# INTELLIGENT AUTONOMY AND PERFORMANCE MEASURES FOR COORDINATED UNMANNED VEHICLES

**A. Scott Lewis[+] and Lora G. Weiss[++]**
[+] Research Associate, asl103@psu.edu
[++]Senior Research Associate, lgw@enterprise.arl.psu.edu
Applied Research Laboratory/The Pennsylvania State University (ARL/PSU)
State College, PA

## ABSTRACT

This paper describes an autonomous Intelligent Controller (IC) architecture directly applicable to the design of unmanned autonomous vehicles and performance measures associated with intelligent autonomy. The vehicles may operate independently or cooperate to carry out complex missions involving disparate sensors or payload packages. An approach to measure the performance achieved with collaborative control is presented and simulation scenarios are provided to demonstrate how the metrics are applied.

**KEYWORDS:** *Emergent capability, collaborative control, intelligent control, unmanned vehicle, performance metrics*

## 1. INTRODUCTION

This paper describes an autonomous Intelligent Controller (IC) architecture directly applicable to the design of unmanned autonomous vehicles and collaboration and coordination between them. Two fundamental issues associated with multiple unmanned vehicle control are: how is collaboration enabled within the architecture and how is performance measured. This paper presents a behavior-based control approach for intelligent autonomy for a group of coordinated vehicles and it describes a metric for assessing collaborative performance.

There are many variants of behavior-based architectures. One of the earliest was the subsumption architecture of Rodney Brooks[1]. The basic concept is that the control system is constructed around a collection of largely independent operational capabilities referred to as behaviors or behavior-generating elements.[2,3] Prototype designs of such systems have shown that the overall capability of a system can exceed that of more conventional architectures, and sometimes to a surprising degree.

For multi-vehicle collaborative control, Chandler and Pachter[4] summarize research issues involved in autonomous control of tactical UAVs. They conclude that decision making through planning and management are the essence of the autonomous control problem, and they determine that hierarchical decomposition is a promising approach.

Stipanovic et al.[5] use decentralized overlapping control for a formation of UAVs. The dynamic model of the formation with an overlapping information structure constraint is treated as an interconnecting system with overlapping subsystems. Their approach, though, does not enable dynamic reconfiguration or the ability to reconfigure the mission plan.

Boskovic et al.[6] present a multi-layer control architecture for UAVs with four layers: (1) Fault-tolerant redundancy management, (2) Trajectory generation, (3) Path planning, and (4) Decision making. They propose a model switching method to address different failure scenarios.

Measuring performance of groups of intelligent systems is a topic of recent interest. Jacoff et al[7] present performance metrics for urban search and rescue robots with emphasis on pertinent robot capabilities and different robotic implementations. Yang et al[8] use performance metrics in the development of a collision avoidance and warning system. Zadeh[9] has introduced the concept of machine IQ (MIQ) to measure the intelligence of smart machines. However, as a metric of intelligence, the MIQ is product specific and does not involve the same dimensions as the human IQ. It is relative and the MIQ of a camera made in 1990 would be a measure of its intelligence relative to cameras of the same era and would be much lower than the MIQ of cameras made today.[10]

Several workshops on performance metrics for intelligent systems have been organized by the National Institute of Standards and Technology (NIST) and their results encapsulated in proceedings. Evans and Messina[11] discuss challenges and issues in defining performance metrics for intelligent systems. They cite government agencies basing major programs on intelligent capabilities and emphasize that there is no consensus on how to define or measure an intelligent system. However, they summarize the traits that an intelligent controller might have including: adaptability, capability of learning, doing the right thing or acting appropriately, non-linearity, autonomous symbol interpretation, goal-oriented, and knowledge-based.

An engineering perspective is given by Lee et al[12] in which they present several questions that should be asked prior to the definition of the metric of system intelligence. Among those are (1) should the intelligence measure be goal-dependent or goal-independent (2) should the intelligence measure be time-varying or time-invariant and (3) should the intelligence measure be resource-dependent or resource-independent? DeLeo[13] proposes measuring classifier intelligence by computing the area under the receiver operating characteristic (ROC) curve and using the concept of the separation index he introduces. Feddema et al. discuss their view of emergent behavior with regard to finite state machines[14].

Albus[15] claims a barrier to the development of intelligent systems is the lack of metrics and quantifiable measures of performance and that there cannot be a science of intelligent systems without standard units of measurement. While the determination of performance metrics and measures with regard to physical entities is precisely defined and accepted, performance metrics and standards for intelligent systems are loosely defined and no acceptable standards exist. This paper presents an intelligent control architecture for collaborative control and an approach for measuring performance.

The Intelligent Controller (IC) described in this paper was initially based on the subsumption approach, but actual system needs presented more challenging requirements. This resulted in a newer, more novel approach to intelligent control architectures[16, 17, 18].

Extending the IC architecture for collaborative behaviors also resulted in a unique approach for coordinated control. This resulted in the derivation of a measure of the performance gained by operating as a coordinated group of autonomous vehicles vs. a group of autonomous vehicles operating on their own accord. This metric is discussed in this paper and calculated for two scenarios.

## 2. INTELLIGENT CONTROLLER (IC) ARCHITECTURE

To appreciate the approach to measuring performance, one must understand the underlying architecture. This section provides the architecture used for collaborative control. The Intelligent Controller (IC) architecture developed at Penn State University's Applied Research Lab (ARL/PSU) is composed of two main modules: Perception and Response. The Perception module is where sensor data is analyzed, information is integrated, and interpretation of the events is generated. The Response module is where the situation is assessed, plans are generated, and re-planning or plan execution occurs. Figure 1 illustrates the IC modules for a single controller. The responses from the Response module are in the form of commands and communications to vehicle subsystems or to external systems. These systems and subsystems may be other ICs, conventional control systems (effectors), or human collaborators.

### *2.1 Perception Module*

The role of the Perception module is to create an internal representation of the external world relevant to the IC, using sensor data streams as inputs. A key capability of the Perception module is to make correct inferences and recognize the existence of properties in the representational objects (e.g., obstacles) from incomplete and potentially erroneous input data. The Perception module contains data fusion algorithms and Continuous Inference Networks (CINETs).[19] CINETs are used to infer properties or events, such as "target" or "friend", by appropriately combining multiple pieces of information in an automatic recognition process.

### *2.2 Response Module*

The role of the Response module is to plan and execute *in real time* a course of action to carry out a specific mission, given the situational awareness derived by the Perception module. The Response module is decomposed into three levels: A Mission Manager, Behaviors, and Actions. The Mission Manager retains the big picture and specifies a mission plan, which is a list of relevant Behaviors to be executed. Each Behavior has its own plan to execute, which is a list of Actions to be conducted. Control is cycled and interrupted appropriately using an Execution Engine within the Response module. The Execution Engine is an application-independent component of the Response module that calls the functions in the Response module in an appropriate order. Figure 2 illustrates components of the Response module for a UAV with a selected set of Behaviors (blue) and Actions (pink).

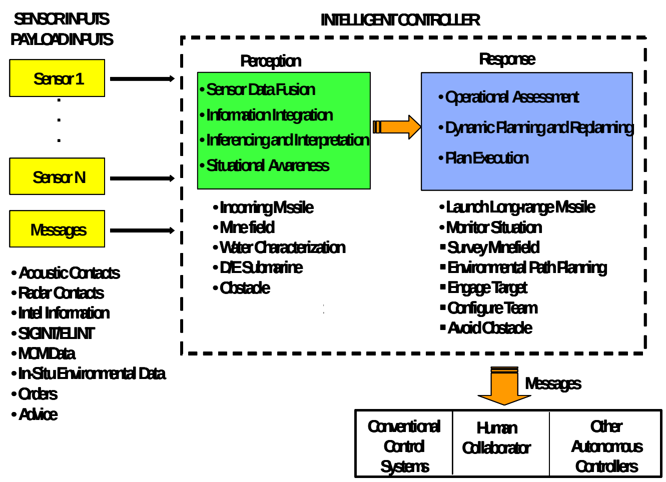


**Figure 1:** High Level Decomposition for a Single IC.

### *2.3 Multiple ICs*

Multiple ICs can be integrated in a hierarchy for coordinated control. Each IC retains the same architecture yet has a different local mission to execute (such as UAVs searching different local areas). This replication of architecture allows management of complexity and considerably simplifies the problem of designing multiple, interacting, intelligent controllers for complex systems.

Just as a collection of Behaviors within an IC needs a Mission Manager for coordination and arbitration, a collection of ICs within a system also requires a supervisor. This role is assumed by a Supervisory IC. Multiple ICs may also exist within a single vehicle in this hierarchical architecture, as determined by design decisions. Figure 3 depicts how multiple ICs communicate.

For multiple vehicles, a significant portion of a mission may be achieved by having the capability of the individual autonomous units carry out their own tasks while operating in a group. Given that the individual vehicles are intelligent and capable of inferring the behavior of other cooperating vehicles through sensing and observation, only a limited number of direct communications may be necessary to achieve significant performance enhancements.

The overall capability of the aggregate system is then an emergent property stemming from the collaboration among individual vehicles coupled with their own abilities to carry out autonomous operations over a range of variations in the missions. For a properly designed collaborative unmanned vehicle system, this emergent capability is greater than that of a system composed of vehicles acting alone.

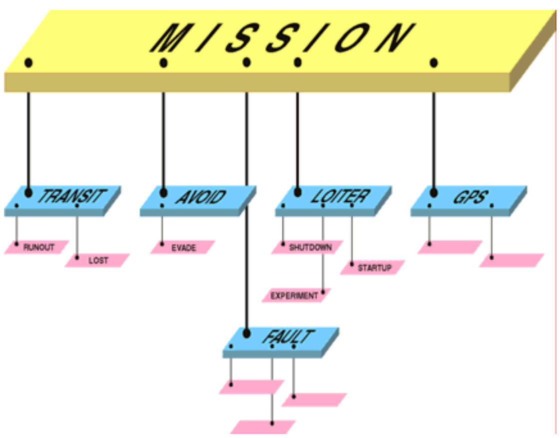


**Figure 2.** Sample Elements of Response Module.

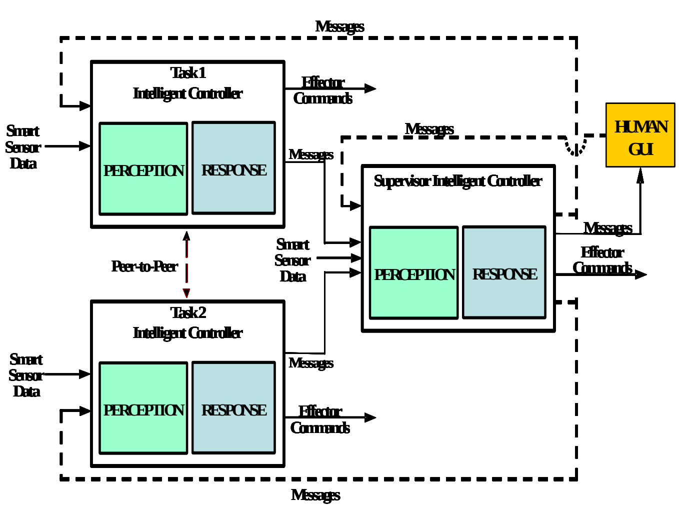


**Figure 3.** Architecture for Multiple IC Communications.

## 3. SYSTEMS OF ICs

The capability of a single IC is the aggregate of the capabilities of its modules. In particular, its operational capability is determined by the aggregate of its Behaviors. To expand the scope of its operational capability, a Behavior is simply added. To remove a capability, a Behavior is removed, which will not affect operation of the remaining Behaviors.

This approach can be extended to a group of ICs, where the architectural relationship between the Mission Manager and its set of Behaviors is replicated to define the relationship between a Supervisor IC and the set of vehicle ICs under its supervision. Figure 3 illustrates this extended Architecture. The hierarchy can be expanded arbitrarily in horizontal and vertical directions.

### *3.1 Communications*

In contrast to the internal communication paths of Response, communication between one IC on a vehicle and another IC on a separate vehicle may not be possible at a given time due to the characteristics of the external medium. Consequently, the architecture supports both peer-to-peer communications and peer-to-supervisor communications.

Permitted message types for peer-to-peer (and peer-to-supervisor) communications are Sensor-data, External-Advisories, and Queries. Sensor data passed among ICs serves to extend the senses of the receiving IC and consequently potentially improves its performance. Bandwidth limitations imposed by the external medium may require that the communicated data be in highly processed form for sufficient compactness. External-Advisories may be used by an IC to inform partners within communication range of its operational status or its interpretation of its local environment. Queries may be sent by an IC to its partners asking for information it needs that they may be able to provide.

There is no requirement that all ICs understand exactly the same language; messages containing Words that are not understood by the Perception processing of the receiving IC may simply be ignored or routed through a central unit that may serve as a translator.

### *3.2 Collaborative Operations*

The operating characteristics of a group of autonomous, coordinated controllers constitutes an autonomous intelligent control system, and their design based on this architecture can be summarized as follows. The autonomous system is composed of one or more ICs, where one of the ICs may possibly be a supervisor ICs. Each IC's objective is to carry out a local mission but in coordination with the global mission and defined by the set of Orders for the collective system. These Orders may be altered during mission execution by receipt of new Orders from a human or a Supervisor IC. Within the constraints of its current Orders and its design, each IC is operating autonomously. There does not exist an "optimal control law" for the system of ICs, and the designers do not attempt to derive one.

Rather, the objective in the design of each IC is for it to be able to operate "optimally" as an individual, given its current set of Orders and its perceived world as created by its Perception processing. This perceived world may include a Representational Class, say "Partner," where an instance of "Partner" represents the status of a partner or peer, including its operational plans and objectives to the extent known. This knowledge will generally be incomplete and changeable.

An autonomous intelligent control system such as this would appear to constitute a close parallel to biological systems such as beehives, ant colonies, and football teams. The system is composed of a collection of individuals with certain specialized characteristics and with some ability to communicate with each other. Operating together, the resulting system can have emergent properties, strengths, and survivability that go beyond the sum of that of the individual units.

The IC architecture also supports collaborative control of heterogeneous vehicles with varying architectures and levels of autonomy. This is accomplished by developing standard interfaces for communications and by providing the level of capability of each vehicle to the other vehicles through a database, where the database is accessed to determine the capabilities of the other vehicles before issuing

## 4. MEASURING EMERGENT COLLABORATIVE CAPABILITIES

### *4.1 The Collaborative Gain Metric*

Collaborative gains result from the communication between platforms, where exchange and interpretation of information is crucial, and from coordinated mission control. Collaboration involves interpretive and behavioral adaptation among the platforms as a result of integrating communicated data into the internal representations of the central system.

Multi-platform collaboration should increase the likelihood of achieving mission objectives of the system over and above that achievable by a base capability. However, a collaborative gain is not automatically positive, since it is possible to design a system in which the communication and collaboration results in conflicts, causing deterioration in the system's ability to perform its mission.

One approach to evaluating the collaborative contribution of a system involves defining an index to measure the collaborative gain ($CG$) of this system. One such metric is:

$$CG = \sum_{i=1}^{M} \alpha_i \beta_i T_i \,, \tag{1}$$

where $\alpha_i$ is a weight reflecting the importance of the task to the overall mission, $\beta_i$ denotes the success (0 or 1) of the task, and $T_i$ is the $i^{th}$ of $M$ mission tasks. The goal is to maximize the CG.

For example, consider two UAVs, A and B, that are similarly capable of identifying a target. Assume platforms A's target has a higher priority and that A has been damaged and incapable of fulfilling its top priority. If B is about to identify its target but has only enough fuel to identify platform A's target, its priority will be reconfigured so that its original target will be ignored and its new target will be that originally assigned to A. Based on the extent of damage to A, platform A might be reassigned to another lower priority task. This type of cooperation leads to controlled emergent behavior, but mathematically quantifying it is an open task. By changing B's target, then $\beta_i$ for A is 1 instead of 0 resulting in a higher CG.

In cases where it is possible to measure partial success of an unmanned vehicle accomplishing its mission, the value of $\beta_i$ becomes a variable, i.e.,

$$0 \le \beta_i \le 1 \tag{2}$$

This allows partial success of an individual UAV or group of UAVs to be captured within the context of this same measure.

### *4.2 Multiple, Coordinated UAV Control and Evaluation*

Controllers based on the IC architecture have been designed for multiple UAVs capable of executing an individual mission and collaborating with other UAVs to execute a larger, overall mission. Performance of one such design is described below.

For this collection of UAVs, the functional capabilities of the prototype group include Navigation, Avoidance, Search, Investigate, Attack, Assist, Communicate, and Supervise. Each of these operations is implemented as an independent Behavior that operates autonomously within its scope, where each conducts real-time planning and analysis of the situation relative to mission execution, and each responds appropriately to the results of that analysis.

Each behavior has one or more Actions that are responsible for carrying out sub-operations and reacting directly to objects of interest as represented in the Perception module. These reactions consist of commands to vehicle subsystems such as an autopilot or sensor control system.

The initial UAV controllers developed are actual controllers operating closed-loop in a virtual environment consisting of a simulation of the external world and vehicle subsystems. These simulated subsystems include an assumed set of sensor systems, effector systems (e.g., an autopilot or other conventional control systems), vehicle dynamics, and interfaces. This closed-loop operation, in which actual controllers are stimulated with synthetic data, allows for issues to be addressed that are indicative of those expected to be encountered by a collaborating group of UAVs.

Multi-UAV control was exercised and evaluated by using a simulation of the external environment and vehicle subsystems, including assumed sensing systems for navigation, avoidance, and target detection. The simulation stimulated the actual controllers. The operational functionality of the prototype collaborative UAV control capabilities was exercised in various scenarios during the design process. Two of these scenarios are described below.

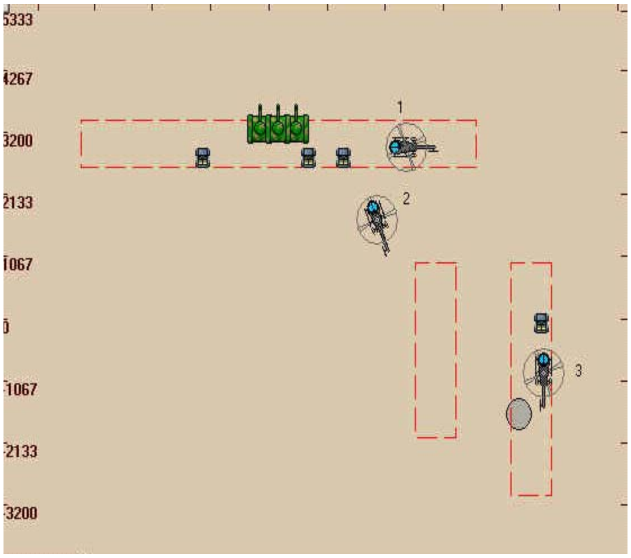

Figure 4: Screen Capture of Three UAVs Collaborating to Search and Attack Large and Small Targets.

**Scenario 1:** A screen capture of the first scenario is presented in Figure 4. In this scenario, three UAVs are provided search areas (red boxes) with the objective being to attack large and small targets. The UAVs are authorized to attack large targets (tanks) without independent target confirmation. However, they are required to obtain independent target confirmation prior to attacking small targets (jeeps). Included in this scenario are way points (x) and an obstacle (large circle), so that the Navigation and Avoidance behaviors are activated. Also in this scenario, towards the end of the overall mission, UAV #1 is shot down before completing its mission. The other UAVs re-plan their missions to ensure the mission of UAV #1 is completed even after it has been removed from the engagement. Such a scenario allows evaluation of the collaborative capability of the multiple UAVs to execute the overall mission of clearing out targets in the specified area.

The performance associated with this scenario can be captured in the Collaborative Gain metric given by equation (1). If the gain is measured by individual UAV success, and where $\alpha_i$, $\beta_i$, and $T_i$ are associated with UAV #*i*, *i*=1,2,3, then the performance of the individuals is given by summing the success of each individual unit accomplishing its mission. In this example, for the individual performances,

$$\alpha_i = 1, i = 1,2,3$$

$$\beta_1 = 0, \beta_2 = 1, \beta_3 = 1$$

so that without collaboration, the performance of the units is given by:

$$CG = 2.$$

If partial success is allowed to be measured (e.g., using equation (2)), then

$$\beta_1 \sim .42,$$

where $\beta_1$ includes the success of eliminating the targets (highest priority that had a 0.833 success rate) followed by successfully returning to a rendevous point for updates (lower priority with 0 success). Thus, the performance of the individual UAVs is given by

$$CG \sim 2.42.$$

When the UAVs are allowed to cooperate to execute the mission, UAV #2 completes the mission of UAV #1, so that

$$\beta_1 = 1$$

and

$$CG = 3.$$

Thus, enabling collaboration between the units provides a level of payoff in mission success.

**Scenario 2:** As another example of the coordinated control, one of the evaluation scenarios evolved as follows: Five UAVs were collaborating. UAV #1 was designated as the supervisor and delegated missions (search areas and rendezvous points) to the five individual UAVs. See Figure 5. During the course of operations, UAVs #2, #4, and #5 crash, and UAVs #1 and #3 return to a rendezvous point. The supervisor UAV requests the status of individual UAVs and reassigns the search areas of the downed UAVs to itself (UAV #1) and to UAV #3. See Figure 6. To further demonstrate the collaboration, the scenario then has UAV #3 go down. When the supervisor returns to the rendezvous point and identifies that UAV #3 is unresponsive, it re-plans and searches the area that UAV #3 was responsible for, and it completes the overall mission.

The performance associated with this scenario can also be captured in the Collaborative Gain metric given by equation (1). If the gain is measured by individual UAV success, and where $\alpha_i$, $\beta_i$, and $T_i$ are associated with UAV #*i*, *i*=1,..,5, then the performance of the individuals is given by summing the success of each individual unit accomplishing its mission. In this example, for the individual performances,

$$\alpha_i = 1, i = 1,\dots,5$$

$$\beta_1 = \beta_3 = 1$$

$$\beta_i = 0, i=2,4,5$$

so that without collaboration, the performance of the units is given by:

$$CG = 2.$$

If partial success is incorporated into this metric, the performance will be slightly higher, but not as high as for cooperating units. When the units are allowed to cooperate to execute the mission, UAV #1 completes the mission of the other UAVs, so that

$$\beta_i = 1,\ i=1,\ldots,5$$

and

$$CG = 5.$$

Again, enabling collaboration between the units provides a level of payoff in mission success.

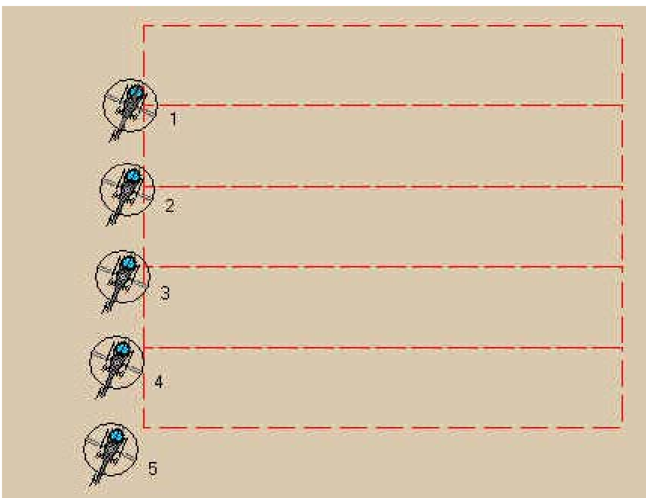


**Figure 5:** Screen Capture of Five Collaborating UAVs and Their Assigned Search Areas.

## 5. CONCLUSIONS

ARL/PSU's experience in unmanned vehicles lead to the development of a unique, robust, universal architecture for the design of intelligent autonomous vehicles. This IC architecture provides a reliable approach to the design of a single unmanned vehicle or of a system of autonomous intelligent units that collaborate with each other and with humans to carry out complex missions.

When this high level of intelligent autonomy is integrated into a system of collaborating, unmanned vehicles, an even larger gain results. This gain is measured with the quantity called Collaborative Gain. Examples indicate that the performance of collaborating units can exceed that of individual units operating on their own accord, and the improvements can be significant.

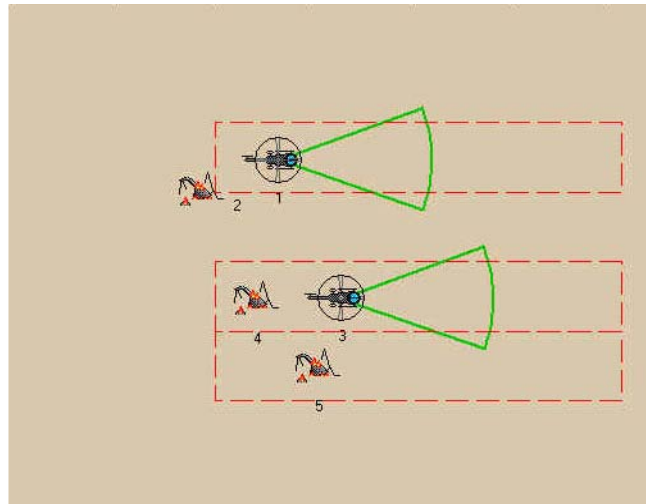


**Figure 6:** Screen Capture of Two Collaborating UAVs Completing the Missions of Three Downed UAVs.

## 6. ACKNOWLEDGEMENTS

The authors would like to acknowledge several researchers at Penn State's Applied Research Laboratory, including M. Roeckel, J. Stover, S. Neal, J. Miller, and C. Walker.

## 7. REFERENCES

1. Brooks, R.A., "Intelligence Without Representation, "Artificial Intelligence," 47, pp. 139-159, 1991.
2. Albus, J.S. Albus, "Outline for a Theory of Intelligence," IEEE Transactions on Systems, Man and Cybernetics, Vol. 21, No. 3, pp. 473-509, 1991.
3. Kumar R. and J.A. Stover, "A Behavior-Based Intelligent Control Architecture with Application to Coordination of Multiple Underwater Vehicles," IEEE Transactions on Systems, Man, and Cybernetics, 30, pp. 767-784, 2000.
4. Chandler, P.R. and M. Pachter, Proceedings of the American Control Conference, 1998, Vol.: 1, 24-26 June 1998, pp. 394-398.
5. Stipanovic, D. M., Inalhan, G., Teo, R. and C.J. Tomlin, Proc. of the 41st IEEE Conference on Decision and Control 2002, Vol.: 3, 10-13 Dec. 2002, pp. 2829-2835.
6. Boskovic, J.D., Prasanth, R. and R.K. Mehra, Proceedings of the American Control Conference, 2002, Vol.: 3, 8-10 May 2002, pp. 1825-1830.
7. Jacoff, A., Messina, E., Weiss, B. A., Tadokoro, S. and Y. Nakagowa, Proceedings of the 2003 IEEE International Conference on Intelligent Robots and Systems, Las Vegas, Nevada, October 2003, pp. 3396-3403.
8. Yang, L., Yang, J.H., Feron, E., and V. Kulkarni, Proceedings of the Intelligent Vehicles Symposium, June 9-11, 2003, pp. 316-321.

9. Zadeh, L. A., "Fuzzy Logic, Neural Networks, and Soft Computing," Communications of the ACM, 37 (3), pp. 77-84, 1994.
10. Zadeh, L.A., "The Search for Metrics of Intelligence-A Critical View," Proceedings of the 2000 PerMIS Workshop, pp. 105-111, Aug. 14-16, 2000, Gaithersburg, MD.
11. Evans, J. M. and E.R. Messina, "Performance Metrics for Intelligent Systems," Proceedings of the 2000 PerMIS Workshop, pp. 101-104, Aug. 14-16, 2000, Gaithersburg, MD.
12. Lee, S., Bang, W. C. and Z.Z. Bien, "Measure of System Intelligence: An Engineering. Perspective," Proceedings of the 2000 PerMIS Wksp., pp. 112-117, Aug. 14-16, 2000, Maryland.
13. DeLeo, J., "Measuring Classifier Intelligence, Measuring the Performance and Intelligence of Systems," Proceedings of the 2002 PerMIS Workshop, pp. 26-31, Aug. 13-15, 2002.
14. Feddema, J. T., Robinett, R. D., and B.J. Driessen, "Designing Stable Finite State Machine Behaviors Using Phase Plane Analysis and Variable Structure Control," Journal of Intelligent and Robotic Systems, No. 36, pp. 349-370, 2003
15. Albus, J.S., "Metrics & Performance Measures for Intelligent Unmanned Ground Vehicles," Proceedings of the 2002 PerMIS Workshop., pp. 61-68, Aug., 2002.
16. Stover, J. A. and R.E. Gibson, "Modeling Confusion for Autonomous Systems," SPIE, Science Artificial Neural Networks, 1710, pp. 547-555, 1992.
17. Stover, J. A. and R.E. Gibson,"Controller for Autonomous Device", US Patent #5,642,467, Issued June 1997.
18. Stover, J. A. and R.E. Gibson, "PIC 95 Project Report," Tech. Mem. #00-128, Applied Research Lab., Penn. State Univ., State College, PA, Feb. 2002
19. Stover, J.A., Hall, D.L., and R.E. Gibson, "A Fuzzy-Logic Architecture for Autonomous Multisensor Data Fusion," IEEE Transactions on Industrial Electronics, 43, pp. 403-410, 1996.