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An Overview of Emerging Results in Cooperative UAV Control

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Abstract— **Inexpensive fixed wing UAVs are increasingly useful in remote sensing operations. They are a cheaper alternative to manned vehicles, and are ideally suited for dangerous or monotonous missions that would be inadvisable for a human pilot. Groups of UAVs are of special interest for their abilities to coordinate simultaneous coverage of large areas, or cooperate to achieve goals such as mapping. Cooperation and coordination in UAV groups also allows increasingly large numbers of aircraft to be operated by a single user. Specific applications under consideration for groups of cooperating UAVs are border patrol, search and rescue, surveillance, communications relaying, and mapping of hostile territory.**

The capabilities of small UAVs continue to grow with advances in wireless communications and computing power. Accordingly, research topics in cooperative UAV control include efficient computer vision for real-time navigation and networked computing and communication strategies for distributed control, as well as traditional aircraft-related topics such as collision avoidance and formation flight.

Emerging results in cooperative UAV control are presented via discussion of these topics, including particular requirements, challenges, and some promising strategies relating to each area. Case studies from a variety of programs highlight specific solutions and recent results, ranging from pure simulation to control of multiple UAVs. This wide range of case studies serves as an overview of current problems of interest, and does not present every relevant result.

Index Terms — UAVs, formation flight, computer vision, communications and control, hybrid systems, control architectures, multi-agent systems.

I. INTRODUCTION

The cooperative control of groups of small, inexpensive UAVs (unmanned aerial vehicles) is of great interest in military and civilian applications, including mapping, patrolling, and search and rescue. These tasks may be repetitive or dangerous, making them ideal for autonomous vehicles [29]. In these types of applications, the group of UAVs becomes a mobile sensor network, and must have capabilities including aircraft to aircraft communication, navigation, and collision avoidance.

Part of the growing interest in UAVs stems from the increasing feasibility of these goals due to advances in small and efficient processors, cameras, and wireless networking [38]. The cooperative UAV control problem is of further interest due to the challenges of distributed control over wireless networks, the highly non-linear flight dynamics of light fixed-wing aircraft, and the difficulty of real-time computer vision and depth perception.

In the following sections, we present an overview of current work in cooperative control of fixed wing UAVs. Section II describes the specific problem domain to be presented and major areas of development, and section III introduces current issues in these areas. Section IV presents developments based on a number of case studies. Finally, section V draws some conclusions about the current state of development and possible future directions.

II. PROBLEM DOMAIN AND ASSUMPTIONS

This paper addresses the cooperative control of groups of UAVs in sensing applications. These applications use small, fixed-wing UAVs with onboard processing capability, vision or GPS navigation and wireless communication. Programs emphasize communication, sensing, and group control in order to safely negotiate unknown environments while efficiently collecting information. Therefore, solutions include wireless communication protocols, robust computer vision algorithms, vision-based navigation, and distributed control strategies for scalability to large groups.

III. ISSUES IN COOPERATIVE UAV CONTROL

Current issues in cooperative UAV control are presented by topic. *Aerial surveillance and tracking* allows vision-based control. *Collision and obstacle avoidance* and *formation reconfiguration* ensure safe cooperation for groups of aircraft. *High level* control is needed to coordinate large groups of UAVs and for real-time human interfacing, and all of these depend on system *hardware and communications*.

A. *Aerial Surveillance and Tracking*

Surveillance, detection and tracking have been studied and developed in the past for static security cameras, ground vehicles [13], [24], [11] and manned aircraft [21]. The

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main challenges of migration to UAVs are due to the physical constraints of the platform and the strict real-time requirements of the applications. It is usually not feasible to carry significant amounts of hardware due to size, weight, and power limitations. At the same time it is of paramount importance to process the sensor input at a real-time rate: while some seconds of delay in the recognition of an intruder for a security camera application may not be a problem, this could result in loss of the target in a UAV application due to the high speed of the aircraft.

B. *Collision and Obstacle Avoidance*

Collision and obstacle avoidance are the basis of safe UAV flight. Here, collision avoidance refers to non-collision among cooperating UAVs, and requires that aircraft either detect each other using sensors or report their positions. With the limitations of onboard vision processing and the popularity of GPS navigation, GPS position reporting is common. Collision avoidance is usually incorporated into a cooperative flight algorithm. A formation flight algorithm can guarantee aircraft safety through specific relative position requirements (a fixed formation: [25], [32]) or through general rules governing UAV interaction [35], [36].

Obstacle avoidance is distinguished by lack of knowledge and cooperation: an obstacle may take any form and may be either inert or hostile (including seeking a collision), hence detection is a primary problem. The ability to see and avoid obstacles is a necessary condition for flight in civil airspace [9], and for low altitude applications such as urban canyon navigation. Once an obstacle has been detected, the flight path must be altered in order to ensure aircraft safety while minimizing deviation from the optimal path and continuing to ensure collision avoidance.

C. *Formation Reconfiguration*

When UAVs perform a cooperative task by flying as a group, they can be considered flying in a formation. A formation may be rigidly defined by desired relative position vectors, or loosely defined such as through artificial potential field methods. Formations must safely reconfigure in response to changing missions, UAV populations and environments.

Using a hybrid systems approach, a specific formation can be seen as a finite state machine, where transitions between different formations (or state machines) can be triggered by changes in mission or environment [38]. The transition processing must reassign aircraft to positions in the new formation and provide trajectories from the initial formation positions to the new ones. These trajectories must guarantee aircraft safety, be compatible with aircraft dynamics, and may be governed by a time constraint, such as when reconfiguring a formation to pass between obstacles.

For a loosely defined formation such as a flock, reconfiguration may be inherent in the formation flight algorithm [22].

D. *High Level Control*

High level control for a group of UAVs may include a user interface, a communications framework, and the logic to translate mission-level commands into resource allocations and individual UAV or formation assignments. A user interface may fuse sensor data from all of the UAVs and present it in a comprehensible form, such as a combined threat map [26]. The communication framework must allow the UAVs to communicate adequately for navigation and reporting, while reconfiguring itself in response to communication range limits. The choice of control methodology and the communication requirements are strongly coupled, and so must be considered simultaneously.

The overall logic is generally modular in order to decompose the otherwise large control problem. It should also be flexible with regard to specific hardware implementation, sensor and UAV types [26].

E. *Hardware and Communication*

Recent academic efforts have concentrated on small, low-cost aircraft, severely restricting the payload, endurance and capabilities of the vehicles. Sensor choices are intimately tied to the platform and constraints on payload size, weight, and power. Vision systems utilizing conventional and/or infrared cameras are commonly used for mapping and obstacle detection/avoidance applications because of their relatively low cost and power requirements. However, they require considerable on-board computation. Radar systems are also used as an alternative or to complement other sensor packages for this same set of applications.

A major un-resolved issue for collaborative unmanned aircraft is wireless communication with other cooperating aircraft and/or the ground. The aircraft to ground problem generally involves out of line-of-sight, long-range communications. The most challenging requirements are to deliver real-time video to the ground over long ranges, possibly including encryption to ensure security.

Aircraft-to-aircraft communication is a more recent problem with the increased availability of wireless LAN and GSM technologies, and to date the authors have not found a field-tested COTS solution. Difficulties include finding antennas with suitable (ie. truly omni-directional) patterns and low power requirements. In addition, high-bandwidth communications may be needed. Cooperation algorithms may require either small packets with short rotation times, or large packets, such as imagery, with longer rotation times. Aircraft-to-aircraft communications may also be required in out of line-of-sight conditions due to distance or obstacles. Finally, novel communications protocols must be introduced to provide reliability and scalability under these conditions, as some applications may require a hundred or more UAVs.

IV. CASE STUDIES

In this section we present a number of case studies from programs throughout the country, focusing on progress in hardware implementation, aerial surveillance and tracking, fixed formation flight, flocking formation flight and high-level control.

A. *Aerial Surveillance and Tracking*

This section presents work from UC Berkeley, Sarnoff Corporation, and the University of Massachusetts at Amherst on target recognition, tracking, and image mosaicing.

1. The Convoy Protection System

The aim of the convoy protection system developed by the C3UV (Center for the Cooperative Control of Unmanned Vehicles) group at Berkeley is to provide local and over the horizon camera coverage for a ground vehicle (GV) from a UAV, which will provide the GV driver with knowledge of the surrounding environment.

The first version of the system [18] relied on an external GPS signal to track the vehicle. This dependence made the system unusable for hostile targets or under GPS scrambling, which led to the vision-based second-generation system [14].

The main challenge is to provide precise and robust tracking without dedicated hardware and using minimal processing power, since the CPU is shared with other time-critical applications.

A "cascade" approach, previously used for digit recognition in [1], was taken for target detection. First, lightweight and less discriminating classifiers with a near-zero false negative rate are applied, followed by more complex and precise ones in areas that were initially judged interesting.

The classifiers employed detect targets relying on independent motion, brightness and shape cues. A moving object can be detected as follows: first, two successive frames are "registered", i.e. aligned. Traditionally this is done using an affine transformation, with parameters found iteratively using the Levenberg-Marquardt algorithm to minimize the square difference in intensity on the overlapping areas [34] between the first frame and the second (affine transformed) one. Then they are subtracted. If we observe an almost 2D scene (as the ground appears from a plane), the results of such an operation are the moving objects.

A two-step approach speeds image registration. First, correspondences between successive frames are found using feature tracking techniques. Traditionally, this is done by selecting a window around the feature in the first frame and then finding the most similar window (in terms of square difference of the pixel intensities) in the second frame [19], [4].

Then, registration transformation parameters are computed from the feature flows. To speed up computation and given the small displacements between successive frames, the transformation has been approximated by pure translation.

Unfortunately, this motion-based approach does not work if the environment is not flat: 3D features appear to have independent motion, called "parallax motion". This problem has been addressed by filtering out false positives using different classifiers in cascade. The resulting strategy is lightweight and robust.

Fig. 1. Successive frames are aligned and subtracted [8]

2. Aerial Video Surveillance System

The aim of the "aerial video surveillance system" (AVS) developed by the Sarnoff Corporation is to provide enemy observation, resource monitoring, and search and rescue [17]. The core of the AVS system is the ACADIA chip [44], for fast image alignment, moving object detection and tracking, geo-registration, and video mosaicing (i.e. stitching many frames together to create an aerial map).

The AVS also relies on motion cues for object detection. Dedicated hardware allows fast and precise image registration. The displacement of every pixel between two successive frames is modeled as the sum of global (background) motion and parallax motion. The traditional two step approach is replaced with a faster, robust single step method [2], [16].

Tracking of moving objects is obtained by recording their state information (motion, appearance and shape) over time. Based upon this state, a maximum a posteriori (MAP) algorithm updates the state at every instant using an expectation maximization approach [37].

The AVS system also has geo-referencing features: given an environment database, a frame can be registered with that environment for localization. This capability has been used by MLB [20], to detect static objects (e.g. hidden explosives) in the scene. The frames captured on-board are georeferenced and then presented to a human, along with frames from the database, for comparison and detection of any suspicious changes. A fully automatic solution was explored but resulted in unacceptable numbers of false-positives.

3. Related Work

An alternative approach to image mosaicing has been taken at the University of Massachusetts at Amherst. Though not applied to the particular case of target detection, the high quality registration and 3D scene reconstruction can be used for that purpose.

This "parallel ray interpolation for stereo mosaicing" (PRISM) algorithm [40], [41] follows three steps. First, the image is rectified, i.e. transformed to appear as if the camera was looking straight down. To perform this step, the UM system relies on a GPS/INS and laser profiler system. Then, overlapping slices of successive frames are

registered, and then the third step conducts 3D reconstruction. This algorithm's performance is not currently real time: it processes at 1 fps [42].
Alternative non-motion-based approaches may be very fast but usually require an a-priori model of the target, and can therefore rarely be used for surveillance. An example of this is the Berkeley BEAR helicopter landing project, where the position of the landing platform is estimated by detecting a white pattern on the black platform using brightness thresholding [47]. Then the single blocks are detected using a standard connected component algorithm [12]-[10], and the corners of the blocks are determined. The position of the platform is then reconstructed from the position of the corners. The resulting video detection system is extremely fast (30 Hz) and robust.

B. *Fixed Formation Flight*

Here we present work from the UC Berkeley C3UV group. Murray and others at California Institute of Technology also have relevant results using structural potential functions [23] and model predictive control [7].
The Berkeley C3UV program is introduced in the first case study of the previous section. One should note that the ground vehicle's velocity may be less than the minimum UAV forward airspeed, calling for a tracking algorithm as well as formation flight.
The tracking algorithm generates an orbital trajectory which satisfies aircraft dynamic constraints and causes the UAV to pass over a point of interest (defined relative to the ground vehicle) at a specified frequency. As the ground vehicle speed increases from zero to the UAV airspeed, the orbital trajectory transitions smoothly from a circle to a figure eight to a sinusoid with decreasing amplitude [18].
The formation controller is based on generalized formation coordinates, L (location), O (orientation), and S (shape). The desired location and orientation of the formation are determined by the orbital trajectory, and the formation controller produces an individual trajectory for each member of the formation based on the shape.
Because each vehicle is controlled relative to a common reference point (rather than nearest neighbor only), the formation will be string or mesh stable. This means that a disturbance will be attenuated as it propagates through the formation, as derived in [25] and [32]. This of course requires sufficient communication for each aircraft to know the location of both its neighbors and the aircraft that define the reference point position.
These algorithms have been verified using a formation of two SIG Rascal UAVs (see figure 3) equipped with Piccolo avionics boards and the associated ground station, as well as through hardware in the loop simulations.

C. *Flocking Formation Flight*

Here we present flocking strategies for obstacle avoidance from California Institute of Technology and UC Berkeley. The UAV flocking and stability research at the University of Pennsylvania is also of note [35], [36].

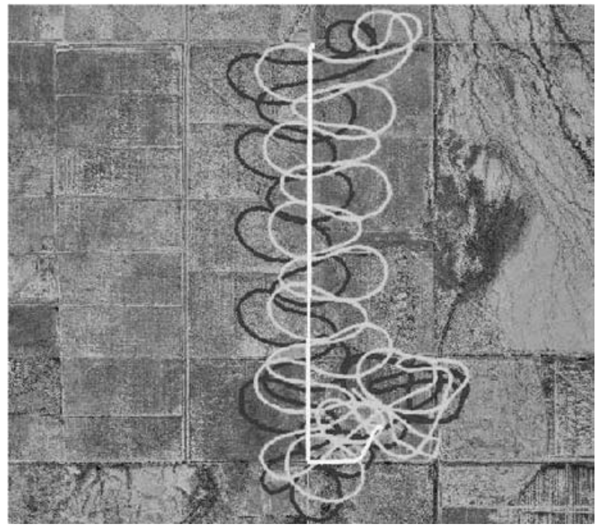

Fig. 3. Aircraft and truck paths [31]

1. Graph-based Flocking with Obstacle Avoidance

Murray and Olfati-Saber at California Institute of Technology use graph theory as a basis for the analysis and control of large groups of cooperating agents. Flocking behavior is based on prioritized interactions between three agent types. When a flock member (α) detects an obstacle, it creates virtual β and γ agents, and its behavior is then determined by the locations of all agents, prioritized to ensure obstacle avoidance.
Interactions between α agents are represented using a structural net [3] and can be characterized as attempting to keep a specified neighbor separation. The control law is based on the structural energy of the flock. A development of interest is the representation of Reynolds' three boid protocols [28] using a single protocol for α- α interaction [22].
Net stability is addressed for α- α interaction, and obstacle avoidance results are shown through simulation of 100 agents flocking through 6 obstacles, including split and rejoin and squeezing maneuvers [22].

2. Genetic optimization for flocking parameters

Swarming behavior depends on a balance between attractive and repulsive forces, which is established by constant parameters in an artificial potential field function. Zodhi at UC Berkeley employs a genetic algorithm [6] to select optimized parameters for a swarm flying through specific obstacles toward a target. Optimization is performed offline for a variety of scenarios, resulting in a library of real time artificial potential field controllers.
In this scenario, the potential field is decomposed into forces due to neighbors, obstacles, and the target, each of which is described by two parameters: alpha and beta. A cost function is defined which favors rapid proximity to the target and heavily penalizes collisions. Classic gradient-based optimization methods are not robust with

regard to this cost function, leading to the use of genetic search methods [43].

The genetic search method employed requires simulation and evaluation of the swarm behavior for many values of the six potential field parameters (alpha and beta for neighbors, obstacles, and the target). Therefore, a computationally efficient method to integrate the swarm members' equations of motion is an important part of the optimization. This is accomplished by controlling the time step size and number of iterations to meet specified error tolerance in the solution of discretized differential equations [43].

In this implementation of genetic search, the two best designs are retained into the next generation. This insures that the maximum performance does not decrease, and also reduces simulation requirements because those designs do not need to be simulated in the next generation. This method has been successfully simulated for large swarms moving through a variety of obstacle configurations.

D. *High Level Control*

High level control of groups of cooperative agents is a very popular problem, and many developments for robots or other autonomous vehicles can also be applied to UAVs. Some additional programs of interest are at UCLA [45] (in cooperation with CalTech, MIT, and Cornell), SRI International [33], and Carnegie Mellon University's Robotics Institute.

The UC Berkeley MICA (Mixed Initiative Control for Automata Teams) Architecture presents an integrated solution for UAV navigation in unknown hazardous environments. By dividing the large scale UAV control problem into a number of hierarchical, modular tasks, this architecture is adaptable to a variety of missions, strategies, and sensors.

The architecture includes the following modules: a team manager, UAV managers, and a sensor information processor. The team manager is responsible for group control such as resource allocation. The UAV manager (one per UAV) can receive high-level commands for a single UAV, such as "search an area for threats" [26]. A low level autopilot, such as the Piccolo system, is subordinate to the UAV manager.

The sensor information processor integrates sensor data from a group of cooperating UAVs. It combines sensor data with any previously known information as a probability map, which is updated using Bayes' rule when new threats are detected. This results in a shared risk map, which is used by the UAVs for safe path planning.

Current mission implementations include "strategic search" (safe navigation between points) and "threat search" (area threat mapping). Both of these make use of a "safe flight" algorithm [27], which decreases a UAVs forward progress to allow sufficient processing time to search the forward area for threats.

Strategic search follows an optimization strategy for the minimum risk path to the desired location. Each time the risk map is updated, the least-risk path is reoptimized from the current location. This has the completeness benefit of guaranteeing finding a safe solution if one exists.

For threat search, the UAV manager first generates a space filling curve (a series of way points) to map the designated area. The UAV navigates by following the minimum risk path to the next way point, updating the risk map as threats are detected.

These tasks have been simulated using the described architecture on the MICA Open Experimental Platform.

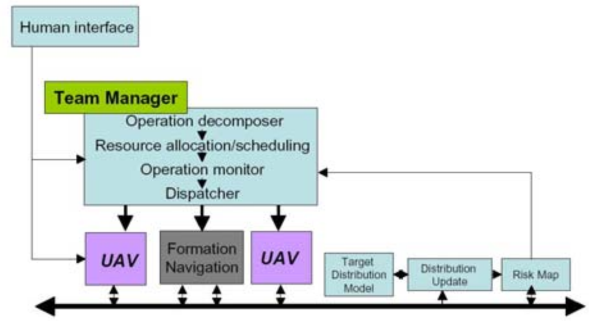

Fig. 4. MICA Architecture [26]

E. *Hardware and Communication*

The most common platform is a small, heavily modified fixed-wing aircraft comparable to a SigRascal, with a wingspan of 6 to 10 feet, powered by either a glow or gasoline engine and with a payload capacity on the order of 10 pounds. This type of airframe is used by UC Berkeley [14], Stanford [46], the University of Pennsylvania, and MIT. The avionics for the aircraft are typically either custom-built systems [46] or a COTS autopilot unit like the Piccolo, made by CloudCap Technologies [49].

An additional computing platform, typically a PC104, is usually onboard the aircraft to provide higher-level control, trajectory planning, and sensor data processing. That platform typically runs some version of the QNX real-time operating system. The typical sensor configuration includes GPS, an IMU, and vision, IR or radar. Aircraft to aircraft communication solutions include a joint UCB-UCLA effort using PCMCIA radios and 802.11b. The solution is untested as of yet but research efforts are ongoing.

V. CONCLUDING REMARKS

As computer processing and wireless communication hardware becomes smaller and cheaper, UAVs will continue to be desirable in new applications and in replacement of manned aircraft, with increasing requirements for autonomy and reliability. These will be contingent upon continued progress in computer vision, vision-based navigation and obstacle detection, and distributed onboard control. System architectures must be developed to allow navigation, mapping, and fault handling at a group as well as individual level.

This paper has focused on a few representative UAV research programs. All of the areas discussed, especially computer vision and distributed control, incorporate solutions from a variety of fields such as robotics and computer science, which are critical to progress in UAV control.

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