# GeoTrack: Bio-Inspired Global Video Tracking by Networks of Unmanned Aircraft Systems

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## ABSTRACT

Research from the Institute for Collaborative Biotechnologies (ICB) at the University of California at Santa Barbara (UCSB) has identified swarming algorithms used by flocks of birds and schools of fish that enable these animals to move in tight formation and cooperatively track prey with minimal estimation errors, while relying solely on local communication between the animals. This paper describes ongoing work by UCSB, the University of Florida (UF), and the Toyon Research Corporation on the utilization of these algorithms to dramatically improve the capabilities of small unmanned aircraft systems (UAS) to cooperatively locate and track ground targets.

Our goal is to construct an electronic system, called GeoTrack, through which a network of hand-launched UAS use dedicated on-board processors to perform multi-sensor data fusion. The nominal sensors employed by the system will EO/IR video cameras on the UAS. When GMTI or other wide-area sensors are available, as in a layered sensing architecture, data from the standoff sensors will also be fused into the GeoTrack system. The output of the system will be position and orientation information on stationary or mobile targets in a global geo-stationary coordinate system.

The design of the GeoTrack system requires significant advances beyond the current state-of-the-art in distributed control for a swarm of UAS to accomplish autonomous coordinated tracking; target geo-location using distributed sensor fusion by a network of UAS, communicating over an unreliable channel; and unsupervised real-time image-plane video tracking in low-powered computing platforms.

**Keywords:** Unmanned Aircraft Systems, Biologically Inspired Technology, Geolocalization, Estimation, Swaming.

## 1. INTRODUCTION

This paper describes a joint project between by researchers at the University of California at Santa Barbara, at the University of Florida, and at the Toyon Research Corporation. The goal of this project develop an electronic system, called *GeoTrack*, in which a network of hand-launched UAS use dedicated on-board processors to perform multi-sensor data fusion. The nominal sensors employed by the system will be EO/IR video cameras on the UAS. When GMTI or other wide-area sensors are available, as in a layered sensing architecture, data from the standoff sensors will also be fused into the GeoTrack system. The output of the system will be position and orientation information on stationary or mobile targets in a global geo-stationary coordinate system.

Our program will design and build a *modular system*, compatible with many existing UAS platforms. GeoTrack will interface with the existing UAS sensor through a composite video connection, and interface with the UAS autopilot (obtain platform state data) via RS-232 or a similar interface. For compatibility with small platforms, our target weight for the device is 1 lb, with a power consumption under 5 watts. *Scalability* is also another key design constraint: the system may be used in groups ranging from a single UAS to dozens of UAS, tracking a single target or up to dozens of targets.

The GeoTrack device will enable small UAS to track ground moving targets cooperatively and autonomously, producing target position/orientation information in a global geo-stationary coordinate system. This functionality will be achieved utilizing ICB distributed estimation algorithms, ICB research in distributed sensor fusion over networks, and Toyon's automatic video tracking technologies. Table 1 summarizes the features and benefits of GeoTrack. The design of the GeoTrack system with the desired capabilities requires significant advances beyond the current state-of-the-art in the following areas:

1. distributed control for a swarm of UAS to accomplish autonomous coordinated tracking;

2. target geo-location using distributed sensor fusion of GPS, IMU, and vision data by a network of UAS, communicating over an unreliable channel;

3. unsupervised real-time image plane video tracking (EO and IR) in low-powered computing platforms.

These advances will be achieved by leveraging recent research results and technology developments in these areas by UCSB, UF, and Toyon.

1. **Distributed swarm control** → Algorithms described in[1,2] will be used to achieve tight UAS formations using minimal inter-UAS communication, even in the presence of measurement noise and communication losses (Section 3.2).

2. **Distributed sensor fusion** → Using the multi-sensor fusion and tracking algorithms in,[3–5,5–8] GeoTrack-equipped UAS will be able to exchange minimal local information to obtain a near-optimal position estimate of the target (Section 3.1). Furthermore, these algorithms have been shown to be robust with respect to communication failures.

3. **Low-powered video tracking** → Toyon has begun embedding portions of our Image Plane Video Tracker (IPVT)[9] in FPGA with very promising results. Under this project we will complete this process to provide automatic video tracking capabilities on-board small UAS (Sections 4.1 and 4.2).

| **Limitations of Army UAS architecture (CURRENT)** | **Applicable research** | **Anticipated benefits for the Army UAS architecture (FUTURE)** |
|---|---|---|
| **Data accuracy requirements:**<br>• Geo-location of targets in video from small UAS is inaccurate or impossible | ▷ UAS video will be synchronized with UAS state telemetry to geo-register video frames<br>▷ ICB distributed estimation algorithms will be used to fuse measurements from multiple UAS and create accurate geo-registration of targets in video | ⋆ Prosecution-level geo-location accuracy of targets identified in small UAS video<br>⋆ Ability to re-acquire a target that has left the video field-of-view |
| **UAS operator requirements:**<br>• One or more human operators per UAS<br>• Line-of-sight from operator to UAS limits UAS range<br>• Operator fatigue may endanger UAS missions | ▷ Biological self-coordination and flocking algorithms will be used to assist in the control of Army UAS<br>▷ Toyon's video tracking algorithms will automatically process and fuse video data | ⋆ One operator can view and understand information from many UAS<br>⋆ A single UAS operator can control multiple UAS simultaneously (reduced operator-to-UAS ratio)<br>⋆ Reduced UAS operator demand & fatigue<br>⋆ Inter-UAS cooperation & increased UAS autonomy |
| **UAS network bandwidth requirements:**<br>• UAS operation and video requires constant, reliable, high-bandwidth wireless communication<br>• May require line-of-sight from base station to UAS, limiting UAS range | ▷ UAS will transmit track estimates instead of video, significantly reducing network bandwidth and network reliability requirements<br>▷ Track updates can arrive infrequently and at irregular intervals without significant performance deterioration | ⋆ Reduced bandwidth requirements for wireless UAS communications<br>⋆ Improved UAS surveillance and tracking performance |

**Table 1.** Features and benefits of the proposed GeoTrack research

## 2. SYSTEM ARCHITECTURE

Figure 1 shows the GeoTrack system architecture. The system will collect data from four different sources.

1. GPS data will provide the position of a UAS in a geo-stationary (Lat-Lon) coordinate system. This data is typically quite accurate, but available only at a low sampling rate (10 Hz).

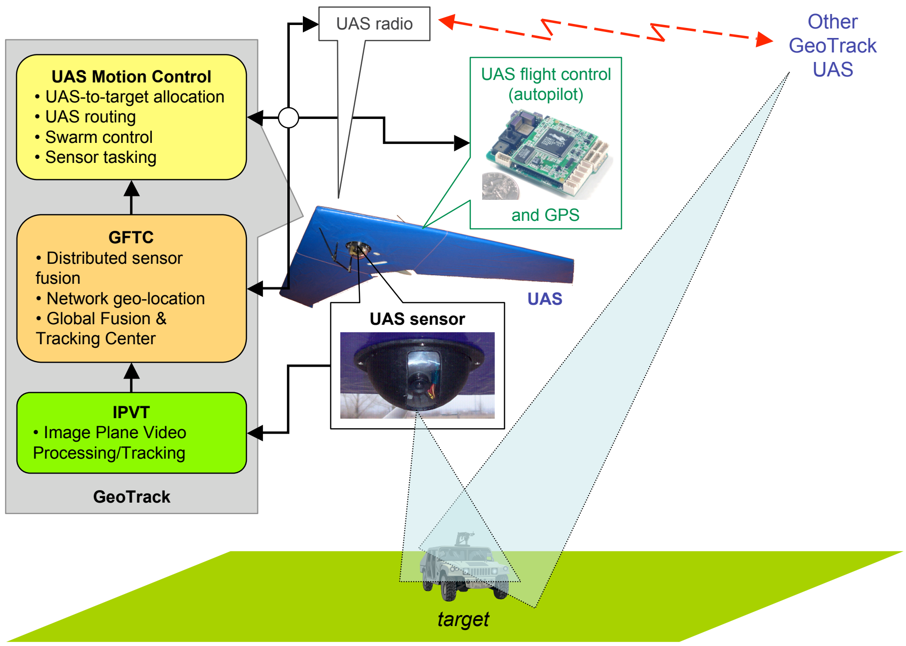



**Figure 1.** GeoTrack system architecture

2. IMU kinematic data will be used to propagate the position estimate of the UAS between GPS updates. This data is typically available at a high sampling rate but exhibits error in the form of drift. (Some UAS flight control systems will provide GPS/IMU fused data.)

3. image plane video data on targets within each sensor's FOV (combined with sensor location, orientation, and terrain information yields target positions and velocities in the geo-stationary coordinate system).

Since the GeoTrack system will also support communication between multiple UAS, each GeoTrack node may also have available:

4. Geo-registered measurements or target state estimates computed and relayed by other UAS in the team.

Video data from the UAS sensor is processed using Toyon's IPVT algorithms (Section 4.1). Target detections and/or target tracks in the image plane are sent to a fusion and tracking database, which we refer to as the Global Fusion and Tracking Center (GFTC) because it will process video data from multiple UAS and geo-reference this data in an Earth-based coordinate system (Section 4.2). The GFTC also receives state telemetry about the UAS platform and sensor from the Autopilot. This information is synchronized with the video data to geo-locate the image plane detections/tracks in latitude/longitude coordinates. UAS motion control algorithms that assist the operator in routing the UAS platform and targeting the UAS sensor in order to optimize the tracking performance will use these track locations (Sections 4.4, 4.5, and 4.6). Track locations and future routing/tasking plans for this UAS are sent to the UAS autopilot for execution, and are also conveyed to other GeoTrack UAS to facilitate cooperative tracking and improve target estimate accuracy (Section 4.3).

## 3. BIOLOGICALLY INSPIRED TECHNOLOGIES

Research on the fundamental principles by which groups of animals coordinate their actions led to the development of distributed estimation algorithms for data fusion in networks of relative measurements,[3–5,5–8] as well as the developed of distributed swarm motion control algorithms.[1,2] This research and corresponding algorithms can be used to dramatically improve localization and tracking capabilities of UAS.

### 3.1 Distributed Sensor Fusion over Networks

Under an ICB project on Decentralized Computation and Control in Large-Scale Networks, the UCSB/UF team has developed distributed algorithms for data fusion in networks of relative measurements.[3,5] These estimation algorithms were inspired by swarming behavior observed in flocks of birds and schools of fish.

Migratory birds such as ducks, geese, and pelicans provide some of the best examples of motion coordination. Especially in long-range migrations, these birds fly in a V-shape formation with a bird in the lead followed by the remaining birds trailing behind in two straight lines. It has been theoretically shown that the increased aerodynamic efficiency of formation flight can allow 25 birds to increase its range by about 70% as compared to a bird flying alone. Fish schooling refers to the synchronized motion of individuals of similar size, generally moving in the same direction. It is believed that this complex behavior can be observed in over 10,000 species, which raises the question of what evolutionary mechanisms could be responsible for schooling. The most widely accepted hypotheses are related to anti-predatory adaptation. Schooling may have evolved as a “cover-seeking” response, as each individual tries to reduce its chance of being caught by a predator.

One of the most well-known biologically inspired models for swarming was introduced by Reynolds in 1987[10] for the creation of computer animations of flocking behavior. This work eventually granted Reynolds the Scientific and Engineering Award presented by The Academy of Motion Picture Arts and Sciences for pioneering contributions to the development of three-dimensional computer animation for motion picture production. Reynolds’ key observation was that cohesion motion for a swarm was possible based solely on local interactions between an agent and its neighbors. For birds flying in a V-formation, each animal senses its neighbors though vision and turbulence in the airflow. Turbulence sensing is crucial for maintaining formations that result in energy savings; however, turbulence can typically be sensed only by birds flying very close to each other. Reynolds’ heuristic model for swarming was based on three rules to govern flocking behavior: cohesion, which causes an individual to stay close to nearby flock-mates; separation, which prevents collision with nearby flock-mates; and alignment, which is responsible for matching velocity with nearby flock-mates. Although a complete analysis of these types of algorithms is still unavailable, some of its simplest forms are sufficiently well understood to be applied to distributed estimation and control problems.[4,5,11]

### 3.2 Distributed Swarm Control of UAS Across Networks

Fish schools and flocks of birds are believed to use simple control laws to maintain relative positions, such as the following law

$$\dot{x}_u = -c_u \sum_{v \text{ neighbor of } u} (u_u - x_v - r_{u,v})$$

where the velocity $\dot{x}_u$ of the agent $u$ is adjusted proportionally to the difference between the relative position $x_u - x_v$ of the agent $u$ with respect to its neighbor $v$ and the desired value $r_{u,v}$ for this relative position. We have studied the robustness of this law with respect to noisy measurements and shown that for highly connected networks, this type of control law can yield a tight formation.[4] The required connectivity is present in fish schools that can grow to millions of animals, while maintaining good performance. However, V-formations do not exhibit sufficient connectivity, which explains the fact that these formations do not grow beyond a certain scale. In this project, we will use our past results to guarantee that the communication topologies used to support formation control permit a high level of robustness with respect to measurement noise.

## 4. BASIC RESEARCH UTILIZED IN GEOTRACK

The following research accomplishments are crucial to the successful development of the GeoTrack system (see[3,5] for details):

1. We have shown that Reynolds’ rules for maintaining a formation are robust with respect to communication failures, for both stochastic and deterministic characterizations of faults.

2. We have shown that Reynolds’ rules can be implemented in an asynchronous manner, meaning that formations will be maintained even if the exchange of information between agents is not synchronized by a common clock.

3. We have shown that the bio-inspired rules that rely only on communication between direct neighbors can be combined with the ability to forward small messages (which is generally not possible in bird formations, but is straightforward with RF digital communication). This new algorithm, known as the OSE (Overlapping Subgraph Estimator) algorithm, can significantly shorten the speed of convergence to the desired formation.

4. Finally, we have shown that the basic formation control algorithm proposed by Reynolds as well as our OSE algorithm can be adapted to a wide range of estimation and control problems, including the one that will be formulated in Section 4.3 [formalized by the equation (1)].

The following key bio-inspired technologies will be utilized in this project:

1. A modified version of the OSE algorithm[3] will be used to solve the distributed target location estimation problem. This algorithm will combine relative position measurements between targets and UAS and IMU propagation data to obtain the current best position estimate of the target.

2. Distributed swarming algorithms based on local interactions between agents will be used to control the UAS so as to maximize target localization accuracy. In addition, the communication topology will be optimized to permit a high level of robustness with respect to measurement noise.

Technical details on these and other key technologies are summarized in the remainder of this section.

## 4.1 Unsupervised Real-time Image Plane Video Tracking

Toyon has developed advanced algorithms for video-based target tracking in a wide range of applications. As shown below, the primary components of Toyon's IPVT are: camera motion compensation; statistical modeling and change detection; moving target detection; multiple-target tracking; motion-based target discrimination; and cue generation.

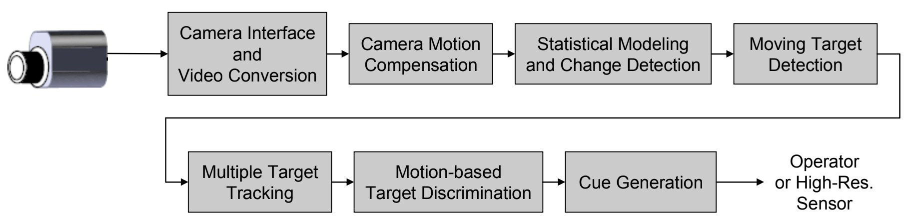



**Figure 2.** IPVT components

Innovative statistical background modeling and change detection enables detection of moving targets in the presence of significant motion clutter, including swaying vegetation, and sea surfaces. Novel target feature extraction and exploitation allows for persistent tracking through move-stop-move and high target density conditions, as well as multiple-camera measurement-to-track and track-to-track fusion. Advanced multiple-target tracking algorithms, including an efficient track-oriented multiple hypothesis tracker (MHT), reduce track breaks and improve long-term tracking performance (see Figure 3).

These components work together to create our IPVT software, which has demonstrated nearly perfect human detection and false detection rates during the day and night, across water, through moderate fog, through partial obscuration from vegetation, in sunlight and shadow, on the surface of the ocean, with swaying vegetation and rippling waves in the field of view, with illumination changes leading to sudden sensor gain changes, and with moving cameras, in sensing modes including RGB visible, $I^2$ night vision, MWIR, and LWIR.

## 4.2 Automatic Target Geo-location

One of the distinguishing technologies employed by the GeoTrack system will be unsupervised real-time geo-location of targets in the image plane. This means that GeoTrack will use a Global Fusion and Tracking Center (GFTC) capable of fusing video tracking data from the IPVT with UAS state data to geo-locate an image plane track in a global coordinate system. Toyon's IPVT algorithms will be used to process the video from the UAS sensors, perform image plane tracking, and transmit this image plane track information to the GFTC. The UAS state data will be sent into the GFTC from the UAS autopilot.

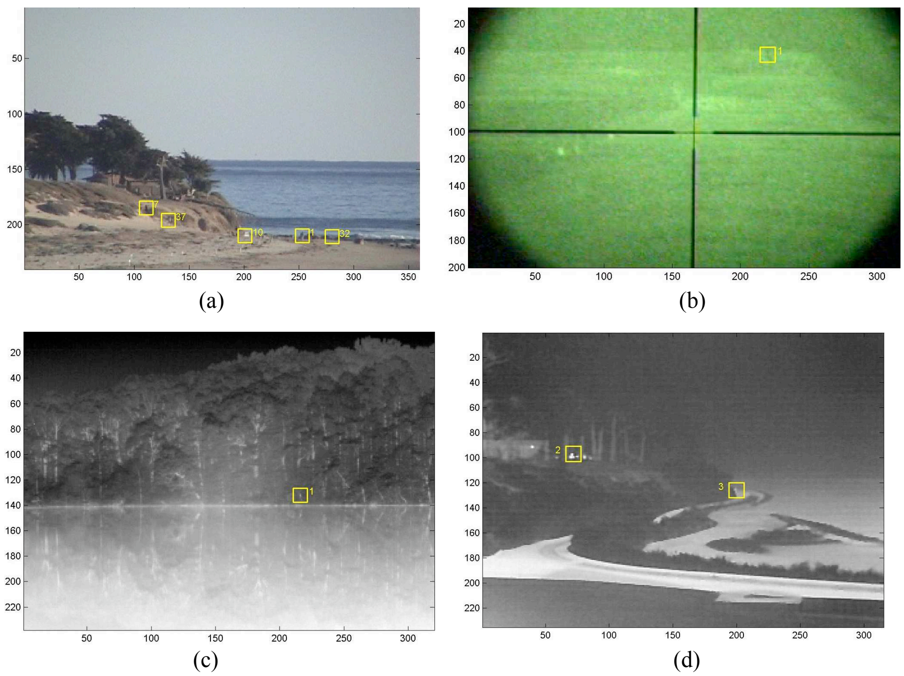



**Figure 3.** In (a), we demonstrate detection and cueing at 2,000 m during the day in the presence of swaying vegetation and large ocean waves. In (b), we demonstrate detection of a human at a range of 600 m at night using image intensified ($I^2$) video. In the MWIR image in (c), the human is almost completely obscured, yet the IPVT obtains detections consisting of a single pixel. In (d), LWIR video is used to detect and track multiple humans partially occluded by vegetation near a lagoon, including some detections at long range, imaged with only 3 pixels on target.

Figure 4 shows the geometry of the image plane target geo-location problem. Solving this problem in real-time requires extremely tight synchronization of the UAS video frames with the UAS state data. Therefore, there is a significant performance advantage associated with performing this computation *on-board* the UAS platform.

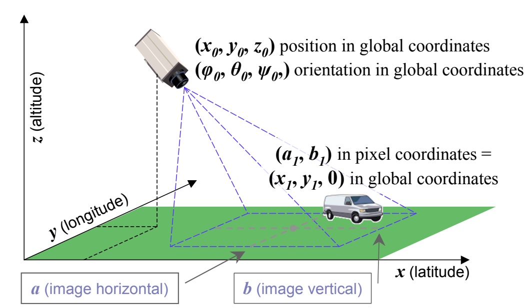



**Figure 4.** The geometry of image plane target geo-location

Toyon has already developed a prototype GFTC that fuses EO and IR video tracking data from the IPVT with state data from one or more cameras to geo-locate an image plane track in a global coordinate system. Toyon's GFTC is already set-up to receive track state input from multiple sensors, and use these different video data streams to provide higher target estimation accuracy. The GFTC algorithms have been tested in real-time, processing tracks received from UAS as well as stationary cameras. The system maintained track on a target to within a two-meter error.

Under this project, we will adapt Toyon's GFTC to the GeoTrack system architecture. A significant technical challenge will be embedding this software on a small, low-power FPGA to enable it to run on-board the UAS platform. Working from Toyon's existing, tested, operational GFTC software will speed the development of the GeoTrack GFTC, as adaptation of the existing, tested algorithms can be performed much faster than the development of the algorithms from scratch.

### 4.3 Improved Target Geo-location Using Distributed Sensor Fusion over Networks

Although position estimates for each target can be obtained by a single UAS (as described in Section 4.2), by fusing measurements across a UAS network, a more accurate target position estimate can be computed. In addition, track ambiguities (possibly resulting from vehicles that travel very close together) can often be resolved by using information from several UAS.

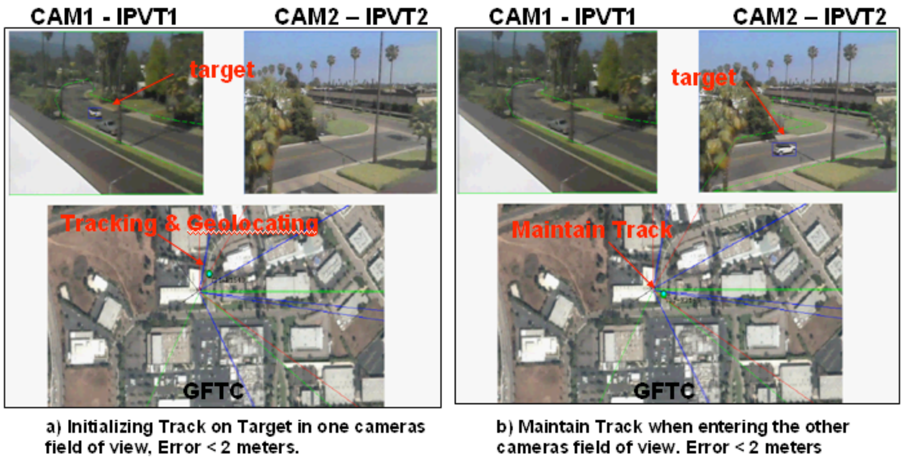
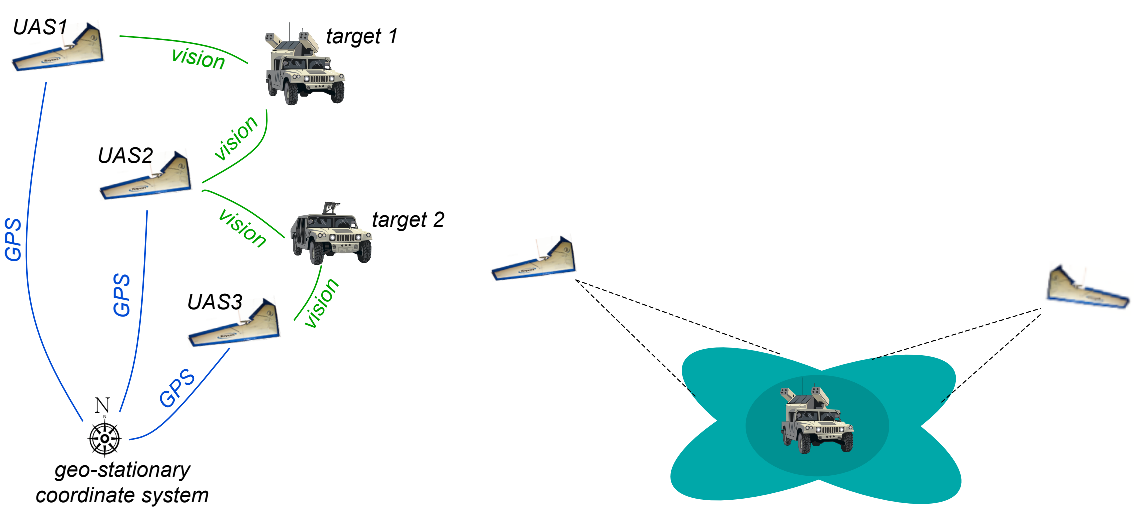



**Figure 5.** Maintaining Tracks from a real-time, live, on-site testing of the IPVT and GFTC combined. Two IPVTs are connected to a GFTC over a wireless network. Each IPVT is wirelessly transmitting local track information to the GFTC, while the GFTC attempts to associate the measurements properly and track the targets in a global coordinate frame. (a) Depicts the tracking of a target in one field of view, while (b) maintains the single track on the target from another field of view.

The advantage of using multiple UAS in accurate target tracking with noisy information can be easily understood from the example in Figure 6. Figure 6(a) shows the measurements available to a team of three UAS as they track two targets. UAS 1 and 2 are both able to obtain position estimates of target 1. If these UAS communicate and combine these two estimates, they can significantly reduce the overall estimation error. This is especially important for highly anisotropic footprints of the estimation errors, as shown in Figure 6(b). These types of error footprints are common in vision-based sensors viewing the ground from low grazing angles: the projection of the image frame onto the ground produces errors that are exaggerated in one direction. If the two UAS are so positioned that the major axes of their error ellipses are orthogonal to each other, as shown in Figure 6(b), the resulting target geo-location estimates will be much more accurate than what a single UAS can provide.




(a) (b)

**Figure 6.** (a) GPS and vision data available to a group of three UAS as they track two targets. (b) Reduction of estimation error by combining estimates from different UAS.

To achieve accurate target geo-location, target positions must be estimated by fusing the positions of the UAS and relative position measurements between UAS and the targets. By relative position measurement, we mean a measurement of the form

$$z_{u,v} = x_u - x_v + \varepsilon_{u,v} \tag{1}$$

where $x_u$ and $x_v$ may represent the position of a UAS (node $u$) and the position of a target (node $v$) at a particular time instant, respectively, and $\varepsilon$ is a measurement noise that is characterized by a covariance matrix. Between GPS updates, a UAS must rely on the IMU data to extrapolate its current position from the position where it received its last GPS measurement. In addition, the UAS can use (perhaps very coarse) models for the target motion to propagate the target position estimates forward in time. Such propagation can be modeled as relative position measurements as well. Therefore, relative position measurements of the form (1) may be available between UAS and targets, between two distinct UAS, between the same UAS at two consecutive time instants, or even between two consecutive positions of the targets. Figure 7 shows the data available at two consecutive time instants to a team of three UAS. At the first instant, the three UAS have GPS data available, but at the second time instant this data is not available and they must use IMU data to reconstruct their own positions and the target positions. Furthermore, estimation of the target positions from all these measurements should be done in a distributed manner. Distributed computation becomes especially important for a large number of UAS to meet the goal of scalable GeoTrack system.

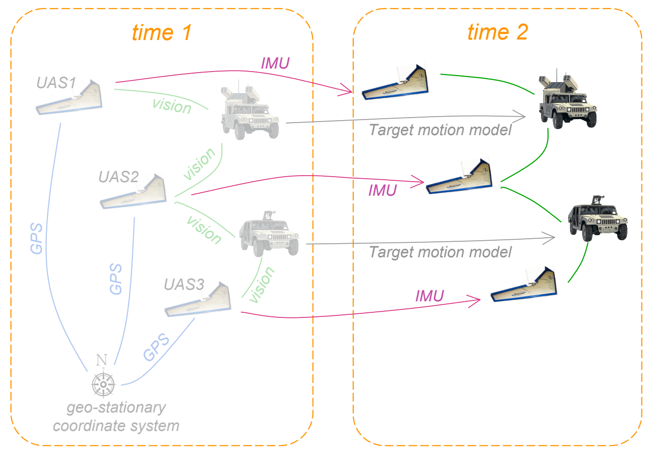



**Figure 7.** Dynamic estimation of target positions by a team of UAS

A modified version of the OSE algorithm that was developed in,[3] will be used to solve the distributed target location estimation problem. In this multi-UAS sensor fusion algorithm, every target is assigned to a particular UAS (see Section 4.6). The UAS will combine the relative position measurements with the target (and possibly other UAS) and IMU propagation data to obtain the current best position estimate of the target. This computation involves solving a linear least-squares problem, which can done in the on-board processor. Figure 8(a) shows the "measurement graph" that represents the situation shown in Figure 6(a) in an abstract manner. The nodes of a measurement graph represent the positions of two target and three UAS at a number of time steps. The edges of the graph represent noisy relative position measurements between the nodes of the form (1). The OSE algorithm was developed for a fixed graph, and is an extension of the Jacobi algorithm[5] that was inspired by swarming behavior in animal groups. In the Jacobi algorithm, a node obtains multiple estimates of its own position by adding relative position measurements to the position estimates of its neighboring nodes, and updates its estimate by averaging them. In the OSE algorithm, nodes carry out a similar procedure, but it averages estimates obtained from nodes further away that were transmitted from the nearest neighbors. The OSE algorithm therefore still uses only local communication, but can be easily extended to the UAS sensor fusion problem in which the graph is increasing with time. In Figure 8(b), the local subgraph of UAS 1 consists of nodes and edges about which UAS 1 has information. UAS 1 receives the current estimates of the absolute locations of its neighboring "nodes", believes them to be the true estimates, and updates the absolute position estimates of the nodes in its subgraph. These estimates are then broadcast to UAS 2, which carries out a similar update. The updates of UAS 2 are retransmitted to UAS 1, which uses them in its next iteration. This iterative updating ensures that the target position estimates are close to the optimal. The information about further away nodes used by the OSE algorithm is an improvement on the swarming behavior that can be observed in nature, which takes advantage of the ability to carry out data forwarding in digital communications. However, the OSE algorithm still inherits the robustness properties of the original Reynolds rules, as we have shown in.[3]

### 4.4 Distributed Swarm Control of UAS Across Networks

The accuracy of target geo-location achieved by fusing measurements from all the UAS will depend on the positions of the UAS vis-à-vis the targets and themselves. The importance of the UAS positions with respect to the targets is illustrated in Figure 6(b). The estimation errors that arise in vision-based tracking are generally characterized by error covariance matrices corresponding to ellipses, with the major axis aligned with the vector from the camera position to the target.

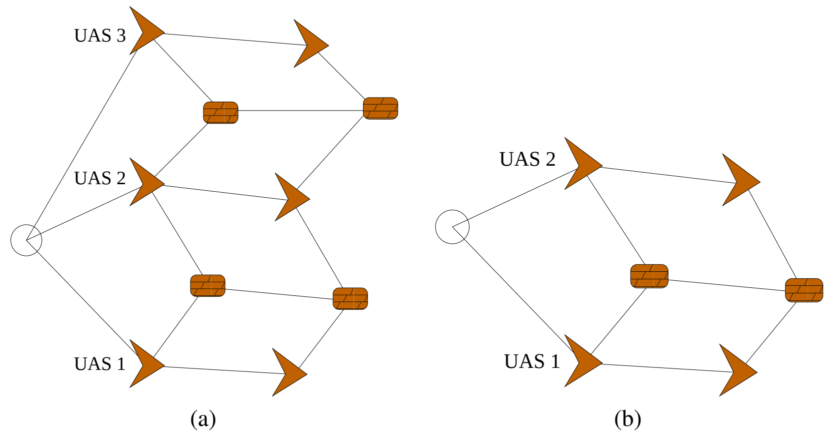



**Figure 8.** (a) A "measurement graph" for the situation shown in Figure 7, with three UAS and two targets in two time instants. (b) The local subgraph of UAS 1, assuming it receives measurements from UAS 2

These types of error footprints shown in Figure 6(b) are especially common when cameras view the ground from low grazing angles: the projection of the image frame onto the ground produces errors that are exaggerated in one direction. If two UAS are so positioned that the major axes of their error ellipses are orthogonal to each other, as shown in Figure 6(b), the resulting target geo-location estimates will be much more accurate than what a single UAS can provide.

In short, improved target geo-location requires the positions of the UAS to be controlled so that "high quality" relative position measurements are obtained. We call this part of the GeoTrack system "swarm control" of UAS. In addition, this swarm control has to be done dynamically, in real-time, since the targets might be moving and UAS may not be able to hover at one location. To be able to operate in a highly dynamic environment, the UAS should decide collaboratively where to position themselves. When multiple UAS are available to track a target, or when precise track of a particularly important target is desired, the UAS should be optimally placed in relation to one another for improved geo-location accuracy.

Automatic UAS routing algorithms can be used to determine UAS-to-target allocation and UAS trajectory generation, or to assist an operator with these tasks. GeoTrack will include technology to generate allocations and trajectories optimized for tracking accuracy. GeoTrack will *not* replace a flight control system. Instead it will generate waypoints to feed into an existing UAS flight control system. To this effect, GeoTrack will determine trajectories of the UAS so as to minimize tracking errors and account for the anisotropic error footprints (such as the ones illustrated in Figure 6(b)).

A phased approach will be used for the development of capabilities. Swarm control of the UAS will be needed when there are multiple UAS, i.e., in the MUST (Multiple UAS/single target) and MUMT (Multiple UAS/multiple target) modes of operation of the GeoTrack system.

1. **SUST (Single UAS/single target) mode.** This basic capability provides the ability for a single UAS to autonomously track and geo-locate a single target. In this mode of operation, the UAS motion may be under direct control of a human operator.

2. **MUST (Multiple UAS/single target) mode.** In this mode of operation a team of UAS will autonomously track and geo-locate a single target. This mode of operation provides high-accuracy location information by fusing the measurements from multiple UAS. The use of multiple UAS also makes tracking especially robust to the common problem of the target momentarily exiting the image plane (Figure 9). The routing algorithm will determine an optimal UAS constellation/formation around the target. Error covariance matrices corresponding to ellipses generally characterize the estimation errors, and the error is minimized when multiple UAS track a particular target by radially distributing around the target. Once a desired constellation has been found, maintaining the formation becomes a distributed control problem similar to the swarming problems analyzed in.[4]

3. **MUMT (Multiple UAS/multiple target) mode.** In this mode of operation a team of UAS is responsible for tracking a group of targets. This requires the UAS to first decide on appropriate UAS-to-target assignments (Section 4.6). The assignment of targets to UAS will not be predefined and will respond the current target/UAS locations. Two different scenarios are possible:

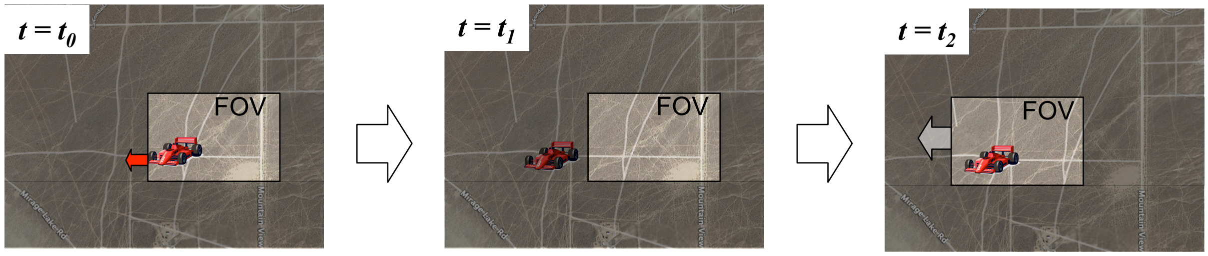



**Figure 9.** A portion of the video tracking scenario in which the target temporarily leaves the UAS sensor field of view (FOV). The global tracking capabilities of GeoTrack enable the UAS to quickly re-acquire the target.

3a. The number of targets is greater than the number of UAS. In this case, multiple targets may be assigned to each UAS. Each UAS will estimate when its targets are likely to get out of its FOV, by using a target motion model. The UAS routing algorithm will then calculate waypoints so that the probability of keeping all the targets in the FOV of the UAS in the next time instant is maximized. Although the focus in this mode is to prevent target loss, higher accuracy than what is possible with single UAS will still be achieved. Since it is likely that some of the targets will be observed not only by the UAS to which they are assigned, but by other UAS as well, we will have a situation similar to the one shown in Figure 8(a). In this case, the sensor fusion algorithm will be able to improve target geo-location accuracy simply by fusing the available measurements between targets and UAS.

3b. The number of targets is smaller than the number of UAS. In this case, pairs of GeoTrack UAS will fuse data between their tracking databases to determine when they are both looking at the same target. The GeoTrack system will then assign each target to one UAS as the primary tracker of that target, and also determine which UAS will provide secondary sensing to the primary UAS for each target. The routing algorithm will then determine the appropriate locations and trajectories of the UAS so that the UAS-to-target relative position measurements will result in the best possible target geo-location. For example Figure 6(a) shows a situation in which there are two targets and three UAS, so that there is one UAS available to serve as a secondary tracker. The best improvement in target geo-location can be achieved when this UAS is placed at the intersection of the two straight lines, which will lead to the maximum orthogonality between error ellipses of the already available target location estimates and the one provided by the secondary UAS. In practice, however, due to constraints on camera gimbals etc., the UAS may not be able to provide measurements of both the targets from that position. The routing algorithm will determine where the UAS should be placed so that it is close to optimal but also satisfies sensor gimbal constraints (Section 4.5). Once the desired positions are determined in this manner, formation maintenance can be achieved by the bio-inspired swarming algorithm in.[4]

4. **Search mode.** In this mode of operation the UAS will search a region for unknown targets and progressively transition to the SUST, MUST or MUMT modes as targets are found. This capability will be provided as an extension to our baseline project and will leverage results from an ongoing AFOSR STTR.

All modes of operation mentioned above (except SUST) will require the team of UAS to cooperate in maintaining appropriate positions with respect to each other and the targets. This will be achieved using motion control algorithms inspired by swarming behavior of biological agents. The properties of such algorithms in terms of speed and robustness to noise have been investigated in.[4] In this paper, we have shown that tight formations can be maintained in the presence of measurement noise and communication losses. In fact, this paper provides explicit results to characterize the errors in the positions of the UAS with respect to their desired values and the influence that the topology of the communication graph has in these errors. This allows for the design of communication graphs that maintain tight formations with a small amount of communication that are robust to noisy measurements.

## 4.5 Automatic Sensor Gimbal Targeting

Toyon Research Corporation has extensive experience in the field of automatic sensor tasking and control. Our approach has been to design sensor tasking algorithms that are tightly coupled with a fusion and tracking system, such as GeoTrack, so that future sensor tasks are selected to improve the performance of the ISR system. In particular, we have specialized in dynamic sensor tasking algorithms that maximize the expected information gain to the fusion and tracking database. We employ a finite-horizon, closed-loop feedback process so that the sensor tasking algorithms are utilizing the most recent information available from the fusion module.

Toyon and Procerus Technologies have developed UAS sensor gimbal targeting logic that is particularly well suited to the GeoTrack system. The algorithms automatically target a gimbaled UAS sensor to view one or more (possibly moving) targets. These algorithms determine a location on the ground (latitude/longitude) at which to point the UAS sensor in order to maximize the expected information gain. The algorithms also stabilize the UAS sensor, enabling it to continuously point at the targeted location independent of the UAS platform motion. The targeting and stabilization algorithms also model the mechanical range-of-motion of the gimbal mechanism, to predict and avoid slewing the gimbal to a position outside its mechanical range. This targeting logic works in a finite-horizon optimal control loop, constantly re-computing the optimal targeting location every second. This targeting logic will be used in conjunction with the geo-location algorithms in Section B.6.5 to mitigate highly anisotropic estimation errors and minimize target total location error.

Additionally, Toyon has developed UAS sensor searching logic that directs the UAS to discover new targets by tasking the UAS sensor to view regions of high target likelihood. This logic will be used by GeoTrack UAS to survey and identify potential threats in an un-scouted region.

## 4.6 UAS-to-Target Allocation Algorithms

Appropriate assignment of UAS to targets is critical for maintaining a cooperative tracking system. Toyon has developed optimal yet efficient assignment software based on the Auction Algorithm.[12] Our algorithm considers the reward for each potential UAS-to-target assignment, weighted against factors like fuel costs, available UAS resources, and wind.

## 4.7 High-Fidelity Simulation

Our research team has the unique advantage of using SLAMEM® for the simulation and analysis phase of this 6.2 research project. SLAMEM is Toyon's high-fidelity battlefield simulation tool. SLAMEM incorporates realistic entities such as terrain, roads, wind, 6-DOF flight models, and detailed sensor models. SLAMEM presents a unique and valuable opportunity for our team to analyze the proposed tracking and control system in a high-fidelity Monte Carlo based simulation. Toyon customers including DARPA, JFCOM, Army, Air Force, Navy, and NRO use the SLAMEM simulation environment. Many of Toyon's existing tracking and control programs also use SLAMEM for testing and evaluation of new algorithms. Indeed, on a current Air Force STTR program managed by Toyon, SLAMEM is playing a crucial role in the transition of our UAS tracking and control algorithms from theory to hardware demonstration. A collection of SLAMEM screenshots appears in Figure 10.

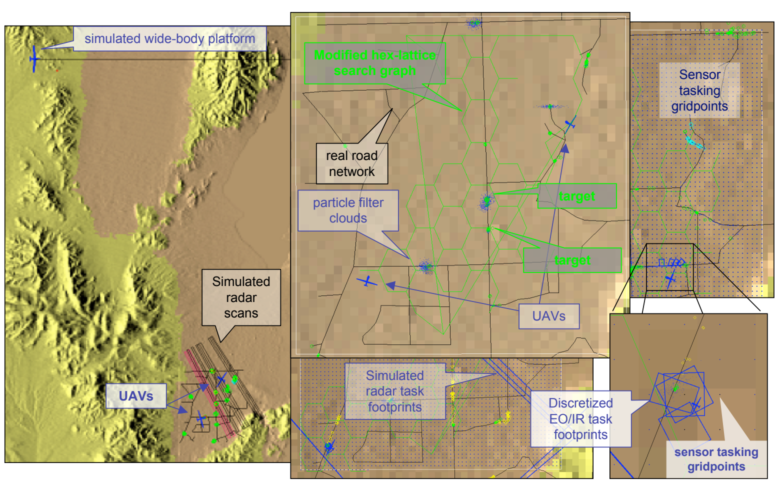



**Figure 10.** SLAMEM screenshots showing many different components of a cooperative UAS routing/tasking system, including: search graph for UAS routing; target probability grid for sensor tasking; video and radar task footprints in ground plane; target probability representation using particle filters; road network and terrain.

## 5. CONCLUSIONS

This paper describes ongoing work on the design of an electronic system, called GeoTrack, that will dramatically improve the capabilities of small unmanned aircraft systems (UAS) to cooperatively locate and track ground targets. GeoTrack-equipped UAS will employ bio-inspired distributed swarming algorithms to accomplish autonomous coordinated target tracking. Targets in GeoTrack video streams will be automatically geolocated on-board using autopilot telemetry. High accuracy geo-location will be achieved from small, inexpensive sensors by using distributed sensor fusion over the GeoTrack network.

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