Command and Control of Autonomous Unmanned Vehicles

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Contents

Abstract

Motivated by Generals Rommel and Guderian's innovative command and control techniques used in Europe in 1940, this chapter begins by using information theory to examine unmanned air vehicle (UAV) command and control (C2). The information-theoretic analysis provides a justification and uses cases for *autonomous* UAVs. An autonomous unmanned vehicle system "Organic Persistent Intelligence Surveillance and Reconnaissance" (OPISR) that is designed to duplicate Guderian's innovations is introduced. OPISR is an autonomous unmanned vehicle system that combines the immediate response to tactical ISR needs provided by organic assets with the time-on-station, minimal logistics provided by persistent unmanned systems. OPISR autonomous vehicles collectively interpret real-time tactical intelligence surveillance and reconnaissance (ISR) objectives submitted by any number of disadvantaged users, gather the required ISR data, and return the needed intelligence directly to the affected user. OPISR is an ad hoc, decentralized system that requires no central base or authority and is capable of functioning in communications-denied environment. The chapter

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describes a series of experiments including 2011 experiments in which 16 fully autonomous unmanned vehicles, including 9 unmanned air vehicles, were used to simultaneously support mounted, dismounted and maritime users. During these experiments users provided abstract mission-level ISR needs to the "vehicle cloud." These needs were interpreted by the vehicles, which self-organized and efficiently achieved the user's objectives.

51.1 Introduction

In the spring of 1940, the combined French, British, Dutch, and Belgian forces outnumbered their German counterparts in troops, mechanized equipment, tanks, fighter planes, and bombers. The ME109E German fighter aircraft was roughly equivalent to the British Spitfire, and the French CharB1 tank was superior to the German Panzer III. In addition, the allies were fighting on their home soil which greatly simplified their logistics. Yet in less than 6 weeks, the Belgians, Dutch, and French surrendered to the Germans, and the British retreated across the English Channel. Even though the allies had superior equipment and larger forces, they were defeated by the Germans who employed *Auftragstaktik*, a command and control technique that enabled "edge" war fighters to directly coordinate on tactical decisions using modern communications equipment (in WWII this was radio). Allied forces were forbidden to use radio because it "was not secure," and allied maneuver decisions were made by generals at headquarters and based upon hand-couriered reports. German decisions were made on the fly by Panzer III commanders and JU-87 (Stuka) pilots conversing over the radio. By the time the French commanders met to decide what to do about the German advance, General Erwin Rommel and General Heinz Guderian's Panzers had travelled over 200 miles and reached the English Channel.

As demonstrated repeatedly in military history, including the German advance in 1940, the speed at which battlefield decisions are made can be a deciding factor in the battle. A process model that describes military command and control is the Observe, Orient, Decide, Act (OODA) loop described by Boyd (Fig. 51.1). Boyd shows that, in military engagements, the side that can "get inside the opponent's OODA loop" by more rapidly completing the OODA cycle has a distinct advantage. In their influential book *Power to the Edge*, Alberts and Hayes use the term agility to describe an organization's ability to rapidly respond to changing battlefield conditions. Modern warfare case studies, such as the Chechens against the Russians, and not-so-modern warfare, such as Napoleon at Ulm, indicate that agile organizations enjoy a decisive military advantage. Alberts points out that a common feature of agile organizations is an empowerment of frontline forces, referred to as "edge" war fighters. Commanders facilitate organizational agility by exercising "command by intent," in which commanders provide abstract goals and objectives to edge war fighters who then make independent decisions based upon these goals and their own battlefield awareness. This empowerment of edge war fighters reduces the OODA loop at the point of attack, providing the desired agility.

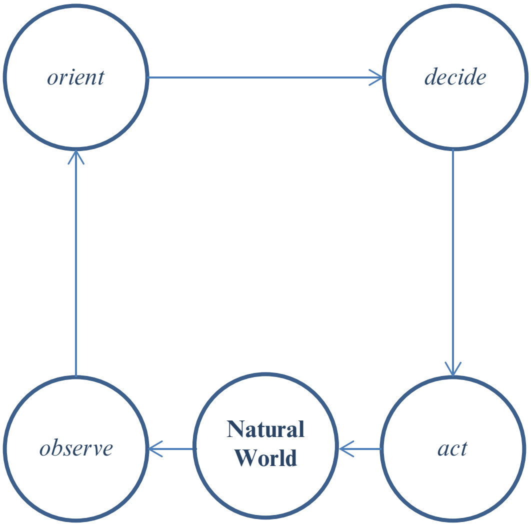

Fig. 51.1 Boyd's Observe, Orient, Decide, Act (OODA) cycle models the military decision-making process. Military organizations that perform their OODA cycle more rapidly than opponents gain a substantial competitive advantage

A distinguishing characteristic of the conflicts in Afghanistan and Iraq is the explosive growth in the use of unmanned air vehicles. Between the first and second Gulf Wars, unmanned vehicles transitioned from a novelty item to an indispensable component of the U.S. military. Field deployable organic unmanned air vehicles such as the AeroVironment Raven are essential equipment for the modern war fighter.

The agility provided by field deployable vehicles comes at a cost, as the use of field deployable units increases logistics and workload demands on frontline forces. When compared to larger unmanned vehicles, field deployable units such as the Raven (Fig. 51.2) offer limited sensing and time-on-target capabilities. Medium-sized vehicles, such as the Boeing-Insitu ScanEagle and AAI Shadow, offer longer time on station and more capable payloads. Medium-sized vehicles also do not make logistics or workload demands on the edge war fighter. Large unmanned vehicles such as the General Atomics Reaper and Northrup Grumman Triton offer still more capable payloads and increased time on station and also do not increase edge war fighter logistics or workload. However, providing timely edge war fighter access to intelligence products produced by medium and large vehicles is a challenge because medium- and large-sized unmanned air vehicles produce massive amounts of data that is difficult to process and disseminate from centralized command posts. In fact, as reported by Ariel Bleicher, "In 2009 alone, the U.S. Air Force shot 24 years' worth of video over Iraq and Afghanistan using spy drones." The trouble is there aren't enough human eyes to watch it all. The deluge of video data from these unmanned aerial vehicles, or UAVs, is likely to get worse. A single Reaper drone can record 10 video feeds at once, and the Air Force plans to eventually upgrade that number to 65. John Rush, chief of the Intelligence, Surveillance and Reconnaissance Division of the U.S. National

Fig. 51.2 An AeroVironment Raven being launched

Geospatial-Intelligence Agency, projects that it would take an untenable 16,000 analysts to study the video footage from UAVs and other airborne surveillance systems. The intelligence, surveillance, and reconnaissance (ISR) capability represented by medium- and large-scale unmanned vehicles represents a tremendous potential for the edge war fighter if only the information could be processed and distributed in time. For the edge war fighter to take advantage of the ISR capability represented by these assets, information relevant to that specific war fighter must be gleaned from the mass of information available and presented to the war fighter in a timely manner. This presents a challenge as crews analyzing UAV payload data (far fewer than Rush's 16,000 analysts) are not appraised of the changing tactical needs of all war fighters, nor do the war fighters have access or the time required to select and access data from UAV sources. Currently, operation centers are used to gather and disseminate information from persistent ISR assets. This centralized information management process introduces a delay between the observation and transmission to the war fighter which reduces force agility and operational effectiveness. While U.S. soldiers are empowered to operate on "command by intent," their ISR systems are all too frequently centralized systems reminiscent of the French command structure. For U.S. forces to become a fully agile force, the ISR systems supporting the U.S. soldier must be as agile as the soldier it supports. Agile unmanned vehicle systems require that some decisions are made at the edge nodes; therefore to become agile, unmanned vehicles must become autonomous.

51.2 Autonomous Unmanned Air Vehicles

UAVs currently in use are described as unmanned strictly because no human rides inside the air vehicle; however, the manual labor required to operate an air vehicle remains largely unchanged as ground-based UAV pilots perform similar tasking to airborne pilots. Because flight procedures have not evolved to match the removal of the human from the air vehicle, the manpower required to operate an UAV equals or exceeds the manpower required to operate a manned aircraft. Because UAV pilots, by definition, fly the vehicle remotely, there is no longer a requirement that a pilot be co-located with the UAV area of operations, and it is not uncommon particularly for large, expensive UAVs for the UAV pilot to operate the vehicle from an office-like environment thousands of miles from the operating area. As the size, range, and capability of a UAV diminish, its use becomes more tactical, and the UAV pilot is located closer to the operating area with medium-sized UAVs such as the Boeing ScanEagle and AAI Shadow being controlled from forward operating bases and the AeroVironment Raven being controlled by a tactical unit in the field. Clearly remote vehicle operations significantly reduce pilot risk when compared to manned aircraft, yet this risk reduction comes at the cost of tactical awareness and involvement. Remote UAV pilots, when emplaced in a hierarchical command structure, have a reduced ability to assist in agile operations; without being immersed in the environment and able to, when required, communicate with actors outside of the current command structure, UAV pilots cannot support tactical operations as well as a JU-87 pilot from 1940.

Automated aircraft control techniques are emerging that allow UAV designers to design and field UAVs with varying degrees of autonomy. For the purpose of discussion, three general levels of autonomy are defined: tele-operation, which is essentially no automation at all; automatic, in which UAVs perform simple actions that can be fully enumerated and tested during design; and autonomy, in which the vehicle independently devises a course of action in response to complex operating conditions. The distinction between automatic and autonomy is subtle but important. Most UAVs being used today are automatic. Engineers of automatic UAVs have designed in action-based commands for pilot use (e.g., follow this path, loiter here, land there), the response matrix has been exhaustively enumerated and tested by development engineers, and the task of managing uncertainty, and complexity, lies with the pilot. Autonomous UAVs, which are not currently in service, are capable of devising a course of action in response to a complex, uncertain situation that was not, in detail, examined by the engineer during design or by the pilot. In other words, an automatic UAV is capable of following a path; an autonomous UAV is capable of finding a path.

The technology required to build autonomous UAVs is available today. Prototype autonomous UAVs that exhibit a variety of complex autonomous behaviors have been developed at academic institutions and industry research centers. Demonstrated capabilities involve relatively simple tasks including search, interdiction, tracking, obstacle avoidance, path planning, logistics, communications, launch, and recovery. While vehicle tasking remains simple, the complex unpredictable nature of the operating environment represents a complex problem requiring an autonomous, not automatic, solution. The bulk of autonomous UAV efforts are conducted at a relatively low technology readiness level (TRL) using low-cost rotorcraft in a laboratory (Kumar and Michael 2012; Bethke et al. 2008). More mature demonstrations of autonomous tier 1 and tier 2 UAVs have been demonstrated outdoors at U.S. government ranges (Scheidt et al. 2004; Kwon and Pack 2011; Tisdale et al. 2008). Arguably the most mature autonomous UAV effort is the DARPA Heterogeneous Airborne Reconnaissance Team (HART) program, providing automatic unmanned air vehicles with an autonomous tactical decision aide (TDA). In these systems simple actions such as waypoint following are performed independently by each UAV, and complex decisions are performed by the TDA algorithm located on the pilot's computer. Prior to execution, the pilot reviews and approves (or disapproves and modifies) the plan. Proponents of HART correctly argue that the pilot is allowed to "auto-approve" plans, effectively making HART an autonomous system; however, the requirement to continually enable the pilot to review and approve all flight plans profoundly impacts the UAV system architecture and performance by delaying the exchange of information between the sensor and the UAV controller. The U.S. Army planned on partial fielding of HART in 2012 (Defense Systems staff 2012).

51.2.1 The Case for Autonomous Systems

Technological availability does not mean that autonomous UAVs will, or should, be used in the field. Autonomous UAV use requires that, when compared to manned aircraft or tele-operated/automatic UAVs, autonomous UAVs provide some tangible benefit to the organization deploying the autonomous UAV. Three general benefits are commonly offered that could justify the use of autonomous UAVs: first, by reducing the manpower required to fly/operate the UAV, autonomous vehicles are less expensive to fly; second, because autonomous UAVs do not require constant communications with a base, they are less vulnerable to electronic warfare attacks and capable of electromagnetic stealth; and third, by making better, more timely decisions, autonomous UAVs can, in certain circumstances, provide more effective performance. This third argument that autonomous unmanned vehicles can improve mission performance and that this performance can be understood and predicted by viewing autonomy as a command and control technique is the central theme of this chapter.

51.2.2 C2 Fundamentals

In *Power to the Edge*, command and control (C2) is defined as the "common military term for management of personnel and resources" but also gives the formal definition of command as found in the Joint Chiefs of Staff Publication, which subsumes some portions of control in that definition. Viewed as a black box the purpose of the C2 system use observations to produce decisions. C2, including UAV C2, involves the production and execution of decisions that, when executed, change the world in which the UAV is operating in ways that benefit the operator. That world (X) is described as a set of states, $X = \{x_1, x_2, \ldots x_n\}$, each one of which represents a unique configuration of actors and attributes within the natural world in which the UAV operates. The command and control system can be viewed as a transfer function ($f(\mathrm{x_i}) \rightarrow \mathrm{x_j}$) that produces a state change in the world. The "quality" of each state can be determined by applying a mission-based fitness criteria to elements within the state. For example, if a UAV mission is to track a target, then states in which the target is within the field of view of the UAV's sensor are evaluated as of higher quality than those states in which the target is not seen by the UAV, and an effective C2 system would cause state transitions that are of high quality when compared to alternative transitions. C2 is a constant battle between chaos and order, with order being state transitions designed to achieve mission goals that are instigated by the C2 system and chaos being unanticipated state transitions produced by adversaries, poorly coordinated teammates or random acts.

C2 can be best understood as an information-theoretic problem. This is apropos as both the situational awareness upon which decisions are based as well as the decision products can be viewed as information-theoretic messages and both the C2 process and the natural world can be viewed as information transfer functions. For an interesting, albeit somewhat off-topic, discussion on the information-theoretic nature of physics, see Wheeler (1990).

The information content (S) of a message (m) is defined by Shannon (1948) as:

$$\mathrm{S(m)} = \log_2(1/\mathrm{P(m)}) \tag{51.1}$$

The more improbable the message being received, the larger the information content. For example, baring a highly improbable change to celestial mechanics, a message stating "tonight it will be dark" has zero information content because the a priori probability that it would be dark is one. By comparison, "tonight it will rain" has positive information content because the a priori probability that it would rain during a given evening is less than one. Information content is measured in bits, which are real numbers. Note that the term "bit" is overloaded, and information theory bits are not the same as computer science bits, which are integers.

The *state space* (p) of the world in which our UAVs operate is the amount of bits required to uniquely identify all possible states in the world, which is referred to as the *state space* of the world.

$$p = \log_2 |X| \tag{51.2}$$

Completely describing the world requires a message of length p. A communication that completely describes the natural world would require a message whose length would be effectively infinite as the natural world includes each blade of grass, molecule of air, quantum states of ions within each atom, and so forth. Fortunately, effective C2 of UAVs does not require such detailed knowledge, and effective UAV control can be provided using artifacts that are abstract, limited, and while potentially quite large in number, expressible in messages that are small enough to be used within a modern computer network. In fact, military C2 systems routinely express tactical "worlds" in finite languages such as the protocols used by the *Global Command and Control System* and the *Link16* network. In practice, the size of a UAV's world as represented by the C2 system can be dynamic, with the state space of the tactical world changing as artifacts enter, or leave, the operational area. That the complexity of a UAV's world, as represented by the state space of the current situation, is subject to change is important to understanding how to control UAVs.

Knowledge of the UAV's world is rarely complete, and UAVs are expected to operate in the presence of varying degrees of uncertainty. Uncertainty in tactical information can be produced by errors in sensor systems, gaps in sensor coverage, or approximation error, which is the difference between the actual ground truth and the coding scheme selected. For example, if the unit representation of a coding scheme used to represent linear position is 1 m, then an approximation error of 0.5 m is unavoidable. Consider the message (m) that encapsulates a C2 systems' current situational awareness (SA). When S(m) $\neq$ p, uncertainty exists and additional information is required to produce complete SA. Now consider a second message (m') that contains all of the missing information required to reduce uncertainty to zero. The information content of m$'$ is information entropy (H) of m, shown as

$$S(m') = H(m) = \sum P(x) \log \frac{1}{P(x)}$$
$$\text{where } x \text{ is the assemblage of information contained in } m \tag{51.3}$$

The information content of m is "negentropy" (N) or "order," Command and control is a battle between the forces of order and chaos, in which the command and control system seeks to generate order by forcing the world into the most beneficial state for the commander and the uncontrollable forces within the world, which may include adversaries, continuously generates entropy that moves the world away from the commander's ideal state.

Together, the information content of m and m' represents the total amount of information potential within the system s.t:

$$S(m') = p - S(m) \tag{51.4}$$

For each bit of order produced by the C2 system, entropy is reduced by a bit. Likewise, each bit of entropy produced by unanticipated change reduces order by 1 bit.

As demonstrated by Guderian and Rommel, C2 systems are temporally sensitive. As time elapses the information content of a message that describes a dynamic scene decreases in proportion to the unpredictable change in the scene. An example of this are unexpected maneuvers made by a target after a sensor observation was made but before the execution of an response to the observation. The loss of information over time is defined as *entropic drag* (Γ) which is expressed mathematically by Scheidt and Schultz (2011) as:

$$\Gamma(x, t, t_0) = \frac{H(x(t)|\, x(t_0))}{t - t_0} \tag{51.5}$$

Note that entropic drag is specific value for each state. Control of UAVs operating in an uncertain world in which multiple states are feasible requires a consideration of all admissible states. The measurement of entropic change that incorporates all feasible states is the normalized form of entropic drag (Γ_{norm}) that is the average entropic drag for all states within the system:

$$\Gamma_{norm}(t) = \sum_{\forall x_i} \frac{H(x_i(t)|\, x_i(t_0))}{(t - t_0) \cdot |X|} \tag{51.6}$$

UAVs acquire, process, and share information over a control infrastructure that includes onboard network and processing, radio downlinks and uplinks, and off-board processing. When processing information, two key characteristics of the control infrastructure are *latency* (δ_0), which is the unavoidable delay in processing an information packet regardless of packet size, and *bandwidth* (β), which is the rate in bits per second at which bits of information can be processed irrespective of the latency. The delay time (δ) required to process a message m of information can be viewed as

$$\delta_m = \delta_0 + \left(\frac{\text{size}_m}{\beta}\right) \tag{51.7}$$

When communicating information from a sensor to a user over a communications link, large amounts of information take more time to transmit and process than small amounts of information. If the information observed by the sensor is a dynamic scene, which is often the case for UAVs, increases in information gathering cause an increase in processing delays that, in turn, cause an increase in entropy. This presents a paradox with respect to attempts to increase information content by increasing the quantity of data. This paradox is defined by the relationships between Eqs. (51.5) and (51.7) that was described by Scheidt and Pekala (2007) and is shown in Fig. 51.3. The figure shows uncertainty as a function of the unit resolution used to describe a dynamic scene using a constant cognitive bandwidth and also assuming that all sensor data is correct. In the plot the highest unit resolution (e.g., least precision) is shown on the right, while the smallest unit resolution (most precision) is shown on the left. Interpreting the plot from right to left shows, as one might expect, that initially increasing the information content of a message substantially reduces uncertainty. As precision increases, the time requires to communicate and process the information increases, which increases information loss due to the entropic drag. Eventually an uncertainty minima is reached at which the information gain from additional information content within the initial message equals the information loss due to entropic drag. Any attempt to use additional precision beyond the minima produces net loss in information content.

If the function of the UAV is intelligence, surveillance, and reconnaissance (ISR), then mission goals are to provide information on targets of interest with minimal uncertainty. Counterintuitively, transmitting all possible information on a target may not be the best approach for an ISR system. The plot in Fig. 51.3 provides a guide as to the optimal amount of data that should be gathered, processed, and

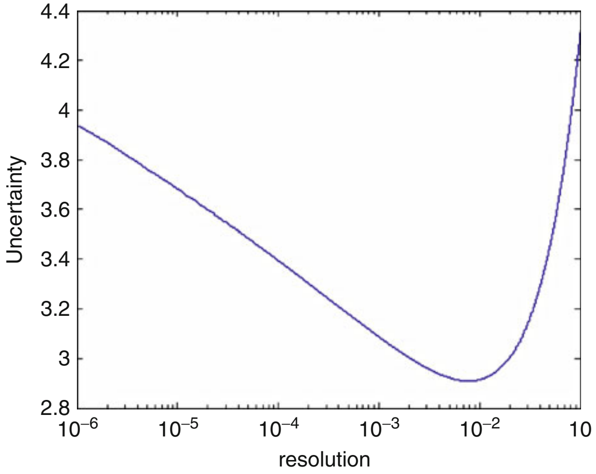

Fig. 51.3 When information describing a dynamic (changing) scene is sent over, a network uncertainty can be minimized by using the optimal resolution (shown by the local minima). The local minima shown is the balance point where the rate of information gain equals the rate of entropy (entropic drag)

Table 51.1 The complexity and rate of unpredictable change vary by mission class

Use case	Description	Complexity, P(x)	Entropic drag, Γ(t)
Strategic	Strategic missions are dedicated to acquiring information on standing infrastructure	–	None
Operational	Operational missions are dedicated to acquiring information on the general movement and condition of large units (e.g., company size or larger)	Low	Low
Focused tactical	Small units (individuals, squads, or platoons) performing tightly defined, focused missions in isolation	Low	High
Multiunit tactical	Small units operating as part of a large engagement that involves multiple units	High	High

provided from a UAV to the UAV operator. The local minima in the plot represents the optimal amount of information that should be transmitted. UAV system that transmit too much information, represented by high-resolution data on the left of the graph, reduces the net information provided due to the large loss of information across all data due to entropic drag. To further understand this relationship, let us examine bandwidth from Eq. (51.7) and its relationship to Eqs. (51.5) and (51.6) in more detail. This is accomplished by viewing canonical ISR missions and operating conditions through information theory and applying these views to differing forms of UAV control. Table 51.1 describes four general classes of ISR missions for UAVs and defines, in general terms, the complexity and entropic drag associated with those missions.

Recall that UAVs may be controlled using three general methods: tele-operation, automatic control, and autonomous control. Descriptions of these methods are:

- Tele-operation – The most common form of UAV control is tele-operation. Tele-operated UAVs use a ground-based pilot to fly the UAV using techniques that are identical those of human-piloted aircraft. Tele-operated UAVs utilize low-level control features found in an airplane cockpit as well and onboard sensor data on the pilot's ground station that are duplicates of those found in the cockpit of a piloted aircraft. All decisions used to control tele-operated planes are made by the ground-based human pilot.
- Automatic flight – UAVs that contain autopilots are capable of *automatic* flight. Automatic UAVs use autopilots to assure stable-controlled flight. The pilots of automatic UAVs provide waypoint locations that direct the path of the UAV. In addition to flying to pre-defined waypoints, automatic UAVs may be preprogrammed to handle simple changes in operating conditions; however, management of complex or unanticipated changes are handled by a ground-based pilot.
- Autonomous flight – UAVs that contain an autopilot and an onboard, intelligent controller are capable of *autonomous* flight. Similar to automatic UAVs, autonomous UAVs provide stable flight between waypoints; however, unlike automatic UAVs, the intelligent controllers onboard an autonomous UAVs define new waypoints in response to unanticipated changes in operational conditions.

Autonomous UAVs fundamentally change the relationship between the human and the UAV because autonomous UAVs, unlike tele-operated UAVs, automatic UAVs, and manned aircraft, do not require pilots. Autonomous UAVs do use human supervision; however, that supervision is performed at a higher level that the typical plane-pilot relationship. The relationship between an autonomous UAV and the supervising human resembles the relationship between a human pilot and an air traffic controller or, for Navy pilots, the Air Boss. Autonomous UAV operators supervise their UAVs by providing abstract, mission-level objectives as well as rules of engagements that are equivalent to the instructions provided to human pilots prior to a mission. During the mission autonomous UAVs devise a course of action aligned with these instructions in response to the current situation. As conditions change during the course of a mission, an autonomous UAV constantly modifies the course of action in accordance with the mission-level objectives. Unlike automatic UAVs, autonomous UAVs respond to complex situations that were not explicitly considered during UAV design.

The different forms of UAV control demand different levels of communications. Direct control of UAV control surfaces requires that tele-operated UAV pilots use low-latency, high quality of service communications to command UAVs. For tele-operated UAVs even small perturbations in service run the risk of loss of control and catastrophic failure. Automatic UAVs are more forgiving, as the pilot is only required to provide guidance at the waypoint level. The communications requirement for automatic UAVs is determined by the rate of change of those operational elements that dictate the mission pace. For example, if the UAV is engaged in an ISR task to track a specific target, the UAV communications infrastructure used to control the UAV must be capable of providing target track data to the pilot prior to the target exiting the UAV's field of view. Depending upon the nature of the target, the response time required for automatic UAVs can range from sub-second intervals to minutes. Autonomous vehicles are the most forgiving of communications outages and delays. In fact, autonomous vehicles are capable of performing without communication to human operators during an entire mission. The ability to function without continual human supervision changes operator and designer perspectives on UAV communications from being a requirement to being an opportunity. When autonomous UAVs can communicate, either to humans or other vehicles, mission performance is improved by the sharing of information and collaborating on decisions; however, when communications are not available, autonomous UAVs are still capable of fulfilling the mission. A synopsis on the communications availability, in terms of latency and bandwidth, for four different classes of conditions is provided in Table 51.2.

When considering whether a UAV control decision should be made be a human operator or by a control processor onboard a UAV, three criteria should be considered: (1) what is the quality of decisions made by the human/machine, (2) what are the ethical and legal requirements for making decisions, and (3) what accessible information is available to the human and the machine? There are ethical and legal advantages and disadvantages for both human and machine decision-making. Arkin provides an excellent overview of the legal and ethical issues, concluding that no consensus exists that would favor human control over machine control or vice versa (Arkin 2009). Regarding the ability to make higher-quality decisions, anecdotal evidence suggests that there exist problem sets for which humans provide better quality decisions and problem sets for which intelligent control algorithms provide better decisions. For example, few would argue that the path planning algorithms provided by Mapquest and Google find superior paths over complex road networks in times unmatched by humans. On the other hand, even the most sophisticated pattern recognition, algorithms are incapable of matching small children in rapidly identifying and manipulating common household items in a cluttered environment. The neuroscience and psychology communities have long-studied human cognitive abilities, and computer science, particularly the subfield of complexity theory (Kolmogorov 1998), has been used to study the performance of cognitive algorithms as a function of the problem space being addressed; however, a comparative understanding between human and machine cognition (or even the tools necessary to achieve this understanding) does not exist at this time.

In order to move the discussion of UAV C2 into a manageable space, two simplifying assumptions are asserted: first, decisions should be made using the maximum amount of information, and (51.2) given equivalent information, it is preferred that decisions be made by a human. These simplifying assumptions allow us to focus on the availability of information as the primary driver for command and control. While it is somewhat disconcerting to ignore the quality of the decision-maker and ethical issues, our focus on information as the driving factor in C2 is consistent with the lessons learned from Guderian and Rommel earlier.

Table 51.2 Communication availability experienced by UAVs during a mission can vary greatly. Depending upon the operational conditions, latency and bandwidth can vary greatly

Communications availability	Description	Latency (δ_0)	Bandwidth (β)
Dedicated communications	Dedicated infrastructure whose access is tightly controlled and not contested by environmental or adversarial activities	Very low	Extremely high
Uncontested broadband	Standing infrastructure that is broadly used that is not contested by environmental or adversarial activities	Very low	High
Contested communications	Standing infrastructure that is broadly used and is not contested by environmental or adversarial activities that produce periodic outages and/or reduction in service	Low	Low
Over the horizon	Operations that involve periodic movement in areas that are beyond communications range or involve periodic, planned communications blackouts	High	Moderate

Having narrowed our focus into the information used to make a decision, three information-theoretic distinctions using between an operator and an onboard computer to determine a course of action are identified. These distinctions are as follows: (a) the complexity of the scene that must be described to make a decision, which dictates the size of the packets that must be communicated and the run time of decision processes; (b) the entropic drag of the system being represented by the data, which dictates the time for which the information is valid; and (c) the communications delay time provided in Eq. (51.7) which defines the earliest time at which the decision could be made. These values may be combined to form an information value g(x) that defines the UAV control problem. The information value is defined as the product of the complexity of the UAV's world and the entropic drag of the world's unpredictable change divided by the delay associated with communicating the world state to the decision-maker s.t:

$$g(x) = \frac{P(x)\Gamma(t_m)}{\delta_m(x)} \tag{51.8}$$

The information value correlates to the utility of the autonomous, automatic, and tele-operated controls approaches. When the world the UAV operates in provides an information value that is high autonomous control dominates, when the world the UAV operates in provides an information value that is low tele-operated control dominates and automatic control is preferred in the midrange. Mapping this relationship to the UAV use cases and communications conditions

Table 51.3 The appropriate conditions for using tele-operated, automatic, or autonomous UAV control are defined by the operational criteria and available communications

Dominant control technique	Dedicated communications	Uncontested broadband	Contested broadband	Over the horizon
Strategic	Tele-operated	Tele-operated	Automatic	Automatic
Operational	Tele-operated	Tele-operated	Automatic	Autonomous
Focused tactical	Tele-operated	Tele-operated	Automatic	Autonomous
Multiunit tactical	Autonomous	Autonomous	Autonomous	Autonomous

defined earlier, operational scenarios that are appropriate for autonomous, automatic, and tele-operated UAV control are defined and enumerated in Table 51.3. As Table 51.3 indicates, there exist real-world circumstances in which UAV C2 should be tele-operated, automatic, or autonomous. Not surprisingly, those times which autonomous C2 is dominant are complex, dynamic situations. Exactly the sort of situation faced by Guderian and Rommel. So, having identified that complex, constantly changing scenarios is best supported by autonomous UAVs, how might we develop such as system.

51.2.3 The Organic Persistent Intelligence Surveillance and Reconnaissance System

OPISR autonomous UAVs utilize a software and communications subsystem that is designed to support the rapid, autonomous movement of information across a tactical force. Commander and/or operators interact with OPISR as a system. When using OPISR, war fighters connect into the OPISR "cloud," task OPISR with mission-level ISR needs and are subsequently provided with the intelligence they need (Fig. 51.4). This capability provides intelligence directly to the war fighter without requiring the war fighter to personally direct or, even know about, the OPISR assets gathering the information. OPISR is autonomous. As a system, OPISR seeks out relevant information, pushing key tactical information directly to impacted soldiers in real time. OPISR is capable of rapidly managing large complex, dynamic situations because it utilizes a decentralized, ad hoc organizational structure. Systems that use decentralized structures such as OPISR are known to be more effective at the timely coordination of complex systems (Scheidt and Schultz 2011). OPISR tracks the location and ISR needs of all blue forces, maintaining a contextual awareness of the war fighter's current tactical needs.

As relevant tactical information becomes available, OPISR presents it directly to the war fighter through an intuitive handheld device. The information requirements that are used to determine information relevance are defined by the war fighter through the same handheld interface. This interface supports abstract queries such as (1) patrol these roads, (2) search this area, (3) provide imagery of a specific location, (4) track all targets of a specific class on a specific route of location, or (5) alert me whenever a threat is identified within a certain distance of my location. Information

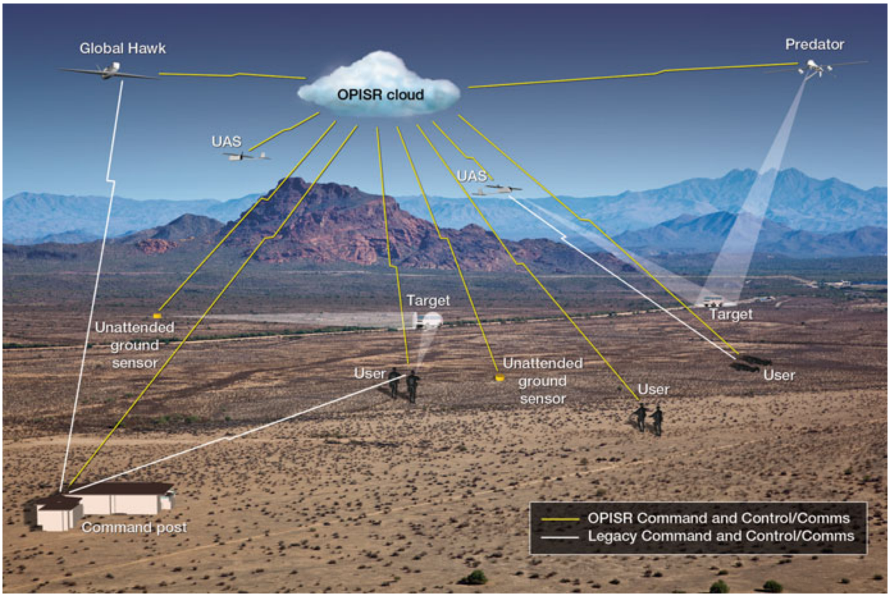

Fig. 51.4 OPISR's concept of operation allows UAVs of various sizes to communicate with each other, with users, and with commanders through an ad hoc, asynchronous cloud. The cloud communicates goals from users to vehicles and sensor observations from users to vehicles

that matches these queries is sent by the system to the handheld device. The handheld interface provides a map of the surrounding area that displays real-time tracks and detections and imagery metadata. The imagery metadata describes, at a glance, the imagery available from the surrounding area. OPISR-enabled vehicles are autonomous; if the information required by the war fighter is not available at the time the query is made, OPISR unmanned vehicles autonomously relocate so that their sensors can obtain the required information. OPISR-enabled unmanned vehicles support multiple war fighters simultaneously, with vehicles self-organizing to define joint courses of action that satisfy the information requirements of all war fighters.

Because war fighters are required to operate in harsh, failure-prone conditions, OPISR was designed to be extremely robust and fault tolerant. OPISR's designers viewed communications opportunistically, designing the system to take advantage of communications channels when available but making sure to avoid any/all dependencies on continual high quality of service communications. Accordingly, all OPISR devices are capable of operating independently as standalone systems or as ad hoc coalitions of devices. When an OPISR device is capable of communicating with other devices, it will exchange information through networked communications and thereby improve the effectiveness of the system as a whole. However, if communications are unavailable each device will continue to perform previously

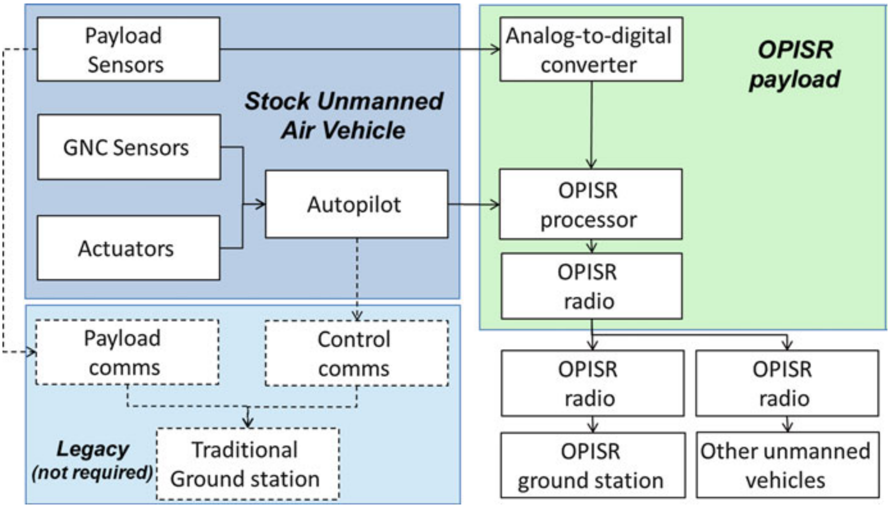

Fig. 51.5 OPISR's hardware architecture is based on a modular payload that can be fitted onto different types of unmanned vehicles

identified tasks. When multiple devices are operating in the same area, they will self-organize to efficiently perform whatever tasks have war fighters have requested.

51.2.3.1 OPISR Hardware

Off-the-shelf unmanned vehicles and unattended sensors can be incorporated into the OPISR system by adding the OPISR payload. As shown in Fig. 51.5, the OPISR payload consists of three hardware components: an OPISR processor that executes the OPISR software, an OPISR radio that provides communications to other OPISR nodes including OPISR's handheld interface devices, and an analog to digital converter that is used to convert payload sensor signals into digital form. Unmanned vehicles that have an onboard autopilot capable of providing stable flight can be modified to become *autonomous* vehicles by connecting the autopilot to the OPISR processor. When the vehicle is operating autonomously, the autopilot sends guidance and control (GNC) telemetry to the OPISR processor. The processor using the GNC data to devise a continual stream of waypoints are sent to the autopilot to follow. The OPISR processor also uses the GNC telemetry to produce metadata that is associated with the sensor data. The combined sensor data and metadata is then used by the OPISR system as a whole.

In service unmanned vehicles frequently use separate communications channels for control and imagery. Since OPISR devices perform both image processing and control onboard the device, these communications channels, and the traditional pilot-ground station, are no longer required. Effectively OPISR devices are capable of operating fully independent of direct human supervision. Note that OPISR devices are still responding to war fighter requests; however, these devices accomplish this without requiring continual communications with the war fighter being serviced. While OPISR does not require traditional control and payload communications, OPISR devices do support these legacy capabilities. Because the OPISR nodes communicate over a separate channel, OPISR functionality may be provided in tandem with traditional control. This is in keeping with the OPISR dictum that OPISR is an entirely additive capability; unmanned vehicle owners lose no functionality by adding OPISR. However, OPISR vehicles are responsive to commands from human operators and will, at any time, allow an authorized human operator to override OPISR processor decisions. Likewise, legacy consumers of information will still receive their analog data streams. Note that even when the OPISR processor is denied control by the UAV pilot, the OPISR system will continue to share information directly with edge war fighters as appropriate.

51.2.3.2 OPISR Software

OPISR is based upon a distributed multi-agent software architecture. Each software agent serves as a proxy for the device on which it is located, and all devices within OPISR have their own agents including unmanned vehicles, unattended sensors, and user interfaces. Each agent is composed of four major software components (Fig. 51.6): a distributed blackboard, which serves as a repository for the shared situational awareness within the agent system; an agent communications manager, which manages the flow of information between agents; a cSwarm controller, which determines a course of action for those devices that are capable of autonomous movement; and a payload manager, which manages the sensor information from the device's organic sensors. All devices within the system, including the war fighter's handheld device, are peers within OPISR.

51.2.3.3 Distributed Blackboard

In the 1980s, Nii (1986) described a method for multi-agent systems to communicate between each other in an asynchronous manner called a blackboard system. Like its namesake in the physical world, blackboard systems allow agents to post messages for peer agent consumption at an indeterminate time. Each OPISR agent contains a personal blackboard system that maintains a model of the agent's environment. Three types of information are stored on each agent's blackboard: beliefs, metadata, and raw data. Raw data is unprocessed sensor data from a sensor within the OPISR system. Metadata is information that provides context to a set of raw data including sensor position, pose, and time of collection. Beliefs are abstract "facts" about the current situation. Beliefs include geo-spatial artifacts such as targets, blue force locations, or search areas. Beliefs can be developed autonomously from onboard pattern recognition software and data fusion algorithms or asserted by humans. Mission-level objectives, the goals that drive OPISR, are a special class of belief that must be produced by a human. The storing and retrieval of information to and from agent blackboards is performed by the blackboard manager. The blackboard manager accepts stores and retrievals from sensors onboard the agent's device, other agents, or pattern recognition/data fusion software contained within the agent. The integrity of the data stored on the blackboard is maintained by a truth maintenance system (TMS). The TMS performs two functions. First, the TMS resolves conflicts between beliefs. The simplest form of conflict resolution is

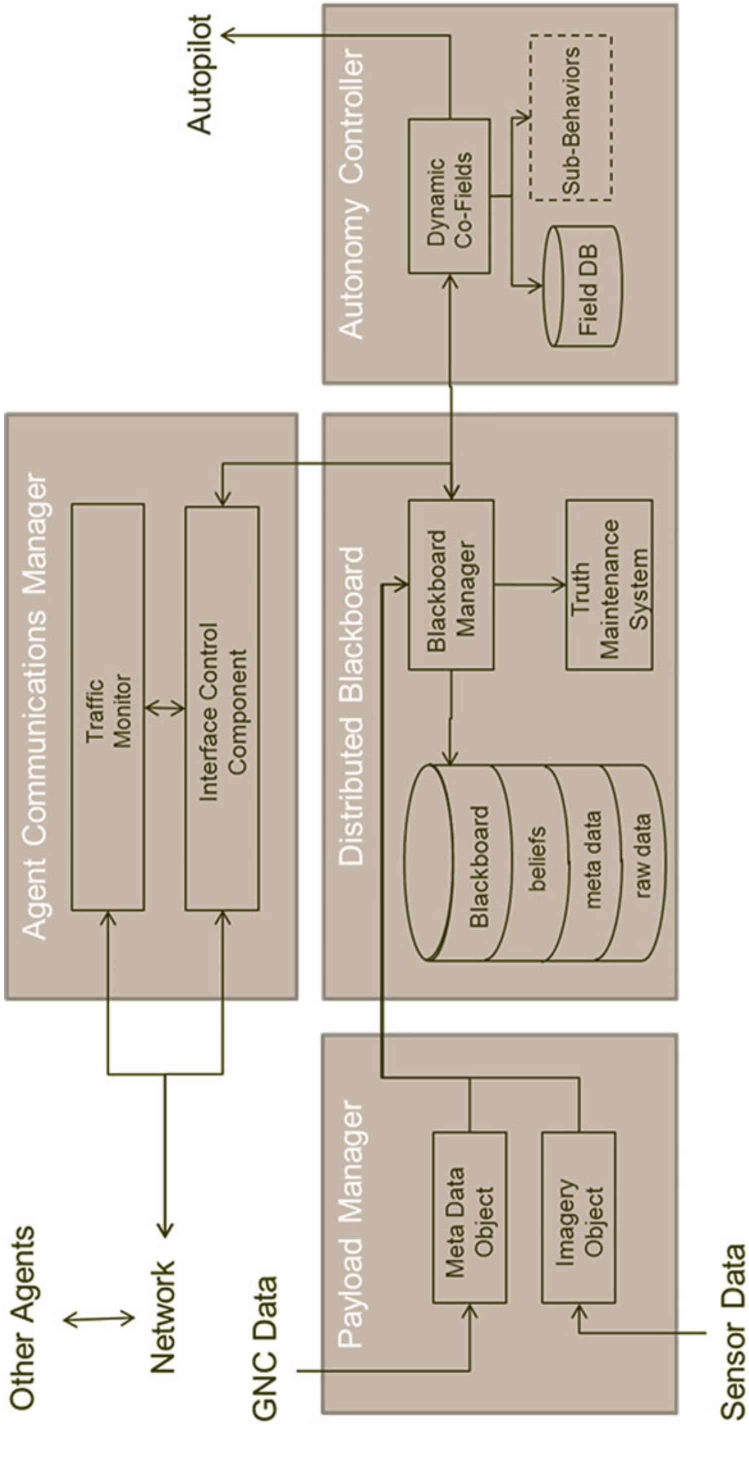

Fig. 51.6 Each OPISR node contains a four major software components that manages information flow and decision-making

accomplished by storing the belief with the more recent time stamp. For example, one belief might posit that there is a target at grid [x, y] at time t_0, and a second belief might posit that there is no target at grid [x, y] at time t_1. More sophisticated conflict resolution algorithms are scheduled to be integrated into OPISR in 2012. The second TMS function is the efficient storage of information within the blackboard. When performing this task, the TMS caches the most relevant timely information for rapid access, and when long-lived systems generate more data than can be managed within the system, the TMS removes less important information from the blackboard. For caching and removal, the importance of information is defined by the age, proximity, uniqueness, and operational relevance.

Coordination between agents is asynchronous, unscheduled, and completely decentralized, as it has to be, for any centralized arbiter, or scheduled communications introduce dependencies that reduce the robustness and fault tolerance that is paramount in the OPISR design. Because agent communication is asynchronous and unscheduled, there is no guarantee that any two agents will have matching beliefs at an instance of time. Fortunately, the control algorithms used by OPISR are robust to belief inconsistencies. Cross agent truth maintenance is designed to the same criteria as agent–agent communications: *Information exchanges between agents seek to maximize the consistency of the most important information but does not require absolute consistency between agent belief systems*. Information exchange between agents is performed by the agent communications manager. When communications are established between agents, the respective agent communications managers (ACM) facilitate an exchange of information between their respective blackboards. When limited bandwidth and/or brief exchanges limit the amount of information exchanged between agents, each ACM uses an interface control component to prioritize the information to be transmitted. Information is transmitted in priority order with priority being determined by information class (beliefs being the most important, followed by metadata), goal association (e.g., if a war fighter has requested specific information that information is given priority), timeliness, and uniqueness.

51.2.3.4 Autonomous Control

OPISR's autonomous unmanned vehicles use dynamic co-fields (DCF), also known as stigmergic potential fields, to generate movement and control actions. DCF is a form of potential field control. Potential field control techniques generate movement or trigger actions by associating an artificial field function with geo-spatial objects. In OPISR, the objects that are used to derive fields are beliefs. Fields represent some combination of attraction and/or repulsion. By evaluating the fields for all known beliefs at a vehicle's current location, a gradient vector is produced. This gradient vector is then used to dictate a movement decision. Developed in 2003 (Scheidt et al. 2005), DCF extends an earlier potential field approach called co-fields (Mamei et al. 2002) by making the potential fields used dynamic with respect to time and also making vehicle fields self-referential. Self-referential fields are fields that induce vehicle decisions that are generated by the vehicle's own presence. Adding these dynamic qualities is key to managing two well-known problems with potential fields approaches: namely, the tendency of vehicles to become stuck in local minima and the propensity to exhibit undesired oscillatory behavior. As implemented in OPISR, DCF is used to effect specific behaviors such as search, transit, or track, as well as behavioral selection. The DCF algorithm is encoded in the cSwarm software module. All unmanned vehicles in OPISR execute cSwarm. DCF behaviors specific to unique classes of vehicle are produced by tailoring the field formula which is stored in a database within cSwarm. OPISR autonomous unmanned vehicles is a variety of behaviors including:

- Searching contiguous areas defined by war fighters.
- Searching linear networks such as roads.
- Transiting to a waypoint.
- Blue-force over-watch.
- Target tracking.
- Perimeter patrol.
- Information exchange infrastructure, in which unmanned vehicles maneuver to form a network connection between an information source, such as an unattended sensor, and war fighters that require information on the source. Note that the war fighter is not required to specify this behavior; the war fighter need only specify the information need, and the vehicle(s) utilizes this behavior as a means to satisfy the need.
- Active diagnosis, in which vehicles reduce uncertain or incomplete observations through their organic sensing capabilities. For example, a UAV with a sensing capability capable of classifying targets will automatically move to and classify unclassified targets being tracked by a cooperating radar.

In addition to the mission-level behaviors enumerated above, OPISR vehicles exhibit certain attributes within all behaviors. These universal attributes are:

- Avoiding obstacles or user-defined out-of-bounds areas.
- Responding to direct human commands. OPISR unmanned vehicles are designed to function autonomously in response to mission-level objectives; however, when operators provide explicit flight instructions, OPISR vehicles *always* respond to the human commands in preference to the autonomous commands.

51.2.3.5 Experimentation

The current OPISR system is the culmination of a decade-long exploration in autonomous unmanned vehicles. Experimentation with DCF began in 2002 as part of an effort to investigate agent-based control of unmanned vehicles to support the U.S. Army's Future Combat System. These early efforts focused predominantly on cooperative search, the results of which are described by Chalmers (Scheidt et al. 2004). Since 2002 thousands of simulated engagements have been conducted with DCF. These simulations have shown that DCF's computational load is independent of the number of vehicles cooperating to solve a mission. Two-hundred vehicle real-time simulations have been run on a single-Pentium class processor. Simulations from a variety of ISR missions have repeatedly shown that vehicle behavior is robust to perturbations in the number of vehicles or the lay-down of those vehicles.

Hardware in-the-loop experimentation with DCF began in 2003 under a joint effort between the Johns Hopkins University, the Army Research Laboratory and Altarum, Inc. In the summer of 2004, this effort conducted a series unmanned air and unmanned ground vehicles experiments at the Aberdeen Proving Grounds (APG). Low-level control was provided by MicroPilot autopilots (air vehicles) and iRobot Mobility (ground vehicles). High-level control of these vehicles was provided by DCF and Altarum's pheromone-based swarming algorithm (Parunak 1997). The distributed blackboard system was used to facilitate sharing between the ground vehicles, although centralized data sharing was used to support UAV control. High-level ground vehicle control software was located onboard the vehicles while high-level air vehicle control software was located onboard a ground station that communicated with the onboard autopilot over a 900 MHz communications link. The air vehicles used in these experiments were Army Mig-27 target drones (Fig. 51.7). These drones have a 6-foot wing span and are capable of air speeds of 60 knots. The ground vehicles used were iRobot ATRV, ATRV-JR, and mini robots. This effort concluded in an October 2004 demonstration in which two air vehicles and four ground vehicles conducted a multi-objective mission at APG. The air vehicles were equipped with GPS for localization and notional EO sensors for target detection and tracking. Mission objectives were provided by three independent human users. Objectives included are as follows: (1) patrol the base, (2) protect the moving convoy, (3) search operator-defined areas, (4) track unclassified targets, (5) classify unclassified targets, and (6) interdict targets classified as threats. AUVs supported objectives 2, 3, and 4. The demonstration started with UGVs patrolling the base and UAVs searching the engagement area. A convoy entered the engagement area with the intention of transiting to the base. The officer leading the convoy requested protection, causing the UAVs to change mode to cover the convoy en route. While patrolling the area infront of the convoy, the UAVs detected a number of dismounts loitering at a road intersection in the convoy's path. This information was relayed to the convoy, causing the human driver to stop prior to the intersection. This same information was relayed to the UGVs, causing the UGV with the acoustic sensor payload to approach the intersection. Once in range of the intersection, the acoustic UGV classified a subset of the dismounts as hostile targets. This information caused the UGVs to pursue the hostile targets, which then fled the area. Once the intersection was cleared, the convoy completed its transit to the base. This demonstration, and variants of it, was successfully performed a number of times. During one demonstration a UGV suffered a hardware fault and went off-line. The other vehicles recognized the sudden absence of their peer, adapting their actions to maintain overall operational effectiveness.

A similar set of experiments were conducted at the Department of Energy's Nevada Test Site in the summer of 2005. These experiments used three Procerus Unicorn UAVs and infrared unmanned ground sensors (UGS). In these experiments all of the vehicles used DCF as their high-level control policy. The UAVs performed area search, road search, target tracking, and, for the first time, airborne information exchange. The engagement consisted of two mounted blue-force patrols,

Fig. 51.7 The first UAVs to fly using OPISR's DCF were modified U.S. Army Mig-27 drones

a single-dismounted aggressor, and two-mounted aggressors. The UGS, using onboard automated target recognition algorithms, detected and identified the dismounted and mounted adversaries. These detections caused the UAVs to track the adversaries and relay the contact information to the blue-force patrols. These experiments were the first in-flight uses of the previously described active-metadata framework.

Also in 2005, DCF was successfully used in experiments to control UAVs detecting, taking samples from and tracking atmospheric plumes. These experiments used three AeroVironment Dragon-eye UAVs. The plume detection experiments were motivated by a desire to provide first-responders with an ability to rapidly identify aerosol contaminants emanating from an industrial accident and to understand and predict the location of those contaminants. These experiments were conducted at a Department of Homeland Security facility in Michigan.

From 2006 to February 2008, DCF has been used regularly in the Naval Postgraduate School's TNT experiments held at Camp Roberts, CA. These experiments have deployed as many as six Procerus Unicorns a fully mission-based swarm. The UAVs used for TNT are fully independent, as the high-level control, a variety of sensors, and the automated target recognition algorithms have been moved onboard the UAVs. Additional behaviors have also been demonstrated at TNT including automated obstacle avoidance (fixed and airborne) and communications. In a 2007 experiment six vehicles cooperated to provide streaming video of arbitrarily defined objects from over the horizon to human users.

DCF has been used as a control metaphor in sea-based experiments conducted predominantly in littoral environments. Starting in 2005 DCF has been used to control several types of unmanned sea surface vehicles conducting search and track n'trail missions at speeds of up to 40 knots with no man in the loop. In 2007 and 2008 OPISR software was used to control unmanned undersea vehicles on search and track missions.

Between 2002 and 2010 twenty hardware experiments were conducted using elements of the OPISR system, including DCF (Scheidt et al. 2005), the distributed blackboard (Nii 1986; Hawthorne et al. 2004), delay-tolerant communications

Fig. 51.8 OPISR vehicles from the 2011 Webster field demonstration including one (of four) ScanEagles, two custom surface vehicles, one (of six) Procerus Unicorns, and an OceanServer Iver2 undersea vehicle

(Bamberger et al. 2004), and simultaneous support for multiple end users (Stipes et al. 2007). As successful as these experiments have been prior to 2011, the full suite of OPISR capabilities described in this chapter had not been demonstrated on a large disparate set of vehicles. In September 2011 a multi-vehicle system consisting of 16 OPISR-enabled nodes, including 9 UAVs in support of 3 users, was conducted at Webster Air Field in St. Inigoes, MD, and the surrounding Chesapeake Bay. The 2011 demonstration mixed air, ground, and sea ISR needs with surveillance being conducted under the water, on the water, and on and over land. The autonomous unmanned vehicles included four Boeing ScanEagles, six Procerus Unicorns, a Segway RMP ground vehicles, custom surface vehicles, and an OceanServer Iver2 undersea vehicle. The air, surface, and undersea vehicles are shown in Fig. 51.8. These vehicles used a wide range of payload sensors to detect, classify, and track waterborne vehicles, land vehicles, dismounts, and mine-like objects, including EO, IR, radar, AIS, passive acoustic, side-scan sonar, and LIDAR. ISR tasking was generated by three proxy operators, two of which were on land (one mounted and one dismounted) and one of which was on the water. ISR tasks requested required the use of all of the vehicle behaviors previously described.

The OPISR capabilities demonstrated by OPISR UAVs at St. Inigoes included a set of six enabling autonomous submission capabilities, which are:

1. Area search – When user(s) requests that one or more contiguous areas should be searched, the autonomous vehicles respond by searching those areas.
2. Road network search – When user(s) request that one or more roads should be searched, the autonomous vehicles respond by searching those roads. This is functionally identical to performing an area search over an area that is confined to (or focused on) roads of interest.
3. Overwatch – A convoy protection mode that when a user requests "overwatch" protection, one or more vehicles circle the protected user. This is functionally identical to track a moving target, except that the U $\times$ V sensors will be directed at the region surrounding the convoy, rather than directly at a target.
4. Communication relay – When an area to be searched (see behavior #1) is farther from the user interested in the area than the vehicle-user communications range, one or more vehicles autonomously form a communications chain to relay data from the searched area to the user.
5. Obstacle avoidance – Obstacles that are known by a vehicle are avoided. Note that obstacles may include physical obstacles detected by vehicle sensors (e.g., trees) and/or abstract obstacles provided by users such as no-fly zones.
6. Behavior switching – Vehicles are capable of exhibiting multiple behaviors depending upon current user goals and circumstances.

One highlight of the experiment was the indirect access to time-sensitive data from a remote camera sensor – located well outside the direct communication ranges of the C2 ground stations and their radios – to OPISR users by autonomous UAV communications chains. This communications link was formed fully autonomously, even to the extent that there was no specific command given to the ScanEagle UAV that it forms a communications chain. The ScanEagle was tasked to patrol the region, and as it became aware of sensor data, it relayed that data to the user, who immediately had the sensor data available on his display.

Another key OPISR feature that was demonstrated in St. Inigoes was the OPISR UAV ability to coordinate on tasks that it (the UAV) cannot satisfy without recruiting other vehicle types. Very importantly in this experiment, command was shown not only from one ground station to multiple heterogeneous vehicle platforms but also commands from multiple users at multiple ground stations could set the goals of any and all OPISR components.

During experimentation sensor and mission information was delivered to both C2 user stations both directly and via UAV communications chaining. This delivery occurred both automatically and in response to specific user requests. All relevant mission data was made available and reported to the C2 user, including the status of assigned search missions, represented as "fog of war" over the map geo display; detections from the various UGS, the two USVs, and the UUV; and camera imagery from the various platforms. Within the flight time windows available, over 65,000 images were collected by the various camera sensors, including onboard UAV payload sensors and relayed to the C2 stations, available to any of the notional war fighter users as their ground node was connected to cognizant portions of the mesh network.

51.3 Conclusion

The OPISR system is a framework that provides a capability through which numerous unmanned platforms simultaneously provide real-time actionable intelligence to tactical units, provide abstract manageable situation awareness to theater commanders, and provide high-quality forensic data to analysts. OPISR is a demonstrated system that includes a distributed self-localizing camera payload that provides imagery and positional metadata necessary to stitch information from multiple sources, a distributed collaboration system that is based upon robust ad hoc wireless communications and agent-based data management, and a user interface that allows users to receive real-time stitched imagery from unmanned vehicles that does not require users to directly control (or even expressly be aware of) the unmanned vehicles producing the imagery. OPISR is a bold vision that presents an innovative approach to ISR, an important enabler emphasized in the Quadrennial Defense Review and other key policy documents, and gives the laboratory an enhanced ability to help sponsors address future capability gaps in this critical area.

References

R.C. Arkin, *Governing Lethal Behavior in Autonomous Robots* (CRC, Boca Raton, 2009)

R. Bamberger, R.C. Hawthorne, O. Farrag, A communications architecture for a swarm of small unmanned, autonomous air vehicles, in *AUVSI's Unmanned Systems North America Symposium*, Anaheim, 3 Aug 2004

B. Bethke, M. Valenti, J. How, Experimental demonstration of UAV task assignment with integrated health monitoring. IEEE Robot. Autom. Mag., Mar 2008

Defense Systems Staff (2012) Army readies on-demand imagery tool for battlefield use. Defense Systems, 1 June

R.C. Hawthorne, T. Neighoff, D. Patrone, D. Scheidt, Dynamic world modeling in a swarm of heterogeneous autonomous vehicle, in *AUVSI Unmanned System North America*, Aug 2004

A.N. Kolmogorov, On tables of random numbers. Theor. Comput. Sci. **207**(2), 387–395 (1998)

V. Kumar, N. Michael, Opportunities and challenges with autonomous micro aerial vehicles. Int. J. Robot. Res. **31**(11), 1279–1291 (2012)

H. Kwon, D. Pack, Cooperative target localization by multiple unmanned aircraft systems using sensor fusion quality. Optim. Lett. Spl. Issue Dyn. Inf. Syst. (Springer-Verlag) (2011)

M. Mamei, F. Zambonelli, L. Leonardi, Co-fields: a unifying approach to swarm intelligence, in *3rd International Workshop on Engineering Societies in the Agents' World*, Madrid (E), LNAI, Sept 2002

H. Nii, Blackboard systems. AI Mag **7**(2), 38–53 (1986); **3**, 82–106

V.D. Parunak, 'Go to the Ant': engineering principles from natural multi-agent systems. Ann Oper Res **76**, 69–101 (1997)

D. Scheidt, M. Pekala, The impact of entropic drag on command and control, in *Proceedings of 12th International Command and Control Research and Technology Symposium (ICCRTS)*, Newport, 19–21 June 2007

D. Scheidt, K. Schultz, On optimizing command and control, in *International Command and Control Research Technology Symposium*, Quebec City, June 2011

D. Scheidt, T. Neighoff, R. Bamberger, R. Chalmers, Cooperating unmanned vehicles, in *AIAA 3rd "Unmanned Unlimited" Technical Conference*, Chicago, 20 Sept 2004

D. Scheidt, T. Neighoff, J. Stipes, Cooperating unmanned vehicles, in *IEEE International Conference on Networking, Sensing and Control*, Tuscon, 19–22 Mar 2005

C.E. Shannon, A mathematical theory of communications. Bell Syst. Tech. J. **27**, 379–423, 623–656 (1948)

J. Stipes, D. Scheidt, R.C. Hawthorne, Cooperating unmanned vehicles, in *International Conference on Robotics and Automation*, Rome, 10 Apr 2007

J. Tisdale, Z. Kim, K. Hedrick, An autonomous system for cooperative search and localization using unmanned vehicles, in *Proceedings of the AIAA Guidance, Navigation and Control Conference*, Honolulu, Aug 2008

J.A. Wheeler, Information, physics, quantum: the search for links, complexity, entropy and the physics of information, in *A Proceedings Volume in the Sante Fe Institute Studies in the Sciences of Complexity*, ed. by W.H. Zurek (Westview Press, 1990)