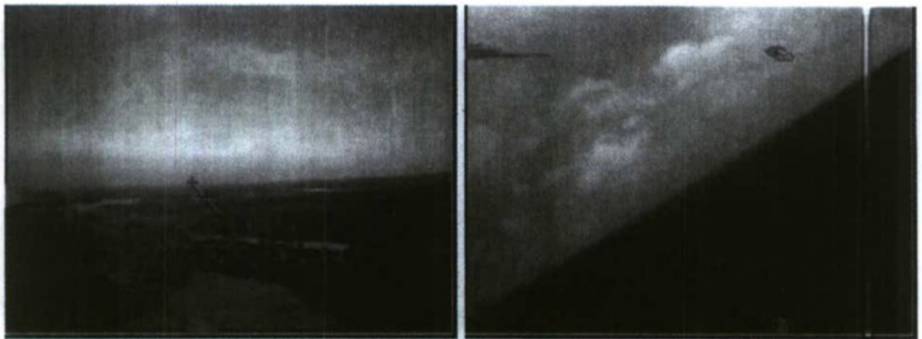


Figure 4: Tracking aerial targets against clutter using particle filtering, horizontal and vertical distributions of target location probability density shown on edges.

Figure 5: Tracking multiple aerial targets using particle filtering.

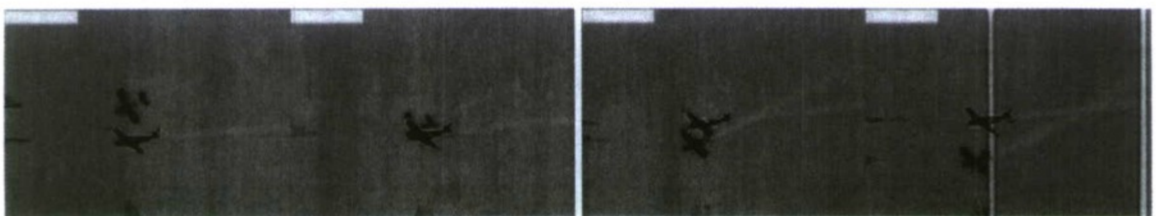


Figure 6: Tracking two occluding aerial targets using particle filtering.

This year we also proposed a fast implementation of the Chan-Vese active contour model that improves the computational speed and the robustness of the image processing. The computational speed of tracking using the fast implementation reaches 100 frames/seconds in typical tracking scenes from several flight tests, Figure 7.

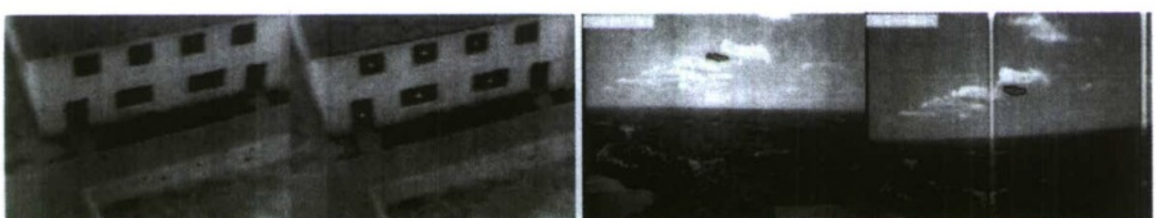


Figure 7: Detecting and tracking with the new method. The two images on the left show detecting several windows. The two images on the right show tracking an aerial target in cloudy sky (computational speed: 100 frames/seconds).

Robust Tracking of Deforming Targets

The investigators Yezzi and Soatto have incorporated feedback ideas from control and estimation theory into their prior framework of "deformotion" (a method to simultaneously track the motion and the deformation of the appearance of a moving and deforming object while distinguishing clearly between the two components of the changing shape). Prior to the beginning of this effort, the framework was used for the purpose of tracking only through the simple notion of a "moving average" via the simultaneous segmentation and registration of several consecutive frames of a video sequence rather than the traditional frame-by-frame approach typically used in active contour methodologies. The recent incorporation of a dynamical model for the deformation and the motion components of this framework by the investigators, thereby allowing the use of causal observers, has lead to tremendous increases in the robustness of the tracker to even severe temporary occlusions of the object being tracked.

In Figure 8, we observe the contour tracking a person in a parking lot where there is a black vertical band of missing pixel data due to a malfunction of the digital camera. As the person passes through this vertical band, almost fully occluded at one point, the dynamical mode helps propagate the contour through the occlusion without wildly spilling or distorting or losing its lock by the time the person reappears on the other side of the bar. Also in Figure 8 we see even more severe occlusion taking place as a student walks behind a very large printer, becoming fully occluded for a number of frames.

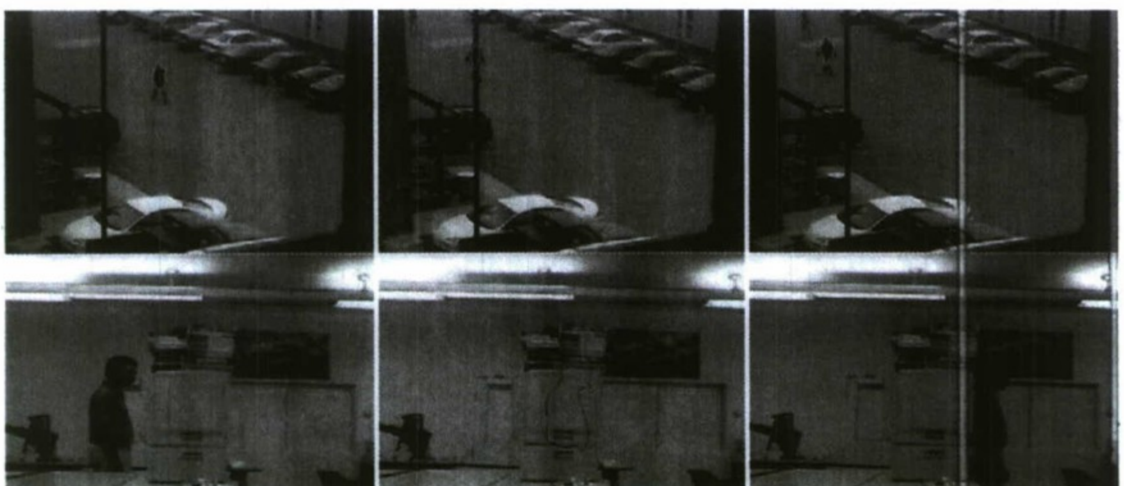


Figure 8: Tracking through occlusions by adding a dynamical model to the "deformotion" framework (top) behind missing pixel data (bottom) behind office equipment.

Optical Flow

In the second year of the program, we formulated a straightforward approach for predicting and estimating large-amplitude optical flows. The optical flow model underpinning the proposed algorithm incorporates temporal coherence, which is captured by an evolution equation to provide the optimal fusing of data from multiple frames of measurements. It allows the formulation of the estimation problem as a state estimation problem, which can be efficiently solved by Kalman filtering. Though such dynamic approaches for estimating optical flows have long been in use, our proposed approach is innovative in that it shows how to adapt both state and measurement models of the Kalman system in order to estimate large-amplitude optical flows, for which the linearized modeling (frequently referred to as the differential optical flow equation) is known to fail. It is done by modeling the optical flow as a composition of its predecessor (i.e., a time-delayed version) and a "complementary" optical flow. Consequently, the former is used to predict the current optical flow and to pre-warp the images to be "connected" using this prediction. After the pre-warping is completed, the resultant images are employed to form a measurement model for the "complementary" optical flow and, then to update the Kalman estimate.

Variational Methods for Shape from Defocus:

Our group has successfully tackled the problem of calibration in visual accommodation. Visual accommodation is the process of extracting three-dimensional information from images obtained by averaging different exposures obtained, for instance, under a changing focal length (shape from defocus) or a moving scene (shape from motion blur). While these problems are classical in computer vision and image analysis, all algorithms published so far required knowledge of the calibration parameters (aperture of the lens, focal lengths, exposure time etc.) in order to return a correct estimate. In practice, this is severely limiting since it requires pre-calibration of the imaging device following a complex protocol. In [Lu et al., 2007], we have characterized the set of all possible surfaces indistinguishable from deblurred images: They are simply parameterized by an affine transformation of the inverse depth, where the affine parameters are related to the calibration of the focal planes by simple algebraic relations. We have showed that the presence of at least one plane in the scene allows disambiguating the reconstruction, since planes are all and only the surfaces that are invariant under affine transformations of the inverse depth, finally, we have showed that even in cases where the correct reconstruction cannot be performed, one can still recover a deblurred version of the original data.

Analysis of the Ambiguities in Motion Analysis:

In [Vedaldi et al. 2007] we have proven a series of theorems that relate to the problem of reconstructing 3-D camera motion (ego-motion) from collections of images or optical flow. It is well known that ego-motion estimation can be posed as an optimization problem, one that is non-linear and non-convex, and that is subject to the presence of many local minima. It is also known that the shape of the L2 residual surface is littered with singularities, that pull the cost function and cause a large number of local minima in the forward direction, that is when the translation vector is aligned with the optical axis. This is arguably the most important case for AFOSR applications, and for the use of vision as a sensor for navigation in general. In this most recent work, we have proven a theorem that shows that if the inverse depth is bounded away from zero during the optimization of the L2 residual, singularities in the forward direction disappear, and the L2 residual is actually a smooth function. This effectively replaces a non-smooth unconstrained optimization with a smooth constrained one, and improves the results of motion estimation algorithms.

Model Based Radiance Estimates for Segmentation

Sometimes contrast between average foreground and average background intensities makes the segmentation task one of the easier aspects of the overall tracking algorithm. However, very few objects can be specified with nearly constant radiances that differ sharply in a scene with nearly constant background radiance. While more sophisticated radiance models have existed for a while (the classic one being the piecewise smooth model used in the Mumford-Shah functional), they have been computationally very expensive, making their utility limited. We explored methods to substantially reduce the computational complexity of more flexible radiance models, with two very promising leads that may make their applicability to visual tracking much more plausible. The first lead deals with a dimensionality reduction technique, based on training data, applied to both shape and radiance measurements accrued from prior images of related targets to be tracked. The second lead deals with an approximation of the class of piecewise smooth functions by basis functions generated by convolution of the input image with families of low-pass filters. We can see the power of these more flexible radiance models for tracking in Fig. 9 where we are trying to track a person's head. Notice that the face would be very poorly approximated by a simple constant or nearly constant radiance.

Figure 9: Adding piece-wise smooth radiance to deformotion method to tracking objects with non-trivial albedos. (Top Row) Tracking results. (Bottom Row) Piecewise smooth radiance models used for the above tracking results (no edge detectors used).

Shape-Driven Observer Theory for Tracking:

We have proposed a deterministic observer framework for visual tracking based on non-parametric implicit (level-set) curve descriptions [Niethammer, Vela, Tannenbaum, 2008]. The observer is continuous-discrete, with continuous-time system dynamics and discrete-time measurements. Its state-space consists of an estimated curve position augmented by additional states (e.g., velocities) associated with every point on the estimated curve. Multiple simulation models are proposed for state prediction. Measurements are performed through standard static segmentation algorithms and optical-flow computations. Special emphasis is given to the geometric formulation of the overall dynamical system. The discrete-time measurements lead to the problem of geometric curve interpolation and the discrete-time filtering of quantities propagated along with the estimated curve. Interpolation and filtering are intimately linked to the correspondence problem between curves. Correspondences are established by a Laplace-equation approach. The proposed scheme is implemented completely implicitly (by Eulerian numerical solutions of transport equations) and thus naturally allows for topological changes and subpixel accuracy on the computational grid.

Local Region-Based Segmentations:

We developed a natural framework that allows any region-based segmentation energy to be re-formulated in a local way [Lankton, Tannenbaum 2008]. By considering local rather than global image statistics and evolving a contour based on local information, localized contours are capable of segmenting objects with heterogeneous feature profiles that would otherwise be difficult to capture correctly just using a standard global method. The technique is versatile enough to be used with any global region-based active contour energy and instill in it the benefits of localization. We have demonstrated the localization of three well-known energies in order to illustrate how our framework can be applied to any energy. The results we have obtained on challenging images to illustrate the robust and accurate segmentations that are possible with this new class of active contour models.

Shape, Scale and Registration

An important issue that needs to be addressed in image-based models is that of scale. Because targets can appear at any scale, depending on their position relative to the sensor, and yet resolution imposes a lower bound on detectable structures, algorithms have to operate at multiple scales of resolution. On the other hand, some objects are detectable only a certain scale, which defines the statistics that make it detectable (see images of a cheetah below). We have developed novel techniques to classify image regions based on automatic scale detection. We believe that this is a crucial step in texture analysis and will play an important role in perspective when complex camouflaged targets will become manageable in real-time fashion.

Another important problem arises from the fact that often the object of interest (template) appears rather different from the actual target when embedded in real scenes. Therefore, standard cost criteria traditionally used in deformable templates often yield catastrophic failure in tracking and registration algorithms. Recently, there has been a resurgence of information-theoretic criteria for tracking, segmentation and registration, driven in particular by medical imaging applications where the benefit of multi-modal registration is immediately obvious. We have developed techniques to perform multi-modal registration of images affected by significant distortions in the multi-modal data collection process. For instance, in registering anatomical atlases to gene-expression data, one attempts to put in correspondence different objects that – without significant amount of prior knowledge at hand – appear to have little in common. The schemes we develop are "low-level, bottom-up" algorithms that do not require explicit domain knowledge, and are therefore portable to other domains [Yi-Soatto, 2008].

Estimation Problem for Moving Airborne Object Tracking

We have developed airborne target tracking algorithms for use on UAVs equipped with monocular based imaging systems. The UAV is to track an object/target within its field of view, requiring an estimate of target relative position. Unfortunately, due to the camera projection equations, the recovery of range is an ill-posed problem for monocular imaging systems. To overcome this, several approaches have been investigated.

The standard EKF for range estimation has traditionally been performed with knowledge of target bearing only, known as *bearings-only range estimation*. The algorithm estimates relative range, line-of-sight angle (LOS), and LOS rate using the visual information obtained from an on-board camera. Range is unobservable except during certain maneuvers, and Leader accelerations can cause an EKF to diverge. Fortunately, the image of the Leader provides indirect observation of the range through measurement of target size in the imaging plane. The size of the target is defined to be the longest axis of the plane (typically approximately the wing span). Measuring the angle subtended by the Leader in the image plane renders range observable. The EKF is augmented with an additional target-size state to utilize the subtended angle information.

Guidance for Formation Flight

The vision-based estimation filter in conjunction with active contours can be used to implement the tracking problem described above. To do so, range and line of sight estimates are compared to desired values and converted into control commands for the UAV. The control commands are obtained using standard guidance and pursuit laws. Referring to Figure 10, in this scenario, each UAV may follow several other vehicles, and may have more than one desired relative range and angle. However, the Leader-Follower guidance algorithm has only two parameters: desired relative range and desired relative angle. This leads one to average the desired ranges and desired relative angles for each UAV (similar to idea of averaging the pseudo-control in [17]).

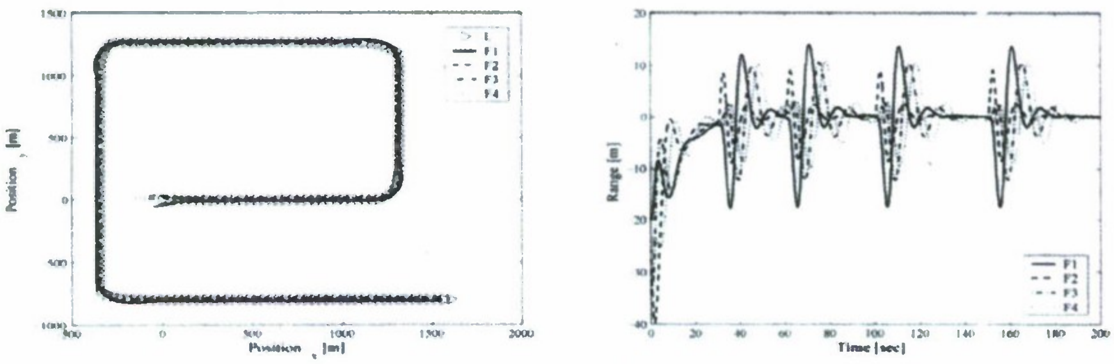


Figure 10: 5-Ship formation 2D simulation (Left) planar trajectories (Right) range errors

We have also explored guidance solutions that allow groups of unmanned vehicles to move in some coordinated fashion while avoiding fixed obstacles. When the target and obstacle size are assumed known, the range can be computed from the geometric relationship involving the subtended angle, object size and range. In this case, we have used an adaptive neural network (NN) to directly estimate the range-rate of the target from range and angular measurements of the LOS vector. The output of the NN is used in the guidance policy for pursuing the target. In the past year, we have also explored a more decentralized, *leaderless* formation scheme. In the latter scheme, each vehicle in the formation implements a guidance policy that is a blend of waypoint tracking, formation control and obstacle avoidance. The scheme increases flexibility of the formations by allowing transitions in the formation shape and reducing dependency on a single vehicle (leader), Figure 11.

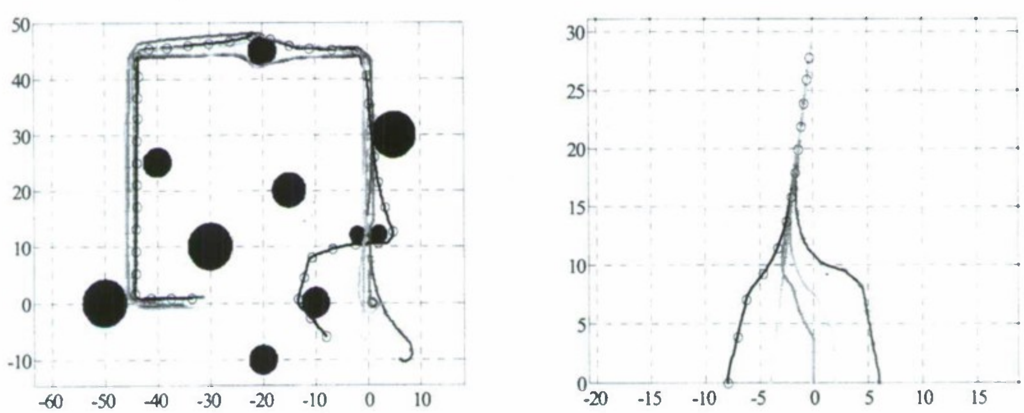


Figure 11: Leaderless formation
(Left) with obstacles (Right) transition to a line-formation

The EKF can produce biased estimates of the range due to the *unknown* target acceleration. We have studied various ways of improving the estimator. One way is to construct an optimal guidance policy by minimizing the variance of the range estimation error in the EKF design. The guidance policy results in maneuvers perpendicular to the LOS vector. Another line of work has involved modeling the target acceleration as Gauss-Markov random processes. While this helped in reducing the bias in the range estimate, we cannot capture various target accelerations with a fixed model. A third line of research involves augmenting the EKF with an adaptive NN (EKF + NN) that produces an estimate of the unknown target acceleration. The NN trains on the residuals, i.e., the error between the image plane measurements and the EKF estimates of these measurements. A typical result is illustrated in Figure 12.

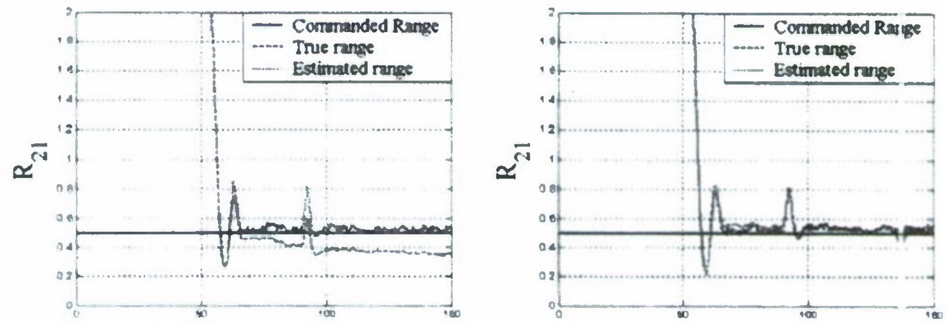


Figure 12: Range estimation results
(Left) basic extended Kalman filter (Right) adding a neural network

We have previously applied output feedback control with a linear reference model to the guidance problem. A linear reference model was designed for the relative motion. The linear output feedback controller was augmented with an adaptive element to compensate for matched uncertainties. A method has recently been explored for tracking control design using a *nonlinear* reference model. The relative motion of the system dynamics in the absence of uncertainties defines an open loop nonlinear reference model. The loop around the reference model is closed via backstepping technique, thus defining a nonlinear closed-loop reference model. The backstepping controller is augmented with an adaptive element and applied to the nonlinear dynamics of the relative motion. The error dynamics in its structure are similar to the previous work, but the unmatched uncertainty is different and is less in norm. The states of the relative motion including the relative range have also been estimated using the adaptive observer from [18].

Guidance for Obstacle Avoidance

A Note on Obstacle Detection: For obstacle avoidance, it is sufficient to concentrate on detecting the edges of obstacles. When we restrict the obstacle and camera motion to a 2D plane, each obstacle appears as a straight line in the camera image plane, and its edges are two endpoints of the line in the image. Those edges can be detected as discontinuities in the optical flow field. Therefore, it is assumed that optic flow is used to rapidly detect the endpoints of all obstacles.

Estimating Time-to-Go (t_{go}) and Zero Effort Miss (ZEM) Distance: An EKF was designed to estimate the relative position of each obstacle edge point with respect to the UAV from its image position measurement. However, in the case of moving obstacles, unmodeled dynamics due to the unknown obstacle motion (target acceleration) may produce biased estimates or even cause the EKF to diverge. The estimates are improved by augmenting the EKF with an adaptive NN that compensates for estimation errors due to the unmodeled dynamics and other nonlinearities [Sattigeri, Calise, Evers 2003]. The estimates of t_{go} and ZEM are obtained from the estimates of relative position. Furthermore, estimates of the absolute positions of all obstacle edge points can be calculated by using the relative position estimates and known camera motion.

Selecting the Most Critical Point: If an obstacle edge satisfies both $t_{go} < t_{\min}$ and $ZEM < d_{\min}$, the UAV must maneuver to avoid the obstacle. The edge point which satisfies the conditions above and has the smallest t_{go} is chosen as the most critical point.

Guidance Law for Obstacle Avoidance: A guidance law for obstacle avoidance was developed based on PN guidance. The vehicle has to avoid the most critical point while minimizing a deviation from the planned path. Therefore, a point of minimum separation from the most critical point is identified, and the vehicle is steered to that point using PN guidance. At the same time, a guidance command for tracking the planned path is created from the known vehicle motion. These two commands are blended with a weighting function to arrive at a net guidance command. The weighting function depends on t_{go} so that obstacle avoidance is given greater priority as t_{go} decreases.

Figure 13 depicts a simulation result of vision-based obstacle avoidance using the algorithms described above. The nominal path is a straight line along Y=0. The vehicle has constant speed and is controlled by its turning rate. We are currently examining the effect of moving obstacles, and evaluating the potential benefit of augmenting the EKF with an adaptive element.

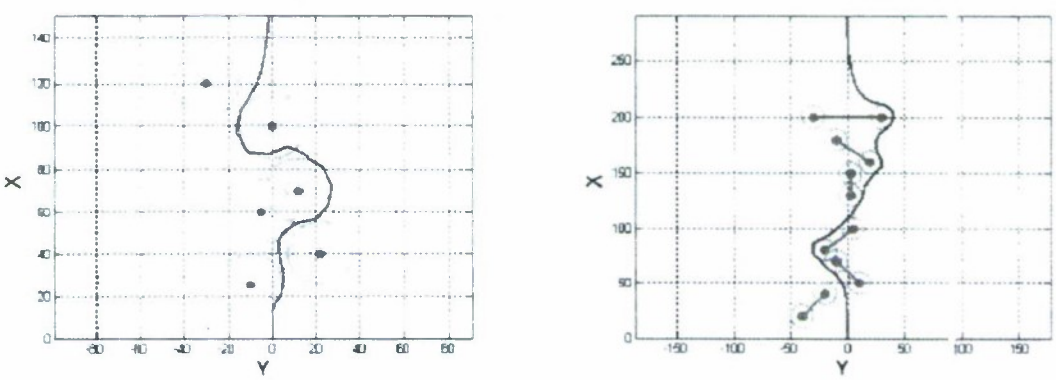


Figure 13: Vehicle Trajectory for Point Obstacles (left) and Line Obstacles (Right).

A 2-D Fixed Object Tracking Method: An obstacle avoidance algorithm that utilizes information from a 2-D passive vision sensor was investigated. It is assumed that a path-planning algorithm provides a trajectory that an aircraft has to follow. However, there are unforeseen obstacles that must be negotiated along the path, requiring a deviation. An EKF was designed to estimate the relative position of each obstacle edge point with respect to the aircraft from its image position measurement. If an obstacle edge satisfies both a time to closest approach and zero-effort miss criteria, then the aircraft must maneuver to avoid the obstacle. The edge point that satisfies the conditions above and has the smallest time to closest approach is chosen as the most critical point. The vehicle has to avoid the most critical point while minimizing a deviation from the planned path. Therefore, a point of minimum separation from the most critical point is identified, and the vehicle is steered to that point. A "minimum effort" guidance law has been developed in this last year, which has greatly improved vision-based obstacle avoidance metrics, figure 14.

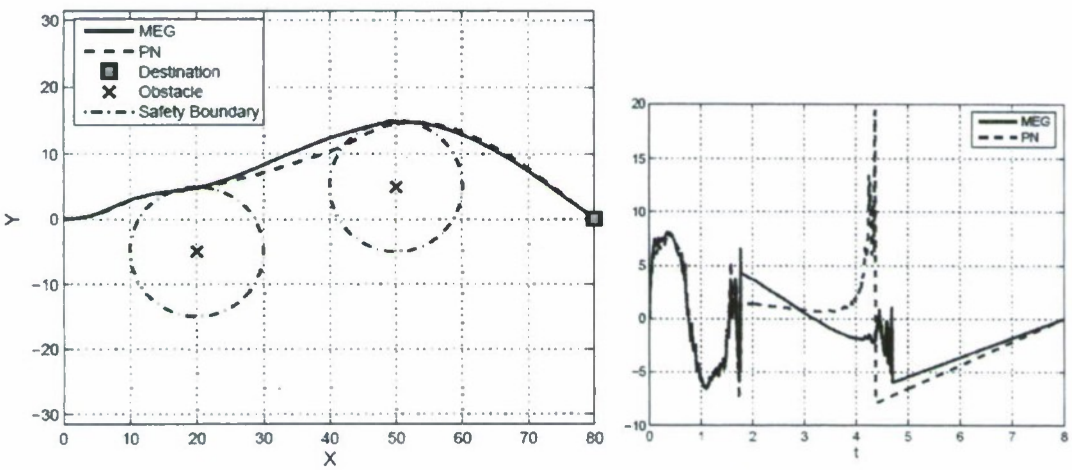


Figure 14: Vehicle trajectory and commanded with and without minimum effort guidance to avoid obstacles (minimum effort solid lines, conventional PN guidance dashed); reduced peak acceleration required, and results in a smoother/safer trajectory

Stochastically Optimized Guidance Design: 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 [Watanabe et.al. 2006]. An extended Kalman filter (EKF) is applied to the relative state navigation. 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 verified that the suggested guidance law significantly improves the estimation performance, and hence improves the overall guidance performance, Figure 15 [Watanabe et.al. 2007].

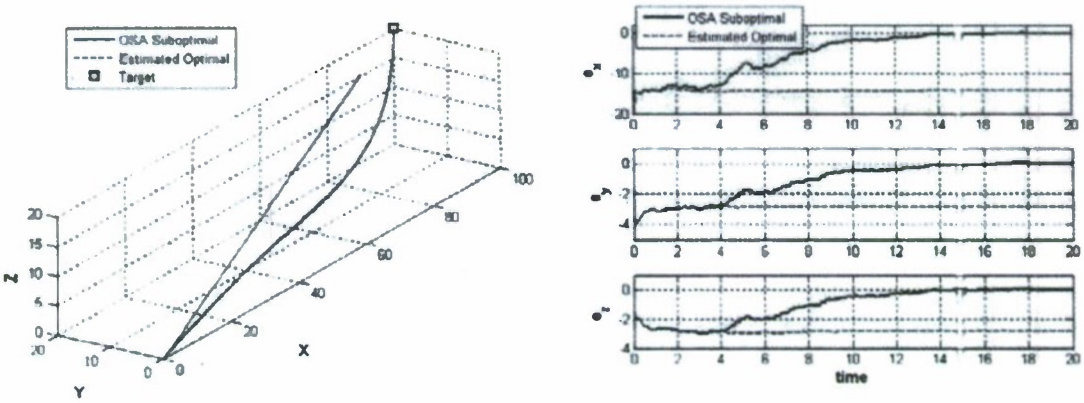


Figure 15: (Left) Vehicle trajectories comparing suggested suboptimal guidance and conventional guidance for vision-based target tracking, terminal miss distance is significantly reduced; (Right) Estimation error converges to zero when using the suboptimal guidance (Conventional green dashed lines, Suboptimal solid blue)

UKF and EMPF-based Visual Tracking Systems: We have developed an Unscented Kalman Filter (UKF) approach to the highly nonlinear vision-based estimation problem [Oh and Johnson 2007]. We have also explored particle filtering for this purpose. While particle filters have many attractive features including their applicability to general nonlinear, non-Gaussian problems without approximations of noise probability distributions, they also suffer from some defects. The most serious defect might be the increasing computational cost in high-dimensional state-space models because. 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 state-space model, direct employment of the particle filtering on this problem is almost impossible 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 an extended marginalized particle filter (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 idea 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 16. This approach can be easily extended to the design of a vision-based tracking system that incorporates probabilistic non-Gaussian vision information.

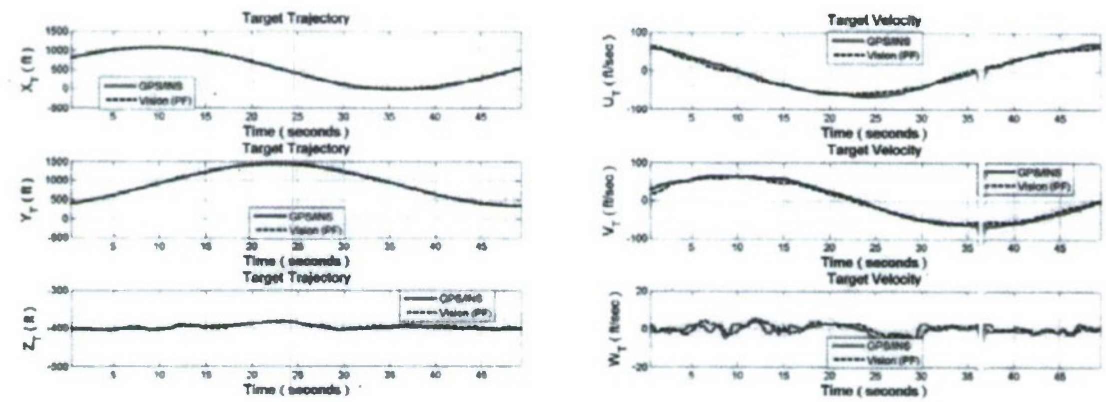
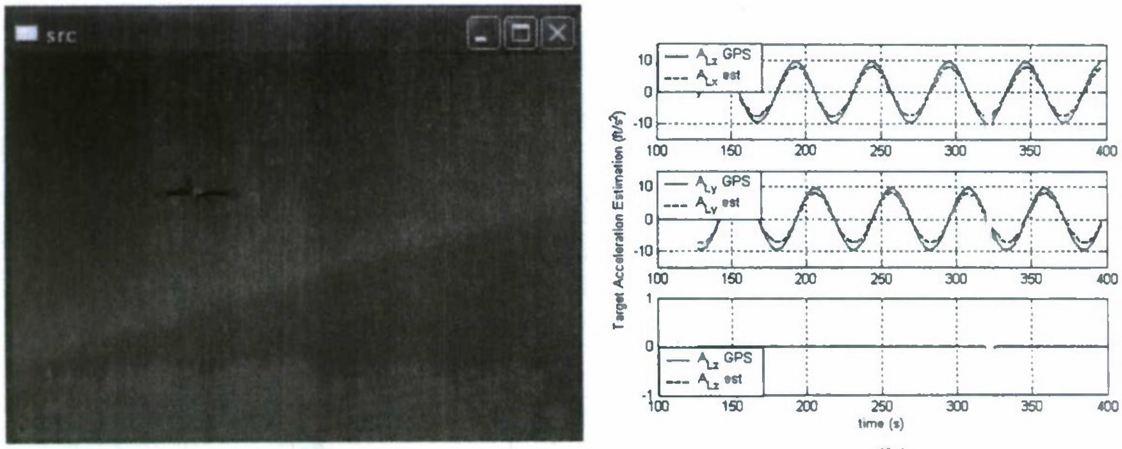


Figure 16: Target position estimation (left) and target velocity estimation (right) using the onboard image processing results obtained during flight testing on June 15, 2006. Image processing results are post-processed to get the vision-based relative motion estimation in the framework of the EMPF. GPS/INS results are independently recorded from onboard integrated navigation systems during the flight test for comparison.

Adaptive Estimation: Our previous contributions have included approaches to adaptive estimation, and this year the estimation design presented in [Sattigeri et.al. 2006] has been validated in the real-time Georgia Tech Unmanned Systems Testbed (GUST) simulation software, which is the final step before flight testing. In GUST the adaptive estimation design is integrated with image processing, guidance and control algorithms, allowing vision-in-the-loop formation flight to been demonstrated in a software-in-the-loop environment. Figure 17(a) shows the leader aircraft in the formation flight simulation. The leader aircraft is turning in a circle at a steady rate in the horizontal plane. Figure 17(a) is a screenshot of the frame-grabber window, which is used by the image processing to track the leader aircraft. The image processing returns the location of the center of the leader aircraft (green crosshair) and the wing-tips (red crosshairs) which are used to compute the LOS and subtended angles in the image plane. Figure 17(b) shows the leader acceleration estimation performance of the adaptive neural network (NN) augmenting the nominal estimator. The nominal estimator is a linear, time-varying Kalman filter wherein the leader acceleration components along the inertial axes are modeled as independent zero-mean, white noise processes. The NN does a very good job of estimating the unmodeled leader acceleration. In the absence of adaptation, there is no compensation for the leader acceleration in the estimator design. This causes the leader aircraft to drift out of the field-of-view of the follower vision sensor and ultimately vision formation cannot be maintained in the absence of adaptation (not shown). Flight test results are expected in the near future, and may be presented at the meeting.



(a) (b)

Figure 17: Formation Flight of adaptive estimator (a) Frame-Grabber window showing output of Image Processing (b) Leader Acceleration Estimation Performance with Adaptive NN (ft/s^2)

Adaptive Disturbance Rejection Controller for Visual Tracking

An adaptive disturbance rejection control architecture is developed in [Stepanyan and Hovakimyan GNC 2005] for a flying vehicle to track a maneuvering target using a monocular camera as a visual sensor. The kinematic equations of relative motion are formulated in the body frame of the tracking vehicle, in which the target velocity is viewed as a time-varying disturbance that is assumed to be in the form of a constant term plus a time-varying term with bounded integral of the magnitude. This means that any maneuver made by the target is such that the velocity returns to some constant value in finite time or asymptotically in infinite time with a rate sufficient for the integral of the magnitude of velocity change be finite. For example, any obstacle or collision avoidance can be viewed as such a maneuver. The challenge associated with the unobservable relative range leads to a reference model, dependent upon the unknown constant parameter associated with the target size. In the meantime the problem is complicated with the presence of unknown time-varying disturbances associated with the unknown target's velocity. Thus two challenges are addressed simultaneously: tracking of a reference command that has an unknown parameter in it, and disturbance rejection problem for a multi-input multi-output system with positive but unknown high frequency gain in each control channel. The proposed guidance law uses the adaptive synthesis approach developed in [19] for rejecting the time-varying disturbances and, as a result, guarantees asymptotic tracking of estimated reference commands.

Tracking of the true reference commands requires identification of the target's size, which otherwise requires convergence of the parameter estimates to the true value. This has been achieved by introducing intelligent excitation technique, [Cao and Hovakimyan ACC 2005]. Following this method, a sinusoid with amplitude depending on the tracking error is introduced in the estimated reference command. This ensures simultaneous parameter convergence and output regulation.

The limitations imposed on the target motion can be removed by considering the visual tracking problem in output feedback framework that involves the target's acceleration, rather than the velocity. In this case, the acceleration is assumed to be piece-wise continuous and bounded, but otherwise with unknown bounds. The system in this general case is of vector relative degree, has in general time-varying unknown parameters associated with the target's geometry and bounded unknown disturbance associated with the target's acceleration. The reference model still depends on the unknown parameters, and perfect tracking can be achieved if the parameter estimates converge to the true values.

To handle this problem, a robust adaptive observer design methodology was developed [Stepanyan and Hovakimyan CDC 2005] for a class of uncertain nonlinear systems in the presence of time varying unknown parameters and non-vanishing disturbances. Using universal approximation property of radial basis function neural networks and the adaptive bounding technique, the developed observer achieves asymptotic convergence of state estimation error to zero, while ensuring boundedness of parameter errors. However, the methodology requires existence of an output injection matrix that makes the linear part to be SPR-like. The latter condition is very challenging to ensure in visual tracking and requires input-output filtering and state transformations, like ones developed in [20] and [21].

L1 Adaptive Estimation and Control:

Given the visual measurement of the target and the relative altitude (such as by geo-referencing the image, captured by the onboard gimbaled camera, with a given database – such as for a ground-target), the estimation problem was formulated in a way such that the recently-developed L_1 fast estimator can be applied for the target's time-varying velocity estimation [Dobrokhodov et. al. 2007]. Arbitrary small estimation precision and transient response can be obtained by increasing the bandwidth of the low-pass filter used in the L_1 fast estimator. The trade-off is that increasing the bandwidth requires larger adaptation rate and faster computation. The performance bound from disturbance/noise in the measurements to the estimation error is systematically derived, which explicitly accounts for out-of-frame events following the analysis on brief instabilities.

Closed-Loop Image Processing, Guidance, Navigation, and Control Simulation

After achieving initial verification of the individual tracking algorithms on specially tailored simulations, we incorporated the components into a real-time simulation of two airplanes, including its guidance and control functions. The complete system, including image processing, estimation, and guidance have been implemented and tested in this way. A scene generator is used as the input to image processing approaches. A typical result is shown in Figure 18.

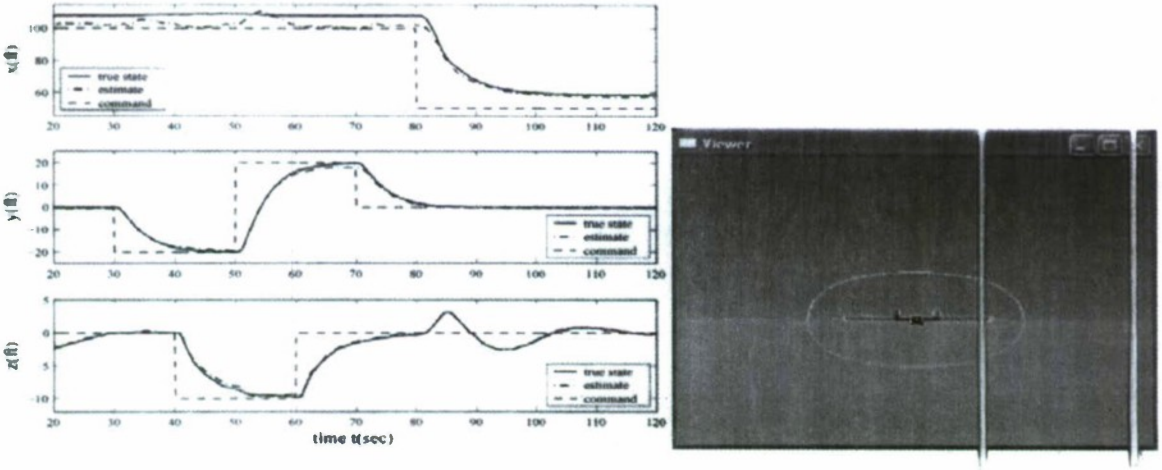


Figure 18: Closed-loop vision-based formation flight high-fidelity simulation results (Left) Relative position command, estimated, and actual for changed in relative position command (Right) Raw image with segmentation results overlay

The adaptive estimation design described above for vision based formation flight was been validated in the same real-time simulation [Sattigeri, Johnson, Calise and Ha 2007]. Here, the adaptive estimation design is integrated with image processing, guidance and control algorithms, allowing vision-in-the-loop formation flight to be demonstrated in a software-in-the-loop environment. Open-loop results with synthetic imagery and recorded flight test data were obtained first. Figure 19 shows results obtained by post-processing recorded flight test data, specifically leader velocity and position estimation performance with the adaptive estimator.

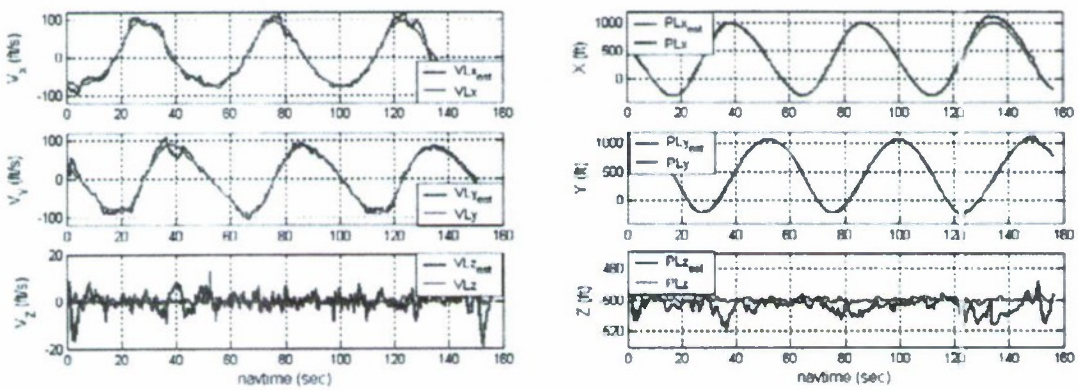


Figure 19. Leader Position Estimation Performance (ft), with Adaptive Estimation – (Left) Velocity North, East, Down (Right) Position North, East, Down, leader flies in a circle

An adaptive integrated guidance and control design developed for line-of-sight formation flight was also integrated and tested in the simulation [Sattigeri, Johnson, Calise 2008].

Adaptive Vision-Based Guidance Law with Guaranteed Performance Bounds for Tracking a Ground Target with Time-Varying Velocity

This work extends early results on vision-based tracking of a ground vehicle moving with unknown time-varying velocity. The follower UAV is equipped with a single camera. The control objective is to regulate the 2D horizontal range between the UAV and the target to a constant. Figure 20 shows graphical illustration of the vision-based target tracking scenario. Let $\rho(t)$ denote the 2D horizontal range between the UAV and the target. The control objective is to regulate $\rho(t)$ to ρ_d, where ρ_d is a given desired 2D horizontal range between the UAV and the target. For simplicity, we consider the case when ρ_d is constant. For this system, the available measurements are visual measurements of the target location within a 2D image, relative altitude by comparison to terrain database, and ownship state.

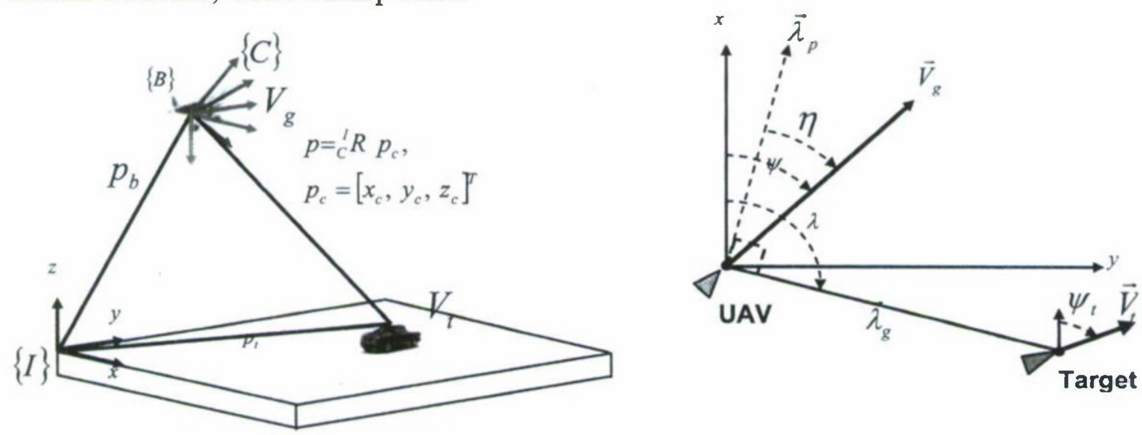


Figure 20: Relative kinematics of UAV-target motion.

The extension has two distinct features [Ma, et. al. GNC 2008]. An earlier developed guidance law used the estimates of the target's velocity obtained from a fast estimation scheme. We explicitly derive the tracking performance bound as a function of the estimation error. The performance bounds imply that the signals of the closed-loop adaptive system remain close to the corresponding signals of a bounded closed-loop reference system both in transient and steady-state. The reference system is introduced solely for the purpose of analysis. This work also analyzes the stability and the performance degradation of the closed-loop adaptive system in the presence of out-of-frame events, when continuous extraction of the target's information is not feasible due to failures in the image processing module. The feedback loop is then closed using the frozen estimates. The out-of-frame events are modeled as brief instabilities. A sufficient condition for the switching signal is derived that guarantees graceful degradation of performance during target loss. The results build upon the earlier developed fast estimation scheme of the target's velocity, the inverse-kinematics-based guidance law and insights from switching systems theory.

Flight Testing and Sensor Development

Flight Testing

A helicopter UAV with automated capabilities that include: searching a prescribed area, identifying a specific building within that area based on a small sign located on one wall, and then identifying an opening into that building was developed and tested. Results include successful evaluation at the McKenna Military Operations in Urban Terrain flight test site. Active contours were used to locate openings, Figure 21. In a separate/related activity, the contours such as those in the figure were successfully used to update an inertial navigation solution, allowing the vehicle to operate without GPS or other aiding for extended periods [Proctor, et. al. 2003].

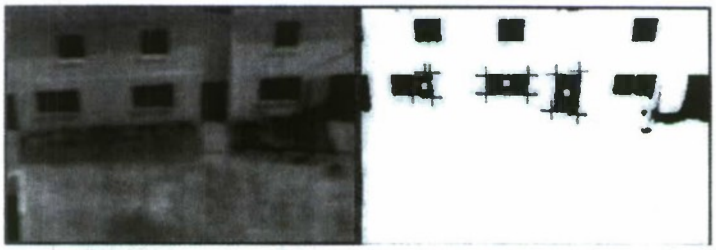


Figure 21: Flight test results segmenting openings into a building

A glider, which is capable of flying from a starting point to a pre-defined ending location using only a single vision sensor, has been flight tested [Proctor, et. al, 2006]. The estimator uses an EKF. The algorithms are tested with a glider instrumented only with a single camera.

We validated the vision-based segmentation, estimation, guidance, and control strategy developed previously in flight test. On June 15, 2006, the project had a particularly significant highlight. One of our 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 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. The Follower aircraft was the GTMax (based on the Yamaha RMAX) research helicopter, utilizing onboard image processing, lead aircraft state estimation, guidance, and control. 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 below in Figures 22 and 23.

Figure 22: Typical segmentation of the image (reproduced from recorded video from the flight). Lead aircraft center and wing tip positions are found in realtime (graphically shown with a "+"), and this data utilized to estimate the position, velocity, acceleration, and size of the Leader. The estimated position, velocity, and acceleration are utilized to fly formation.

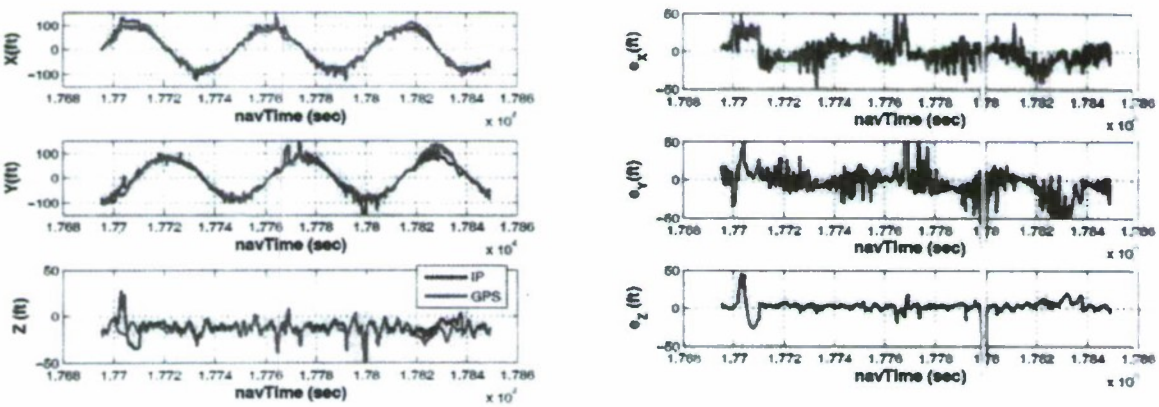


Figure 23: Position estimation (left) and position estimation error (right) during one of the flights on June 15, 2006, comparing onboard vision-based estimate of Leader location with Leader's reported location (GPS/INS solution). For part of two cycles of the circular motion, the Follower is utilizing the vision-based estimate to maintain formation and ignoring the reported GPS/INS solution. (coordinates are North/East/Down in ft. IP = vision based, GPS = GPS/INS solution)

This test result involved some of the simplest of the approaches developed under this project. In the final two years of the project, we anticipate greatly enhanced performance as we incorporate these more advanced methods.

Subsequently, we continued to validate the vision-based segmentation, estimation, guidance, and control strategies developed previously in flight testing. Another significant activity was bringing on-line a second airplane, which we call the GTYak, a 33% scale Yak aerobatic airplane, Figure 24. This has enabled us to switch to two-airplane tests with two airplanes with similar performance capabilities. The first formation flight with this aircraft was in February 2007. The first closed-loop vision-based tests were performed in July 2007.

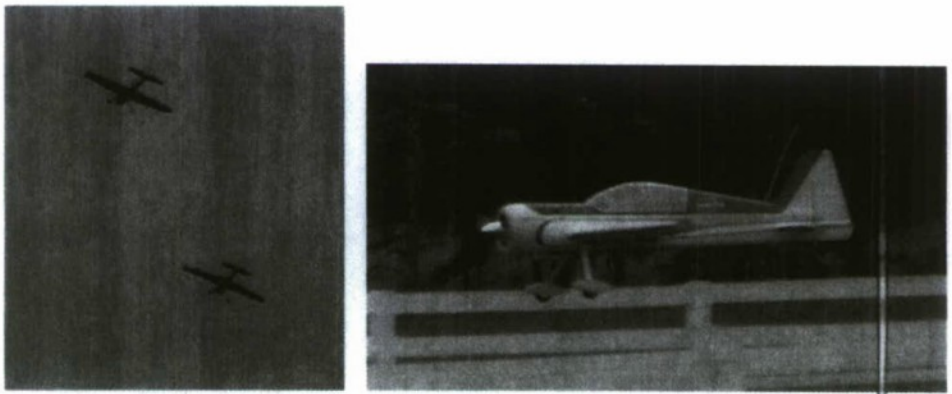


Figure 24: (right) GTYak vision-based tracking tested. Camera is located in pod on right wing. Image processing and estimation computer is in canopy area. (left) GYak flying in formation with GTEdge "target"/"leader" airplane reported on previously.

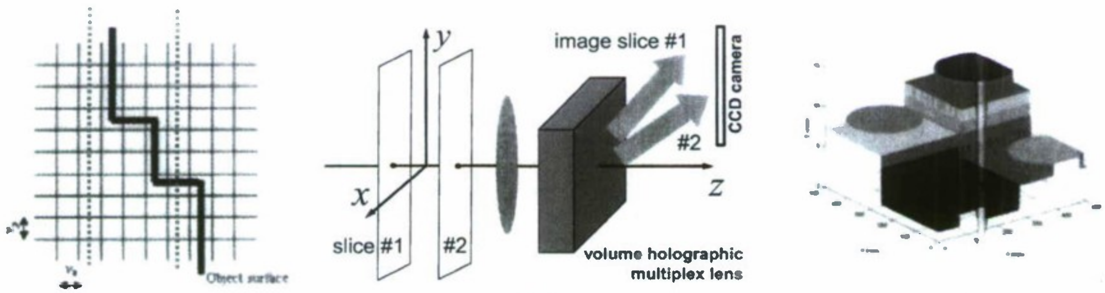
Sensor Design

Another objective of this effort is the development of innovative optical imaging systems for 3D imaging of ground and airborne targets from autonomous vehicles. Our approach is to use a new type of optical elements, called "volume holographic lenses," (VHLs) which perform "optical slicing" on reflective objects (such as tanks and trucks, for example.) Optical slicing means that, when the instrument is focused on a certain plane, only the portion of the target that intersects the same plane is visible; the remainder is dark. By combining several focal planes, the entire 3D target shape is reconstructed. The benefits of this approach are that it does not require multiple views nor structured illumination, and it is not subject to ambiguities such as the "correspondence problem" in computer vision. On the other hand, the VHL method forms images "one line at a time," and so it requires 2D scanning to recover the 3D target in its entirety. The flight path of the autonomous vehicle itself can be used to implement the required scanning.

During the first year we developed two significant improvements on the operation of VHLs, namely (i) a super-resolution method, based on the Viterbi algorithm, which improves the depth resolution of the VHL by a factor of 5, and thus permits the instrument to see features of the target which are finer than diffraction theory would have predicted; and (ii) a method to reduce scanning from 2D to 1D, based on the dispersion properties of VHLs, which permits the instrument to acquire 3D images much faster than we had planned for originally.

Second year accomplishments were focused on a new use of Viterbi which combines the increased resolution and denoising properties with reduction in scanning time; and a new method for acquiring hyper-spectral images (spatial as well as "true" – non-RGB – color information) with passive (sunlight) illumination.

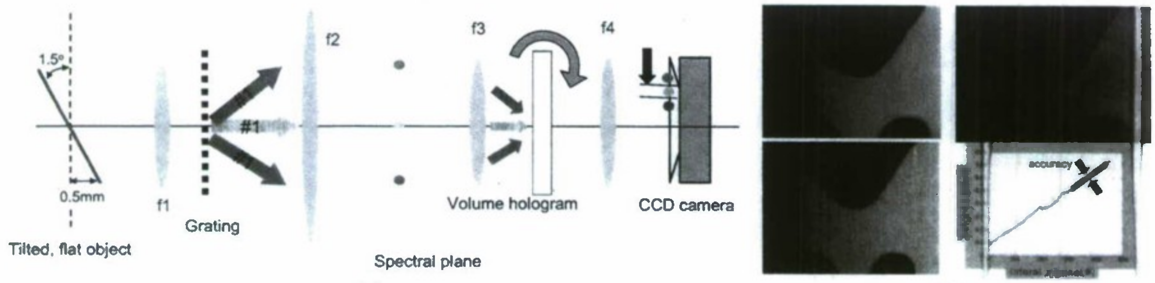
We have previously demonstrated the use of the Viterbi algorithm for improving the quality of volume holographic images; namely, reducing the effects of noise in post-processing when the desired depth resolution is finer than the instrument's classical resolution. However, in the version implemented in our prior research the required number of scanned depths was equal to the number of desired reconstruction depths. We have succeeded in implementing a new version where the number of scan depths can be smaller than the number of reconstructed depths by a factor of approximately 4 (even better is achievable assuming low noise conditions). Thus, the Viterbi algorithm can be thought of as performing a kind of interpolation in this case. Further reduction in scanning is achieved using the multiplexing technique for volume holograms; namely, one combines two or more volume holographic lenses in a single optical element, so that the lenses image simultaneously separate depths in the target space. The images are separated easily because the multiplexed holograms are capable of directing each image onto a separate area of the digital camera (or to separate cameras.) The goal of the experiment, experimental arrangement, and typical results are summarized in Figure 25. This research was carried out in collaboration with Prof. Mark A. Neifeld of the University of Arizona.



(a) (b) (c)

Figure 25 (a) Scanning profilometry with Viterbi interpolation. The thick black line denotes the cross-section of the (reflective) target surface; normally, one would need to scan so as to acquire a separate image for each column of voxels. Yet using the Viterbi algorithm it is possible to acquire only two images, at the voxel columns denoted with dotted red lines, and reconstruct the rest of the target based on these two depth scans only. (b) Experimental arrangement: slices #1 and #2 correspond to the red dotted lines of Figure MIT-1(a), and are being imaged by the volume holographic multiplex lens onto separate positions on the camera, as denoted by the green arrows; thus the two required images are acquired in a single step in this experiment. (c) Reconstruction of a LEGO® object using the experimental setup of Figure MIT-1(b). 8 depth levels were reconstructed in one shot in this experiment. The depth resolution was 1.6mm and the working distance was 0.5m.

We originally reported a novel "rainbow" volume holographic imaging technique, where the target is illuminated by a rainbow, which can be thought of as a multitude of colored slits imaged on the target. The volume holographic imager is capable of performing optical slicing, *i.e.* acquiring slice-wise depth information from each slit of different color in parallel. Subsequent to this, we succeeded in improving this technique by a modification which allows us to (a) utilize passive illumination, e.g. sunlight, and still recover slice-wise depth information; and (b) estimate the color composition of the target as well as its spatial shape in the same step (whereas the original rainbow technique required a color scanning step for non-white targets). Due to its passive nature, we refer to the new technique as "Sun Light" volume holographic imaging. The experimental arrangement of the Sun Light method, and typical experimental results obtained with a home-made reflective target, are summarized in Figure 26.



(a) (b)

Figure 26: The Sun Light volume holographic imaging method. (a) Experimental arrangement showing (for simplicity) a flat, tilted, reflective target at the input plane. The white-light (Sun Light) illumination is first spectrally analyzed by an auxiliary grating and then forwarded to the volume holographic lens, which completes one rotation to fill out the lateral field of view, as shown. (b) Experimental results, clockwise from bottom left: resconstruction of the tilted target profile, indicating the accuracy of the measurement (better than 20μm); and depth-selective images of three (arbitrarily chosen) spectral components: cyan, light green, and orange-red.

Acknowledgement/Disclaimer

This work was sponsored by the Air Force Office of Scientific Research, USAF, under grant/contract number F49620-03-1-0401. The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies or endorsements, either expressed or implied, of the Air Force Office of Scientific Research or the U.S. Government.

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AFRL Point of Contact and Interactions

Primary AFRL point of contact was Johnny Evers, AFRL/MNGN, Eglin AFB, FL, 850-882-2961x2347.

We have had technical interactions with AFRL/MNGN and AFRL/VACA regarding flight tests for unmanned aerial vehicles with vision-based guidance policies. One area of interaction involved improving the nominal autopilot design by making it adaptive. Calise, Tannenbaum, Hovakimyan, Betser, and Vela had extended visits to support related activities. Weekly teleconferences August-December 2004 and other reports were written related to adaptive autopilot design, adaptive guidance and integration of an IMU with GPS measurements. An adaptive autopilot was auto-coded from Simulink and integrated at Eglin by Ali Kutay, a GRA working under the direction of Prof. Calise. Stephen Card, a Georgia Tech student who spends summers working at AFRL/MNGN on these activities, also worked on these projects during the academic year while at Georgia Tech.

We collaborated with Dr. J.V.R. Prasad at Georgia Tech and Sikorsky on a project to implement adaptive guidance laws for unmanned helicopter formation flight with ground and aerial targets. The adaptive guidance laws were flight tested using the Georgia Tech rotorcraft UAV GTMAX while maintaining range from a ground target. The designs and software were transitioned to Sikorsky for integration into a high fidelity simulator.

A number of technical conferences were attended by members of the team, several also by AFRL, including CDC, ACC, GNC, ECCV, CLEO/IQEC, SPIE, and others. A special sessions relating to this project have taken place for the 2004 CDC and the 2005 ACC. One is planned for the 2005 GNC.