A Flexible Human-Robot Team Framework for Information Gathering Missions

Shaun Brown, Jake Toh and Salah Sukkarieh
ARC Centre of Excellence for Autonomous Systems
Australian Centre for Field Robotics (ACFR)
The University of Sydney, NSW, Australia
{sh.brown,j.toh,salah}@cas.edu.au

Abstract

In this paper we propose a reference framework for Human Multi-Robot teams for information gathering. The framework combines a three tiered hierarchical control scheme with the JDL information fusion model. The decision making process is decomposed by function and related to the appropriate information fusion process. We apply this framework to a problem involving search, track and classification of targets in a structured environment and show simulation results of shared control between human and software based decision makers.

1 Introduction

Uninhabited vehicles continue to gain popularity as information gathering platforms for military operations, with many *Uninhabited Aerial Vehicle* (UAV) types successfully deployed. Many other applications for autonomous vehicles are emerging in law enforcement, homeland security, space exploration, search and rescue, bush fire fighting and environmental surveying.

Traditionally, more than one human has been required to operate a single platform. One of the goals of autonomous systems related research has been to allow a single operator to effectively control a group of platforms. Programmes such as the J-UCAS [Prabhala *et al.*, 2003] and the now defunct UCAR [DoD, 2005] are pushing this single operator concept further. These programmes aim to place a human in control of a robot team, interacting and exercising control as would be done with a human subordinates, while still requiring the human to perform complex tasks such as flying. This poses particular challenges for control, automation and operator interaction in a dynamic multi-objective mission environment.

Techniques have been developed for coordinated search for targets in unknown environments [Flint *et al.*, 2003; Cassandras & Li , 2003; Bourgault *et al.*, 2003], the cooperative classification of known targets [Chandler *et al.*, 2002; Ousingsawat & Campbell, 2002], navigating a hazardous environment safely [King *et al.*, 2004; Richards *et al.*, 2002], coordinating the arrival of UAVs at a targets or location [Furukawa *et al.*, 2004; Beard *et al.*, 2002], scheduling sensors according to an operators preferences for search, track and identify [McIntyre, 2004] and performing *Suppression of Enemy Air Defences* (SEAD) [Jin *et al.*, 2003] where UAVs were used to perform Search, Confirm, Attack and *Battle Damage Assessment* (BDA) tasks. These techniques all use some form of decomposition to cope with the complexity of coordinating and controlling multiple sensor platforms. In the above techniques, the authors use hierarchical *function decomposition* to break the process into an allocation phase, where each UAV is assigned a task, and a trajectory planning phase, where the trajectory of the UAV is generated according to the task assigned. This decomposition aids in solving the problem in real-time. An alternative approach based on *time decomposition* [Flint *et al.*, 2003; Cassandras & Li , 2003; Bourgault *et al.*, 2003] combines the allocation and trajectory planning phases and solves as a single optimization process. The planning horizon is then rolled forward during the mission runtime. However, due to the computational load, this places severe constraints on the system look ahead time and leads to myopic mission planning where tasks may be missed as they have no value within the planning horizon.

In this paper we present a reference framework for Human Human Multi-Robot teams using a three level hierarchical functional decomposition proposed by Saridis [Saridis , 2001] and the JDL Data Fusion model [Llinas *et al.*, 2004]. Many of the aforementioned techniques aim to minimize the human intervention in

a multi-platform system. However, as the quality of decisions made by the system are judged against the overall mission and are heavily influenced by context and situation, until a human like ability to reason and inference can be automated, humans should continue to have an active role in control of the system. This view of shared control between human and software based decision makers is echoed by Freed [Freed *et al.*, 2004]. The proposed interaction between different control layers in our framework allows for reconciliation of human and machine intelligence in control, while the interaction between the control and information domains provides for situation and mission dependant decision making.

The reference model framework for a Human Multi-Robot System is presented in Section 2. Section 3 provides an architecture for a single operator multi-UAV system derived from the basic framework in Section 2. The implementation of the architecture in a simulation environment is discussed, along with aspects that have been structured so as to allow demonstration on a real system. Simulation results showing aspects of the framework are presented in Section 4. Directions for future research and conclusions are discussed in Sections 5 and 6.

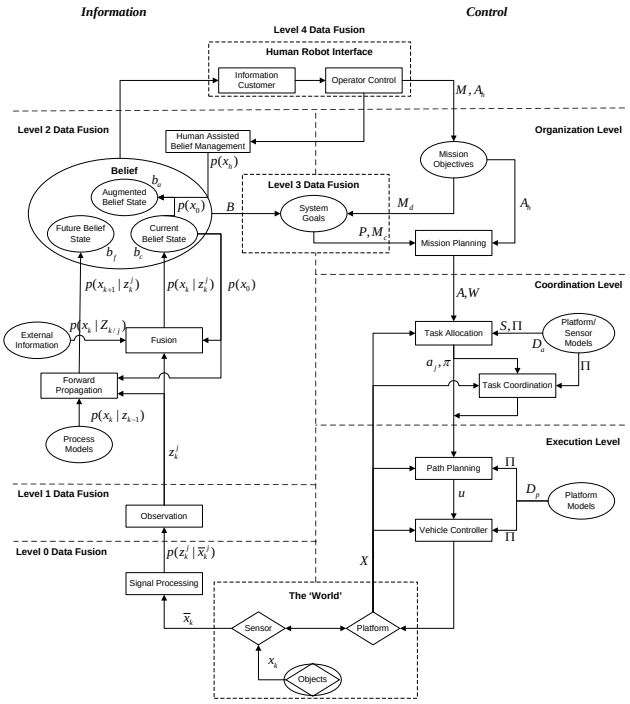

Figure 1: Proposed framework for the Human Multi-Robot System.

2 Framework

2.1 Human Robot Interface

The *Human Robot Interface* (HRI) consists of two distinct components, the Information Customer Interface and the Operator Control Interface. The system may include a number of Information Customers who are passive in terms of control. Adding a link to the Operator Control Interface provides a bridge between the information and control domains at the human level. This allows the sort of active inference, planning and refinement described in Level 4 fusion [Llinas *et al.*, 2004].

2.2 Organization Level

The decision process performed at the Organization level can be summarized as the mapping:

$$O : M \times A_h \times B \rightarrow A, W$$

where M is the system mission, A_h is the set of any discrete tasks assigned by the operator which cannot be properly defined in M, B is the current system belief state generated from all available information, A is a set of tasks, which may contain both continuous and non-continuous members and W is a value or differentiating factor for each $A_{1..i} \in A$. The term W must be consistent within the system but may be a weight, utility or cost function, priority or ranking. The system belief state, B, is:

$$B = f(b_c, b_f, b_a)$$

where b_c is the current belief state, b_f is the future belief state and b_a is an augmented belief state resulting from human input, inference or learning.

Mission Objectives

The 'mission' M describes what is required of the system and is derived from a sematic or parameter description provided by a human being. In the context of a complex or multi-objective mission, M may contain both continuous and discrete components as well as competing objectives. The mission is then mapped to a desired mission state M_d such that may be compared to the belief state of the system.

System Goals

The System Goals provide a bridge between the information and control domains of the model. The connection is provided through an evaluation of situation with respect to the mission objectives. This can be seen as a mapping of the current information B and desired mission state M_d to current mission state M_c and priority set P.

$$G : B \rightarrow M_c, M_d \times M_c \rightarrow P$$

This has been described as Level 3 fusion [Llinas *et al.*, 2004] and unlike the higher level bridge in the HRI, can be readily automated if an appropriate forms for b_c,b_f,b_a and M_d can be found.

Mission Planning
With the current mission state, M_c, and priorities, P being available, the Mission Planning process generates a system task or action set A_s such that the complete set $A = A_h \cap A_s$. Both A_s and A_h may contain continuous and non-continuous members. From the priorities P, a W value is determined for each element of A.

2.3 Coordination Level

In line with the concept of *Increasing Precision with Decreasing Intelligence* (IPDI) [Saridis , 2001], the coordination level operates at a lower level of abstraction and accounts for system capability in processing the task list A. The system capability is determined through mapping approximate models D_a to the task set A. The model set D_a has two main components, sensor models and platform models. For Task Allocation these models can be limited to such information as cruise/maximum speed or ability to traverse region in the *Area of Operations* (AO) for the platform or sensor footprint area and detectable target types for the sensor. Note that at this point any direct human control through A_h has been fully integrated into the control structure through the set A and W, reconciling the different levels of human and automated control of the system.

Task Allocation
The Task Allocation decision process can be seen as an optimization of the mapping

$$C : A \times W \rightarrow \pi$$

where π is an ordered set of tasks with each member corresponding to a sensor or platform. The optimization process seeks to maximize the objective function:

$$J(\pi) = f(W, \eta(S, \pi), \kappa(\Pi, \pi), \gamma(X, \pi))$$

The full $J(\pi)$ term is a function of four factors. The value of the task W, the suitability of the sensor S (or sensors carried by the platform if π is a platform) derived from the task and sensor model provided in D_a, the suitability of the platform Π, which is derived from the task and platform model provided in D_a and the current state of the sensor or platform X.

Task Coordination
Certain tasks may be assigned to multiple platforms or sensors and may need to be coordinated in time and/or space. For tasks which include parameters such as simultaneous arrival or observing a target from different angles, the time and space coordination may require multiple iterations of the path plan for each platform. Using multiple platforms to quickly reduce the uncertainty associated with a single object may require continuous coordination of path planners. These processes are managed through the Task Coordination component as dictated by the assigned task a_j.

2.4 Execution Level

The Execution Level is where physical control of the platforms and sensors is carried out. The control parameters will generally be in state space form, requiring more precise models of the platforms or sensor controllers than at the Coordination Level, represented by the model set D_p. If the task assigned a_j has an associated spatial representation, as will normally be the case, this is used in determining a waypoint or path for the platform. Depending on the path planner available continuous information gain through the trajectory may be included in planning.

2.5 Level 0 & 1 Data Fusion

Processing of sensor returns to associate raw signals to features and provide detection is shown as Level 0 fusion in the model. Associating these features to an entity and determining state is represented by the Level 1 fusion component. This estimation of entity state forms the observation z_k at time k which is passed up through the information domain.

2.6 Level 2 Data Fusion

Level 2 fusion provides for situation assessment by fusing sensor observations with prior information and then predicting the evolution of states. This requires entity to entity association and is thus where elements such as trackers or classifiers reside. The complete set of information, B, is the system belief state which is provided to the Information Customer and the Control portion of the model.

Update
The system's current belief, b_c is obtained by updating prior information $p(x_0)$ with new observations $z_k^{1..i}$. The prior represents the information from all previous observations up to time *k-1*.

Prediction
The system's future belief, b_f is obtained by applying the applicable process model to the elements of current belief. This is provided to the Forward Propagation component as prior information $p(x_0)$.

Augmentation
The system's belief may be augmented by information not available directly from the observations $z_k^{1..i}$. Human reasoning and inference may be used as an information

resource, observations from sources external to the system may become available and learning techniques may be applied to the process models. Note that if the process models are learned or refined probabilistically, they may be considered to reside within the belief state.

2.7 Level 3 & 4 Data Fusion

Level 3 fusion refers to impact assessment or evaluation with respect to the system's goals. This is described by System Goals. Higher level inference, process refinement and resource management, or Level 4 fusion, will occur at the human level via inputs and outputs in the HRI. Any automated situational awareness tool that performs automated inference or reasoning would reside at this level alongside the HRI.

3 Implementation

3.1 Problem Background

The model presented in Section 2 was created as part of research into managing and controlling multiple, autonomous sensor systems in highly dynamic environments. The problem for which the framework was implemented requires management of a heterogenous sensor and platform network for reconnaissance and surveillance in a structured environment using a single operator. The system consists of a number of different *Unmanned Aerial Vehicle* (UAV) types, carrying different sensor payloads. The mission is to provide sensor coverage of the *Area of Operation* (AO) while searching for, tracking and classifying targets. The targets are nominally ground vehicles of varying type and capability, constrained to moving within an urban road network.

3.2 Architecture

The architecture used is a derivation of the generalized model in Figure 1 and is show in Figure 2. The system is centralized with all fusion elements from Level 2 up, and control elements down to Coordination contained within a single process consisting of multiple threads. This is collectively called the Ground Station. The additional components of the architecture described in more detail below.

Organization

The mission M has a fixed structure consisting of search, track and classify components. The operator can specify desired parameters for M via:

- Desired accuracy of target position as a variance (Track entropy).
- Confidence level of target classification.
- Desired time to provide sensor coverage of AO.

The operator is able to explicitly specify tasks via A_h.

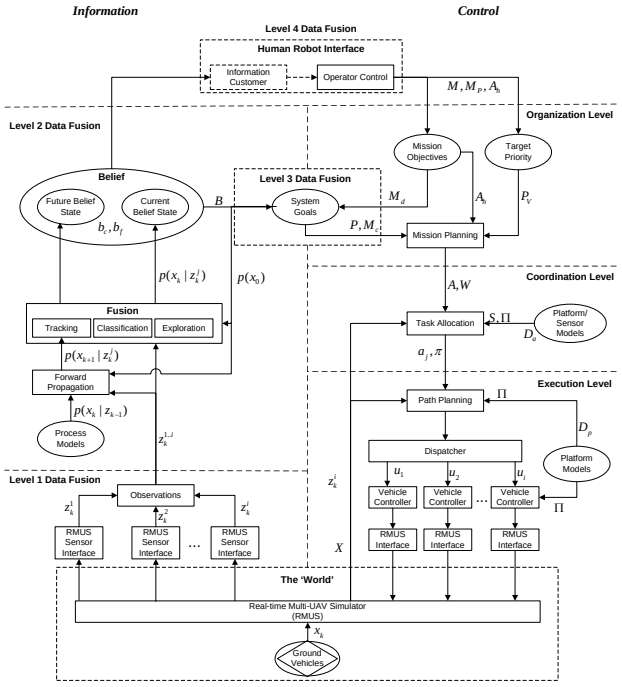

Figure 2: Architecture for a centralized single operator multi-UAV system.

These may or may not fall outside the the bounds of M. If within the bounds of M then $A_h \in A_s$ and $A = A_s$ otherwise $A = A_h \cap A_s$. In order to integrate A_h with system generated tasks and produce the full set A, W, an operator weighting M_p is required for manipulation of W. This may either be hard coded or operator defined.

As the ground vehicles have different type characteristics, target position and classification parameters can be defined by the operator according to vehicle type or sets of vehicle type.

Execution

Path planning for all UAVs occurs in the Ground Station. The Dispatcher coordinates the paths and updates the relevant UAV controller, which in turn interfaces with the *Real-time Multi-UAV Simulator* (RMUS).

Level 2 Data Fusion

Level 2 data fusion comprises three components, Tracking, Classification and Exploration, which together provide the belief state B. The current belief state b_c consists of:

- Target classification information is stored as a *Probability Distribution Function*(PDF) over all possible target types and target type sets.
- Target location uncertainty is represented by ellipses of Gaussian distribution with the mean pro-

viding the two-dimensional coordinate of the target centroid.

- The exploration state is represented by a PDF. The AO is discretized into cells with each containing a probability distribution.

The future belief state b_f consists of:

- Detected targets are tracked using a Variable Structure Interacting Multiple Model tracker. The current target uncertainty is propagated forward to the planning horizon using a constant velocity motion model.
- An information decay function is used on the PDF of each cell and predicted forward to the planning horizon.

3.3 Simulation

The simulation utilizes the *Real-time Multi-UAV Simulator* (RMUS) software developed for integration and pre-flight testing of UAV hardware, systems and mission profiles. The RMUS contains detailed 6-DOF dynamic models of the UAVs used, along with the ability to model atmospheric and turbulence effects. The sensor models are also incorporated into the RMUS.

The UAV controllers are modelled using navigation and autopilot code based on that residing in the real platforms. This is interfaced to the RMUS, which receives control commands and returns information such as air data and navigation solution back to the UAV controllers. A ground vehicle simulaion module also interfaces with the RMUS.

4 Results

A snapshot of a mission is shown in this section to illustrate the application of the proposed framework and the integration of human and machine decision making. Figure 3 shows the system tracking 7 targets with each represented by 1 or more hypotheses. The size of the circles is the graphical representation of the uncertainty of each hypotheses. This example has been simplified to show the use of the architecture and includes only tracking tasks. The system generation task set A_s contains the elements: Track Target 1, 2, 3, 4, 5, 6 & 7. Using the method proposed in Section 3.2, the system assigns a weight W to each task. The operator has also explicitly created 2 tasks A_h, Track Target 2 and Track Target 3. In this case $A_h \in A_s$, thus the system derived task weightings for A_h are revised based on the operator weighting M_p.

The performance of the system is determined relative to the mission objectives and is independent of the decision making process. In this example, the single

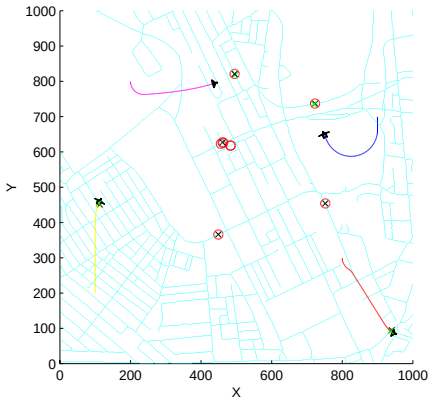

Figure 3: A snapshot of the system tracking 6 targets using 4 UAVs. Track hypotheses uncertainty is indicated by the circle size.

mission objective is specified by a desired target position variance of 40m. The desired variance is converted into a measure of uncertainty, H_{BD} as described in [Toh & Sukkarieh , 2005]. To extend the scenario further the targets are classified as either suspicious or civilian. The operator assigned priority P_V assigned to suspicious targets are double that of civilian. Hence, semantically the mission M has been modified from 'Track all targets such that track variance does not exceed 40m', to 'Track all targets such that track variance does not exceed 40m but it is twice as important to track suspicious targets as civilian targets'. Note that this change has not affected the task set A but has modified the task values W.

Four UAVs are available to the system. Using a mission planner based on minimizing track variance, the resulting UAV paths are shown in Figure 4. The revised paths resulting from information input from the operator are shown in Figure 5. At 30 seconds into the simulation the operator defined tasks, A_h are added and at 45 seconds the target priority P_V is revised. In this simple example the objective function only considers the value of the task and the current state of the UAVs. Hence the utility used for the ordered task set π:

$$J(\pi) = \sum_{1}^{A} \frac{W_A}{\frac{\sum_{1}^{N} X_N^A}{N}}$$

where $W_A$is the subset of W corresponding the the ordered task assignment π with A being the number of UAVs and X the distance of UAV(A) from target hypothesis N. The set $W(w_1,w_2..w_i)$ for i targets is given by:

$$w_i = P_V^i M_p^i H_{BD}^i$$

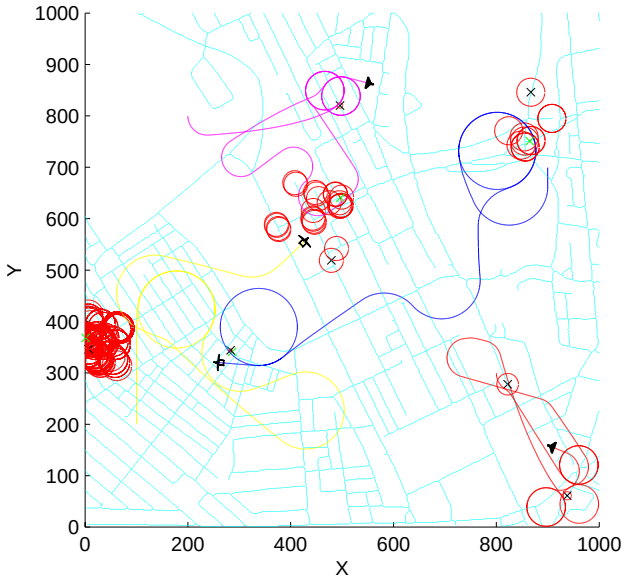

Figure 4: UAV paths without human assisted revision of task value.

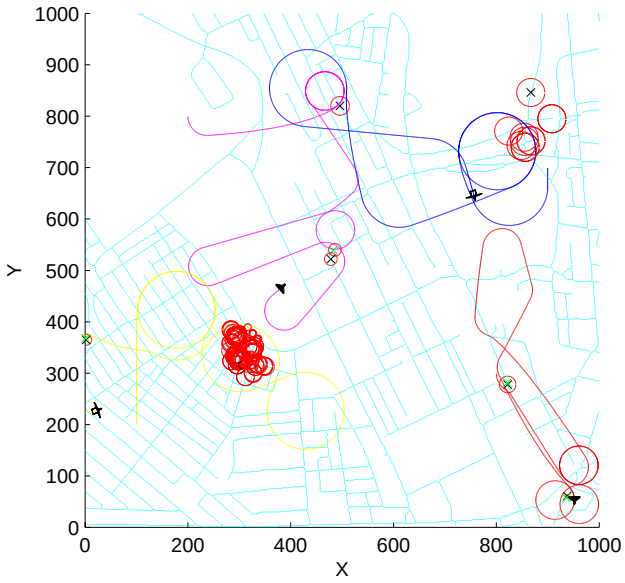

Figure 5: UAV paths with human assisted revision of task value. Note the change in target assignment

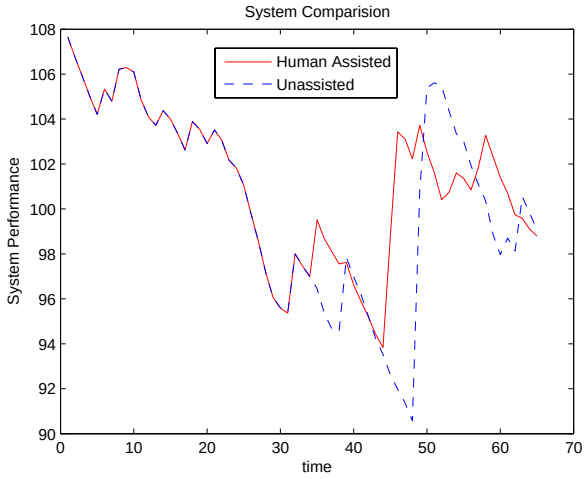

Figure 6: Comparison of system performance with and without human revision of target track value. Note the SP changes at around 30 and 45 seconds.

For the operator created tasks Track Target 1 and Track Target 2, $M_p^i \neq 1$ and for all suspicious targets $P_V = 2$.

A measure of the overall performance of this system relative to the objective can be given by:

$$SP = \sum_{i=1}^{N} \mathrm{Pr_i} \frac{H_{BD}(i)}{H_{BD}(o)}$$

where N is the number of targets, Pr_i is the priority of the i^{th} target, $H_{BD}(i)$ is the uncertainty measure of the i^{th} target's position and $H_{BD}(o)$ is the desired maximum uncertainty in target position. Note that this performance measure can be fully derived only in a simulation environment where true states are known. It does however, provide a useful analysis tool for the control scheme.

Using this measure of system performance, the completely autonomous and the combined human/machine decision making performances are shown in Figure 6. The improved overall performance of the combined decision process can be attributed to the additional information provided by the human interaction. The operator has provided higher level information regarding the importance of target type that is not otherwise available to the system, while the autonomous decision making is based on target position only.

In this example the desired variance was kept constant for both target types. This need not be the case as it is a simple process for the operator to change desired variance for different target sets, modify the desired variance based on proximity to a physical location

as well as modifying priority. With the addition of a probabilistic classifier, refined target sets and ability to set desired cell entropy for particular regions in the AO, it can be seen that a multi-objective mission description M can be quickly created to a desired level of detail.

5 Future Work

Research using the current system is focused on the Organization and Coordination Levels. The aim is to develop a framework for assigning value to expected information gain in context of both the system belief b_c and the mission M. This encompasses both representing multiple competing mission objectives such that they can be easily input and modified by the operator during the mission, and formulating these objectives in information terms. Once in the information space the aim is to map these objectives to the task set A and an associated value set W, where W is derived from the expected information gain for performing each task.

Additional work is also being done to apply the general framework presented in Section 2 to different system structures. This includes decentralized autonomous control, decentralized task requesting, distributed data fusion and various levels of platform autonomy.

6 Conclusions

This paper has presented a reference framework for Human Multiple-Autonomous Vehicle teams for information gathering. The model is generic to any multi-robot system performing such tasks and can be used as a basis for analyzing such systems. We presented and implementation of the framework for search, track and classification of targets using multiple UAVs and shown, via a simple scenario, that combining human and machine intelligence into the decision making framework can improve system performance.

Acknowledgments

This work is supported by the ARC Centre of Excellence programme, funded by the Australian Research Council (ARC) and the New South Wales State Government. This project is partly funded by the US Office of Naval Research .

References

[Beard *et al.*, 2002] R.W. Beard, T.W. McLain, M.A. Goodrich and E.P. Anderson, Coordinated target assignment and intercept for unmanned air vehicles. In *IEEE Transactions on Robotics and Automation*, Vol. 18, Issue 6, pp. 911-922, 2002.

[Bourgault *et al.*, 2003] F. Bourgault, T. Furukawa, A.H. Goktogan and H.F. Durrant-Whyte. Coordinated Search for a Lost Target in a Bayesian World. In *Proc. International Conference on Intelligent Robots and Systems*, Vol. 1, pp. 48–53, 2003.

[Cassandras & Li , 2003] C.G. Cassandras and W. Li. A receding horizon approach for dynamic UAV mission management. *Enabling Technologies for Simulation Science VII.* Edited by Sisti, Alex F., Trevisani, Dawn A. Proceedings of the SPIE, Volume 5091, pp. 284-293 (2003).

[Chandler *et al.*, 2002] P.R. Chandler, M. Pachter K.E. Nygard and D. Swaroop. Cooperative Control For Target Classification. Cooperative Control and Optimization, Edited by R. Murphey and P.M. Pardalos, Kluwer Academic Publishers, 2002.

[DoD, 2005] M.L. Hanson and K.A. Harper. Unmanned Aircraft Systems (UAS) 2005-2030. *United States Department of Defense Report*, 2005

[Flint *et al.*, 2003] M. Flint, E. Fernandez-Gaucherand and M. Polycarpou. Cooperative control for UAV's searching risky environments for targets. In *Proc. of 42nd IEEE Conf. on Decision and Control*, pp. 3567–3572, 2003.

[Freed *et al.*, 2004] M. Freed, R Harris and M.G. Shafto. Human-Interaction Challenges in UAV-Based Autonomous Surveillance. In *AAAI Spring Symposium 2004*, pp 65–70, 2004.

[Furukawa *et al.*, 2004] T. Furukawa, F. Bourgault, H.F. Durrant-Whyte and G. Dissanayake. Dynamic allocation and control of coordinated UAVs to engage multiple targets in a time-optimal manner. In *Proc. of IEEE International Conference on Robotics and Automation 2004*, Vol. 3, pp. 2353–2358.

[Jin *et al.*, 2003] Y. Jin, A.A. Minai and M.M. Polycarpou. Cooperative Real-Time Search and Task Allocation in UAV Teams. In *Proc. of 42nd IEEE Conf. on Decision and Control*, pp. 7–12, 2003.

[King *et al.*, 2004] E. King, M. Alighanbari and J.P. How. Experimental Demonstration Of Coordinated Control For Multi-Vehicle Teams. *Presented at the 16th IFAC Symposium on Automatic Control in Aerospace, June 2004.*

[Llinas *et al.*, 2004] J. Llinas, C.L. Bowman, G.L. Rogova, A.N. Steinberg, E.L. Waltz and F.E. White. Revisions and extensions to the JDL data fusion model II. In *Proceedings of the 7th International Conference on Information Fusion*, Vol. 2, pp. 1218–1230, 2004.

[McIntyre, 2004] G.A. McIntyre. A Comprehensive Approach to Sensor Management and Scheduling. PhD

Thesis, George Mason University, Fairfax, Virginia, 1998.

[Ousingsawat & Campbell, 2002] J. Ousingsawat and M.E. Campbell.Multiple Vehicle Team Tasking for Cooperative Estimation. *Submitted to American Controls Conference 2004*.

[Prabhala *et al.*, 2003] S.V. Prabhala, J.J Gallimore, S. Narayanan. Human effectiveness issues in simulated uninhabited combat aerial vehicles. In *Proceedings of 2003 Winter Simulation Conference*, Vol. 1, pp.1034-1038, 2003.

[Richards *et al.*, 2002] A. Richards, J. Bellingham, M. Tillerson and J.P. How. Co-ordination and Control of Multiple UAVs. *AIAA Guidance, Navigation, and Control Conference 2002*.

[Saridis , 2001] G.N. Saridis. Entropy In Control Engineering. World Scientific, 2001.

[Toh & Sukkarieh , 2005] J. Toh and S. Sukkarieh. Architecture for Human Multi-UAV Cooperation for Information Gathering. *ACFR Technical Report*, June, 2005.