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Chapter 9: Cooperative vehicle environmental monitoring

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Abstract

This chapter reviews cooperative control of autonomous vehicles for environmental monitoring with a focus on methodologies that have been designed, deployed, and proven to provide efficient, reliable, and sustained monitoring of the uncertain and inhospitable ocean environment. Vehicles that communicate their state or measure the relative state of other vehicles in the team can cooperate by using feedback control to coordinate their motion as a mobile, reconfigurable sensor array, responding efficiently to changing signals, scales, and conditions in the environment. In a variety of contexts, a vehicle team with judiciously designed cooperative control can outperform the same team with each vehicle controlled independently. For example, cooperative control methodologies have been developed to improve the richness of information in the data that the vehicles collect, their accuracy in feature detection and tracking, and the robustness of their decisions to uncertainty and failures. The chapter begins with a survey of early work on ocean sampling and environmental monitoring, cooperative control, and collective motion. The theory, methodology, and field deployment are then highlighted for two projects on cooperative vehicle monitoring in the coastal ocean that demonstrated the applicability and associated performance advantages of cooperative control. The chapter concludes with a presentation of more recent developments as well as future directions in cooperative vehicle environmental monitoring.

1 Introduction and Motivation

Over the last decade, methodologies for automated cooperative control of robotic vehicles have been designed, deployed and proven to provide efficient, reliable, and sustained monitoring of the uncertain and inhospitable ocean environment. Unprecedented data sets have been collected from deployments of cooperative vehicles in the field, and both real-time and post-deployment analyses have led to new understanding of the environment. This first decade of success in cooperative vehicle environmental monitoring sets the stage for new opportunities and future gain, especially as the development of cooperative control methodologies can continue to leverage ongoing technological and scientific advances in underwater communication and sensing, energy and computational efficiency, vehicle size, speed, maneuverability and cost, and ocean modeling and prediction.

Indeed, the demonstrated potential of cooperative vehicle control has led to increased demand for fleets of autonomous underwater vehicles (AUVs) for use in measuring ocean physics, biology, chemistry and geology to improve understanding of natural dynamics and human-influenced changes in the marine environment. Further, methodologies for cooperative control of robotic vehicles in the ocean are readily adaptable to applications on land, in the air and in space; likewise, there is much to be learned from developments in these other domains. The recent explosion in research on networks and complex systems, including investigation of mechanisms that explain a "collective intelligence" exhibited by animal aggregations on the move, are also being leveraged to advance design of cooperative vehicle dynamics.

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For environmental monitoring to be successful, physical, chemical, and biological variables must be measured across a range of spatial and temporal scales; in the ocean the monitoring strategy must also contend with a harsh, three-dimensional physical space that is highly uncertain and dynamic. Small spatial and temporal scales associated with the measured variables typically make a stationary sensor array impractical because a very large number of sensors would be needed to get sufficient resolution in space and/or time. An array of mobile sensors, however, may be very well suited to such a challenge since mobility can be exploited to dynamically distribute fewer sensors according to the spatial and temporal scales.

The underlying principle of cooperative control of vehicles for environmental monitoring leverages mobility of sensors and uses an interacting dynamic among the individual sensors to yield a collective behavior that performs better than the sum of the parts. If the vehicles can communicate their state or measure the relative state of others in the team, then they can cooperate and the cooperative vehicle dynamics can provide coordinated motion of the team as a whole. The resulting vehicle network functions as a dynamically reconfigurable sensor array with a capability for high performance in environmental monitoring not available at the level of individuals. High performance has been demonstrated with cooperative vehicle groups in the ocean in terms of richness of information in measurements, accuracy in feature detection and tracking, and robustness of decisions to uncertainty and failures.

Methodologies for systematic generation of feedback control laws that yield provable collective dynamics have been critical to the successful design of high performing cooperative vehicle networks. Feedback control refers here to the automated changes that each vehicle makes in response to its measurements of the sampled fields, the relative state of other vehicles in the network, and any additional available measured or computed signals.

Consider, for example, the task of tracking high density phytoplankton patches in the ocean with a team of AUVs that carry optical sensors for measuring phytoplankton concentration. Suppose also that when any two vehicles in the team are not separated by too great a distance (call them neighbors), they can measure or communicate to each other their relative position and/or velocity. Then, each vehicle can apply a feedback control law, at its sampling or communication frequency, that moves it in the direction of a combination of its best estimate of (1) the direction of increasing concentration, (2) the direction toward its neighbors that are farther than a prescribed separation distance, and (3) the direction away from its neighbors that are closer than a prescribed minimal separation distance. In ideal conditions, the vehicles will move as a regularly spaced array up the phytoplankton concentration gradient; in real conditions, feedback will provide robustness to noise, uncertainty, and disturbance within bounds. An augmentation to this feedback law to further reduce error due to noisy measurements has each vehicle compute a local estimate of the optimal vehicle array resolution for gradient climbing accuracy and then adapt the prescribed separation distances between neighbors to achieve this resolution.

Consider, as another example, the task of providing dynamic sampling coverage of the changing phytoplankton patches over a fixed region with this same team of AUVs. The goal is to enable the vehicles to efficiently sample the patches across the region so that the data can be used to map the phytoplankton patches with minimal mapping error. Each vehicle can apply a feedback control law in response to where its neighbors are collecting data and in accordance with priors on spatial and temporal scales associated with the phytoplankton patches. The feedback control law moves it towards a location that is easily accessible, is away from others, and has not been recently sampled. In this case in ideal conditions, the vehicle network will cooperatively perform dynamic sampling coverage of the patches over the region; again feedback will provide robustness to some noise, uncertainty, and disturbance. An augmentation to this feedback law has each vehicle compute a local estimate of changing spatial and temporal scales to update its priors and adapt how far from other vehicles to move and how frequently to re-sample previously sampled locations.

Feedback has also been used to "close the loop" between cooperating vehicle networks and advanced ocean models when data collected by the vehicle network can be made available for assimilation into the ocean models and the ocean model predictions can be made available to one or more of the vehicles. In the first example of tracking high density phytoplankton patches, the feedback with ocean models allows individual vehicles to modify their gradient climb based on predictions of high density locations. In the second example of dynamic sampling coverage in a fixed region, the feedback with ocean models provides enhanced estimates of uncertainty so that individuals could bias their motion towards sampling locations with the greatest possibility of minimizing uncertainty in the mapping. Forecasts of ocean currents are also useful for navigation.

Cooperative feedback control makes possible a vehicle network that is autonomous, versatile and robust to noise and uncertainty. Further, when each vehicle has the same feedback law, the vehicle network has an added robustness to vehicle failures or additions since an ordering of the vehicles is unnecessary and in particular the system does not depend on any special individuals. Other promising opportunities have been explored with a heterogeneous group of vehicles. In these cases feedback can be used for cooperative subtask allocation or coordinated complementary actions: for example, slow moving autonomous underwater gliders can provide coverage and fast moving propelled underwater vehicles can be allocated to relay information and to move to "hot spots" at great speed. Similarly, unmanned aerial vehicles (UAVs) can provide large scale mapping of sea surface fields and AUVs can complement with in-depth feature tracking below the surface.

In this chapter we describe two projects in cooperative vehicle environmental monitoring with extensive field deployment in the coastal ocean that demonstrated for the first time at large scale and over several weeks the applicability and associated performance advantages of cooperative control methodologies for mobile sensor networks in the ocean. The first of these was the Autonomous Ocean Sampling Network (AOSN) II project [1, 2] with its field experiment in Monterey Bay, CA, over the month of August 2003 and the second was the Adaptive Sampling and Prediction (ASAP) project with its field experiment in Monterey Bay, CA, over the month of August 2006 [3].

For AOSN-II, a methodology was designed [4] and demonstrated [5] that featured small networks of autonomous underwater gliders cooperating to compute temperature gradients and track cold upwelled water. The gliders were also used to demonstrate autonomous coordination of their motion to sample along the path of drifters and thus increase measurement density along fronts. For ASAP, a methodology was designed [6] and demonstrated [3] that featured a network of ten gliders (of two types) to optimize dynamic sampling coverage, minimizing uncertainty for estimation of temperature, salinity and currents in a large coastal region just north of Monterey Bay. In both field experiments, three numerical ocean models ran in near real-time, assimilating data collected by the gliders and providing estimates and predictions that were used in the gliders' adaptive motion planning. Additional real-time data were provided by a research aircraft, satellite imagery, high-frequency radar, moorings, drifters and propelled vehicles. In the ASAP experiment the cooperative behavior of a network of six gliders ran autonomously without failure for almost 24 days straight.

An important factor in the success of the AOSN-II and the ASAP projects was the strong multi-disciplinary collaboration among researchers with expertise in ocean science, vehicle dynamics, and control and dynamical systems theory. The methodologies developed drew inspiration from earlier work in ocean sampling and environmental monitoring, cooperative control and collective motion; we present background and history on these subjects in Section 2. The AOSN-II and ASAP programs in cooperative vehicle ocean monitoring, from theory through full-scale ocean deployment, are reviewed in Section 3. More recent developments and future directions in cooperative vehicle environmental monitoring are described in Section 4.

2 Background and History

The autonomous oceanographic sampling network (AOSN) was introduced in 1993 by Curtin et al. [7] as an approach for dynamic measurement of the ocean environment and resolution of spatial and temporal gradients in the sampled fields. At that time most oceanographic data were collected from satellites, ships with towed underwater profilers, and arrays of moorings and floats. The AOSN concept was to deploy AUVs to take measurements that would complement those from distributed point sensors such as moorings and from remote sensors such as satellites, and enable adaptive sampling to improve forecast skill; the AOSN system would operate successfully with the use of acoustic and radio modems for communication and docking stations for recharging AUV batteries. It was anticipated that control would be critical for the AUVs to accomplish complex missions in the presence of uncertainties and real-world constraints, and that coordinated control of the multiple vehicles would lead to system efficiency and endurance. Bellingham described in [8] how nested approaches would allow sampling the ocean over a range of spatial and temporal scales.

The vision of an integrated ocean monitoring system was made possible with the development of small, relatively inexpensive AUVs. Propelled AUVs such as the Autonomous Benthic Explorer (ABE) [9], the Odyssey [10] and the REMUS [11] were designed to provide maneuverability and speed. Buoyancy-driven autonomous underwater gliders, including the Slocum [12], Spray [13] and Seaglider [14], were designed to provide endurance [15, 16]. ABE was used to map the sea bottom and to search out and study deep-sea hydrothermal vent sites and volcanoes [17, 18, 19, 20]. The Odyssey vehicle was used in experiments under the ice in the Arctic [21]. REMUS was equipped with optical sensors and used to measure bioluminescence [22, 23]. Seagliders were sent on five-month-long missions to measure physics, biology and chemistry off the coast of Washington and in the Labrador Sea [15]. Slocum gliders were introduced as an integral part of the Long-term Ecosystem Observatory (LEO), an integrated observatory off the coast of New Jersey [24, 25, 26].

An early example of a control architecture design for multiple AUVs was described in 1987 by Albus and Blidberg in [27]: the architecture was designed to enable two AUVs to perform cooperative search, approach and mapping using cooperative maneuvers such as "fly-formation", "circle-split-and-rendezvous" and "leader-follower." In [28] the objective was to use multiple AUVs as an imaging system. Virtual chains of AUVs were considered by Triantafyllou and Streitlien in [29]; a technology for one vehicle to track another in a chain-like fashion using an Ultra Short BaseLine (USBL) acoustic tracking system was demonstrated by Singh et al. [30] in Buzzards Bay off Woods Hole, MA in March 1996. In June 1996, two Odyssey vehicles were used along with an acoustic tomography network for mapping in the Haro Strait region of British Columbia [31]. Stilwell and Bishop presented a decentralized control framework for a cooperative platoon of AUVs in [32]. Formation flying to map salinity fronts was tested in the North River in North Carolina using the Ranger micro-AUV [33].

A 1997 survey by Cao et al. [34] described cooperative mobile robotics as a still emerging field rich with opportunities. The robotics community became heavily engaged in the late 1980's first with a focus on simulation [35, 36] and then physical implementations [37, 38]. Collective behavior in animal groups was an early inspiration [39], with a behavioral-based approach becoming popular in the 1990's [40]. However, according to [34] in 1997, "few applications of cooperative robotics" had been reported, and supporting theory was "still in its formative stages."

Interest in very large-scale stationary sensor networks surged with advances in wireless communication technology and micro-sensors, and environmental monitoring was an early, important application driver for development of network architectures and algorithms in this context [41, 42, 43, 44]. Energy considerations were used to justify the use of large numbers of stationary sensors over mobile sensors. However, the balance tipped the other way in the case of undersea sensing due to the challenges of undersea communication and the emergence of relatively inexpensive, high endurance vehicles such as the autonomous underwater gliders.

Bretherton et al. [45] in the 1970's applied the technique of objective analysis (OA) [46], which uses classical linear estimation theory to compute objective maps, to address the problem of deployment design for an array of stationary or passively drifting sensors in the ocean where the aim was to provide coverage and minimize uncertainty in the estimates made from the data collected. Adaptive ocean sampling, as described by Robinson and Glenn in [47], built on this concept to consider the design of a trajectory for a mobile sensor platform, complementing another sensor platform moving along a predetermined track, in order to minimize uncertainty in an ocean forecasting model. A performance metric that accounts for both spatial and temporal sampling requirements was derived by Wilcox et al. [48]; it was used to evaluate oceanographic survey performance with AUVs in [49]. A methodology for control of multiple sensor platforms based on information theory was presented in [50] and sampling strategies driven by distributed parameter estimation were described in [51, 52].

Motivated by the many potential applications and the rich theoretical possibilities, researchers in the control theory community began a significant effort in the early 2000's to use systems theoretic approaches to design and study cooperative control. Artificial potentials presented an attractive methodological basis for cooperative control of network formations [53, 54, 55, 56, 57, 58] both because convergence and performance could be proved using Lyapunov stability theory (see, e.g., early work on robot navigation and obstacle avoidance [59, 60]) and because control laws derived from artificial potentials resembled the distributed, cohesive and repulsive forces used to model animals that move together [61, 62].

Artificial potential methods were also used by Bachmayer and Leonard in [63] to design cooperative gradient climbing strategies for a group of vehicles that could each only take a scalar measurement at a time of the field of interest (e.g., ocean temperature). Capitalizing on this idea and building on the methods of [55, 56], Ögren et al. [4] developed a provable methodology to control the shape of the formation as well as the rotation, translation and expansion of the formation (see also [64]); this was used to design control strategies for a network of vehicles to adaptively climb gradients in the sampled field and thus robustly find peaks (see Section 3.1 below for a review of the implementation of this methodology in the field). These ideas were extended further by Zhang and Leonard [65, 66] to design provable control laws for cooperative level set tracking, whereby small vehicle groups could cooperate to generate contour plots of noisy, unknown fields, adjusting their formation shape to provide optimal filtering of their noisy measurements. Related work addressed environmental boundary tracking [67, 68], coverage control [69, 70], target tracking [71, 72], and maximization of information [50].

Researchers in control also took a strong interest in the dynamics of consensus within a network; the topology of the sensing and communication interconnections among agents was encoded using graphs, and the convergence of consensus dynamics was proved with approaches that exploited graph theory allowing for time-varying communication graphs and time-delayed communications [73, 74, 75, 76, 77]. Consensus in the positions of agents was used to address a variety of other problems including formations [78] and rendezvous [79].

In most of this consensus literature the dynamics are linear, and yet the problem of consensus on direction of motion that mobile robots must make is nonlinear, since the space of directions in the plane is a circle (and not a line). Consensus on the circle is called synchronization, and it has been studied extensively in the context of coupled phase oscillators used to model a variety of interconnected periodic processes in biology and physics (e.g., firefly flashing and neuron firing) [80, 81]. Justh and Krishnaprasad developed a geometric framework to design steering control laws to coordinate the motion of vehicles in [82]. This approach was generalized in the work of Sepulchre et al. [83, 84] using a model that extends coupled oscillator dynamics, in which the phase of each oscillator represents the direction of motion of a vehicle, to include the spatial dimensions, which represent the positions of the vehicles. These works provided a systematic methodology for designing provable, distributed control laws that stabilize motion patterns in the plane (see, e.g., [85, 86, 87] for 3D); each vehicle uses a feedback law that depends only on what limited measurements it can make, and the controlled system can cope with a time-varying communication network and with real-time changes in the number of vehicles in the group. Because the methodology is systematic and robust and because distributed control of vehicle motions patterns is central to environmental monitoring, the methodology of [83, 84] was developed into an adaptive sampling methodology for mobile sensor networks in the ocean [6] (see Section 3.2 below for a review of the implementation of this methodology in the field).

3 Advances in Cooperative Vehicle Ocean Monitoring

The AOSN II and ASAP projects were driven by an interest in developing sustainable, portable, adaptive ocean observing and prediction systems for use in coastal environments. The projects used cooperating autonomous underwater vehicles carrying sensors to measure the physics and biology in the ocean together with advanced ocean models in an effort to improve the ability to observe and predict ocean dynamics. A central focus was on reliable, efficient and adaptive coordinated control strategies for mobile sensor platforms to collect data of high value. Both the AOSN II and ASAP experiments were designed to bring together new techniques in sensing, forecasting and coordinated control; see [88] for a summary of goals and progress. The 2003 AOSN II experiment brought these techniques together for the first time, yielding an unprecedented data set. The 2006 ASAP experiment fully integrated these techniques to even greater benefit, demonstrating their potential in a versatile and high performing adaptive coastal ocean observing and prediction system. The methodologies derived, integrated and demonstrated are adaptable to a wide variety of environmental monitoring problems and settings.

3.1 Cooperative gliders in AOSN II

In summer 2003, a multi-disciplinary research group as part of the AOSN II project produced an unprecedented in-situ observational capability for studying upwelling features in Monterey Bay over the course of a month-long field experiment [1, 2]. A highlight was the simultaneous deployment of more than a dozen, sensor-equipped, autonomous underwater gliders [15], including five Spray gliders (Scripps Institution of Oceanography) and up to ten Slocum gliders (Woods Hole Oceanographic Institution). Autonomous underwater gliders are high endurance, buoyancy-driven vehicles that move up and down in the ocean by controlling their net buoyancy using pumping systems. Their fixed wings and tail give them lift, which helps them make forward progress by following sawtooth-shaped trajectories. To control their attitude, gliders actively redistribute internal mass. The Slocum uses a rudder to control heading, and the Spray shifts mass to the side to roll, bank and turn. During the field experiment the gliders were operated to achieve a fixed velocity relative to the flow. Their effective forward speed was of the same order as the stronger currents in and around Monterey Bay: approximately 25 cm/s in the case of Spray and 35 cm/s in the case of Slocum. Thus, when the currents were too strong, the gliders did not make progress if they were moving against the currents.

As part of the field experiment, sea trials were run with groups of three Slocum gliders controlled into triangular formations [5]; see also [6] for a survey. Feature tracking capabilities of the glider formations were demonstrated under the challenging conditions of limited communication and limited feedback as well as a strong flow field. Two sea trials tested strategies for cooperative motion control and cooperative gradient estimation for the gliders at relatively small scales in the region, i.e., on the order of 3 kilometers. In a third sea trial, a Slocum glider was used to track a Lagrangian drifter in real-time and collect data in a volume surrounding the path of the drifter. This demonstrated the utility of a glider, and the possibilities for a network of gliders, to track Lagrangian particle features such as a water mass encompassing an algal bloom [5].

The Slocum gliders were operated to 200 meter depth and were deployed far enough from the coast to avoid shallower water. Each glider surfaced every couple of hours, although the gliders did not surface synchronously. At the surface each glider got a GPS fix for navigation, and using Iridium satellite and ethernet, sent back to shore the data it had collected and received updated mission commands from the shore computer. Since the gliders were not equipped with underwater communication, the communication with the shore computers was the only means for (indirect) communication between gliders.

The strategy for coordinated motion control was based on the *virtual body and artificial potential* (VBAP) methodology for control of multiple vehicles described in [4]. VBAP is a general coordinated control strategy that stabilizes the translation, rotation and expansion of a formation of autonomous vehicles; it is especially well suited to missions that require a changeable mobile sensor array such as gradient climbing in a scalar, sampled field, where expansion and contraction of the network modify the resolution of the array. The virtual body refers to a collection of moving reference points, each with dynamics that are computed centrally and made available to the autonomous vehicles. Spring-like control forces for the vehicles, and the virtual body, are derived from artificial potentials between the vehicles and the virtual body; they are designed to stabilize the dynamics of the vehicles and the virtual body into a formation. In the computation of its control law, each vehicle uses a measurement of the relative position of neighboring vehicles and nearby reference points on the virtual body.

The local gradients of a sampled scalar field can be estimated on-board or centrally, if the samples taken on-board the vehicles can be communicated among them or to a central computer. The group will control its motion in the direction of the gradient if the virtual body dynamics are designed to move it in the direction of the gradient; for example, if the dynamics of the virtual body move it towards the coldest water, as determined from an estimated temperature gradient, the vehicle group will move toward the coldest water as well since it moves with the virtual body in formation. In the VBAP methodology, stability and convergence of the vehicle formation is guaranteed with a feedback control on the speed of the virtual body.

Ideal assumptions, including continuous communication and feedback for the autonomous vehicles, were used to prove the control theory and algorithms described in [4]. Thus, in order to make the control methodology applicable to the conditions of the cooperative control sea trials of 2003, the VBAP control methodology was modified in a few key ways. For example, the algorithms were integrated with the on-board glider waypoint tracking routine and adjusted to accommodate the constant speed of the gliders, the high speed ocean currents, the asynchronous surfacings of the gliders, as well as other latencies (see [89] for details). The approach was later systematized as part of the ASAP project in a fully automated software suite, the Glider Coordinated Control System (GCCS) [90]. The GCCS automates the decentralized coordinated control methodology of [6] for adaptive sampling motion patterns.

The main idea behind the integration of VBAP with waypoint control was to use VBAP to produce waypoint lists, corresponding to coordinated glider trajectories, that the gliders would then follow using their on-board waypoint control [89, 5]. Accordingly, VBAP was run in a "planning" mode using a simulation of the gliders with initial conditions defined by the gliders' most recent GPS fixes and average flow measurements. The VBAP planned trajectories were discretized into waypoint lists. Each Slocum glider uploaded its waypoint list when it surfaced, and followed those waypoints for the subsequent two hours until its next surfacing.

For the Slocum vehicles, a waypoint is prescribed as a vertical cylinder in the ocean since it refers to a position in the horizontal plane and a radius that sets how close the vehicle should come

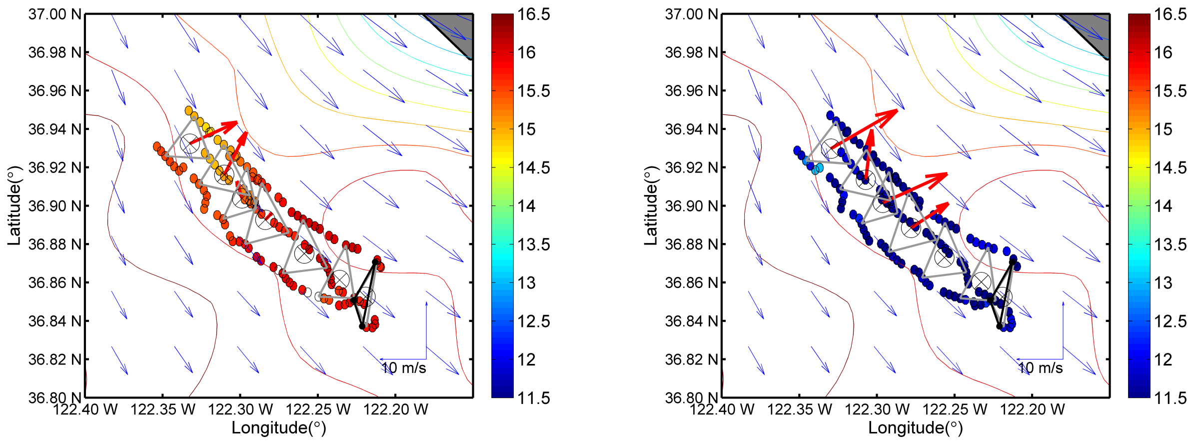


Figure 1: From [2]. Three gliders moving northwest in triangular formation (gray lines) from 18:00:00Z August 6 into late morning August 7, 2003. Colored dots indicate the temperature in °C (see color scale) at the 5 m (left) and 30 m (right) depths; black circles and lines show initial position and formation; and open circles with a cross inside triangles illustrate the path of the center of the triangle. Red arrows correspond to estimate of the negative gradient of temperature in the horizontal plane along the path of the center of the triangular formation. The color contours indicate sea-surface temperature in °C (see color scale) as sampled by the Naval Postgraduate School's TWIN OTTER aircraft.

to the waypoint position. Thus, when a sequence of waypoints is prescribed, the glider follows the waypoints by passing through each of the corresponding cylinders in the prescribed sequence. To follow a sequence of waypoints, each glider uses its on-board low-level heading control which depends on its own heading (measured on-board) and a deduced reckoning estimate of its own position [91]. The deduced reckoning position is computed by integrating an estimate of horizontal speed using the most recent GPS fix as the initial condition. The horizontal speed is estimated from depth and vertical speed, which are estimated from on-board pressure measurements. The method also uses the glider's estimate of average flow, computed from the difference on the surface between its GPS and its deduced reckoned position.

The first sea trial in which three Slocum gliders coordinated their motion in an equilateral triangle formation was run over a period of sixteen hours on August 6-7, 2003, with asynchronous two-hourly surfacings. The distance between gliders was prescribed to be three kilometers and the formation prescribed to move along a linear path heading northwest to measure the incipient upwelling front. In the first half of the sea trial there was no prescription on the orientation of the formation so that it could most efficiently maintain array resolution and follow its path. In the second half of the sea trial, to test the orientation control feature of the methodology, the orientation was prescribed such that one edge of the triangle would always be normal to the path of the center of mass of the group. The prescription of glider array resolution and linear path made it possible for in-situ estimates of gradients to be computed in near real-time from the gliders' scalar measurements. The results suggest that the gliders could successfully be programmed to autonomously follow their estimate of the gradient if so desired.

Figure 1 shows a sequence of snapshots of the triangular glider formation over the August 6-7, 2003 sea trial. Temperature measurements are shown on the left at 10 m depth and on the right at 30 m depth. As shown, the three vehicles stayed in formation moving along the desired linear path despite relatively high speed currents. The red arrows on the plot show a few example glider estimates of the negative gradient of temperature. These vectors point in the direction of the cold water, as verified from independent temperature measurements. The resolution corresponding to three kilometers between gliders led to remarkably smooth gradient estimates over time.

Three gliders again coordinated their motion in an equilateral triangle formation in a second sea trial on August 16-17, 2003. This time the distance between gliders was prescribed to start at six kilometers and then contract to three kilometers. This was meant to demonstrate the expansion and contraction feature of the methodology and test the effect of the different glider array resolutions on the gradient estimates. The formation was prescribed to move along a zigzag path heading southwest across the upwelling front. Despite facing currents with magnitude as high as the Slocum's effective speed of 35 cm/s, the glider formation moved and contracted remarkably well. The results suggest that the gliders could successfully be programmed to autonomously adapt their formation size in response to changing scales in the sampled field.

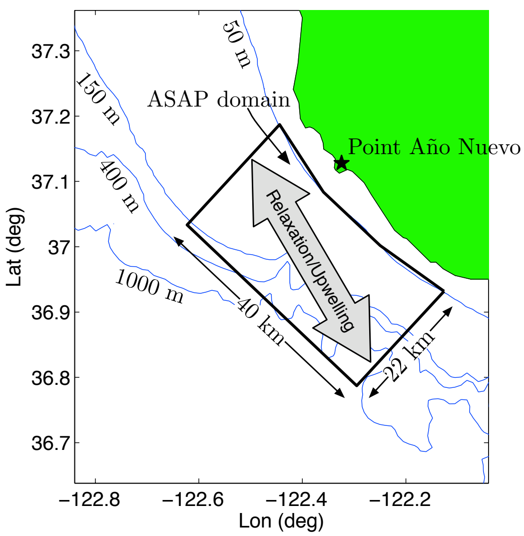
In the August 6-7 sea trial, the coordinated glider network measured the front close to its inception, while in the August 16-17 sea trial, the network measured the front after it had been advected further to the south across the mouth of Monterey Bay [2]. As a result, the data collected from these two sea trials added new insight into the evolving vertical structure of the upwelling plume. Notably, the gradient estimates from the glider networks would not have been possible using conventional profiling floats or drifters. Since frontal dynamics are typically nonlinear, precise gradient estimates are critical in forecasting frontogenesis and evolving instabilities.

In the third sea trial on August 23, 2003, a single glider followed a surface drifter in real-time, making zigzags across and below its projected path. This demonstrated yet another opportunity for environmental monitoring with coordinated vehicles, namely that a glider or glider formation could collect scalar samples and thus estimate gradients both across and along tracer paths.

3.2 Cooperative gliders in ASAP

In summer 2006, a multi-disciplinary research group as part of the ASAP project performed an unprecedented field experiment, building on the successful efforts of the AOSN II project. The ASAP project demonstrated a full-scale adaptive ocean sampling network featuring a coordinated network of gliders controlled autonomously over the course of a month to efficiently sample a 22 $\times$ 40 km and up to more than 1000-m-deep region of coastal ocean just northwest of Monterey Bay as shown in Figure 2(a) [3]. The coordinated sampling of the gliders was integrated with an assortment of additional mobile and stationary sensing platforms, three real-time numerical ocean models, numerical optimization and prediction tools, a virtual control room, and a participating team of scientists.

When gliders move without taking into account, e.g., through feedback, the relative position or motion of other gliders in the group, they are susceptible to strong currents driving them into clumps. In the AOSN II experiment current-driven clumping was observed and shown to lead to sensor redundancy with negative impact on sampling performance [6]. This motivated the development of coordinating feedback control laws that enforce dynamic distribution of vehicles to enhance sampling performance. The methodology proposed and justified in [6] provides this coordinated feedback control with two components: 1) the design of coordinated motion patterns for high-performance sampling and 2) the design of feedback control laws that systematically and automatically stabilize vehicles onto the desired coordinated patterns. The methodology of [6] was implemented in the 2006 ASAP experiment, which provided a proof of concept for the applicability of the methodology to the field.



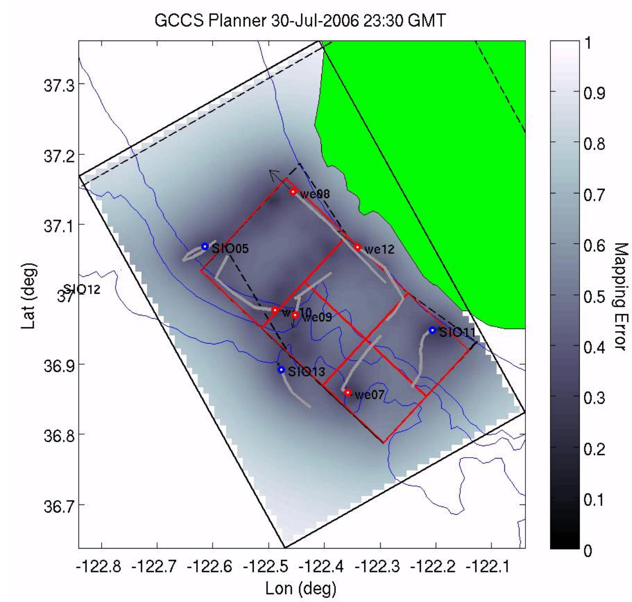


Figure 2: From [3]. (a) Region of glider fleet operations in the 2006 ASAP field experiment, just northwest of Monterey Bay, California. The summertime ocean circulation in Monterey Bay oscillates between upwelling and relaxation. During an upwelling event, cold water often surfaces just north of the bay, near Point Año Nuevo and tends to flow southward across the mouth of the bay. During relaxation, poleward surface flow crosses the mouth of the bay past Point Año Nuevo. (b) Objective analysis mapping error plotted in gray scale on the ASAP sampling domain for July 30, 2006 at 23:30 GMT (Greenwich Mean Time); see text for details on the mapping error. Eight gliders are shown; their positions are indicated with red (Slocum) and blue (Spray) circles.

The methodology proposed in [83, 84] was used for the second component, i.e., the systematic generation of feedback control laws for stable coordination of a network of autonomous vehicles to a family of motion patterns. The patterns, which consist of vehicles moving on a finite set of closed curves, are distinguished by a small number of parameters that encode synchrony. For example, two vehicles that move in parallel around two separate curves have synchronized heading directions, while two vehicles that move around the same curve but always on opposite sides of the curve have anti-synchronized heading directions. The corresponding feedback laws the vehicles use are likewise distinguished by control gains that depend on the same small number of synchrony parameters. The control laws are distributed, which means that each vehicle applies its own control law that depends on its own measurements. Furthermore, the control laws are reactive, i.e., they do not require a prescription of where each vehicle should be as a function of time, but rather each vehicle moves in response to the relative position and direction of its neighbors. Each vehicle is constantly adjusting what it does to keep moving and stay close to its assigned curve and importantly to maintain the desired spacing with respect to the other vehicles, as encoded by the synchrony parameters. Because the responsive behavior of each individual can be defined as a function of the state of a small number of other vehicles, independent of the total number of vehicles, the control methodology is scalable. And because there are no leaders or special individuals in the network, the methodology is robust to vehicle failure.

The Glider Coordinated Control System (GCCS) software infrastructure described in [90] and tested in [92] was used to implement the methodology in the field. In the ASAP experiment it was observed that vehicles maintain their prescribed relative spacing in the presence of strong currents by moving off their assigned curve as needed: when a vehicle was slowed down by a strong opposing flow field, it cut inside its curve to make up distance, while its neighbor on the other side of the curve that was sped up by the strong current cut outside the curve to avoid overtaking the slower vehicle and compromising spacing.

There are several advantages to designing the coordinated motion patterns independently from the design of control laws to stabilize vehicles to those motion patterns. First, the patterns can be independently chosen to optimize a sampling performance metric. Second, the pattern can be chosen for minimal performance sensitivity to disturbances in vehicle motion. Additionally, the pattern can be chosen to account for design requirements and constraints, such as avoiding or focusing on certain regions, leveraging information on the direction of strong currents so vehicles move with them rather than against them, and accommodating additions or removals of vehicles. Human-in-the-loop supervisory control, which can be critical for highly complex settings, can be fairly easily integrated when it is warranted. In the ASAP experiment, a team of scientists made supervisory decisions based on visualizations of observational data, modeling output, system performance and availability of vehicles. A method was in place to translate these decision into formal adaptations of the desired motion patterns, which could be refined using numerical optimization tools. To implement an adaptation, an intermittent, discrete change in the pattern was input to the GCCS and the vehicle network responded accordingly.

The sampling metric used to design motion patterns [6] is computed from the mapping error of the data assimilation scheme known as objective analysis (OA) [46, 93]. OA provides a linear statistical estimation of a sampled field, and the mapping error measures the residual uncertainty. OA mapping error is a sampling performance metric since reduced uncertainty implies better measurement coverage. The mapping error at a given position and time is the error variance at that position and time. It can be computed from an empirically derived model of the covariance of fluctuations of the sampled field about its mean and from where and when data are taken. The OA mapping error is plotted in gray scale on the sampling domain in Figure 2(b). The sampling metric is computed as the negative log of the integral of the mapping error over the sampling region. In the

ASAP experiment the mapping error was computed in real-time so that humans making adaptation decision could evaluate sampling performance.

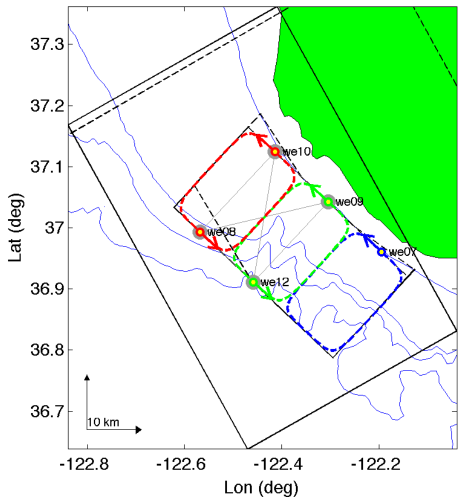
An examination of the oceanographic and atmospheric conditions during the ASAP experiment using data and model output is described in [94]. The oceanographic focus of the ASAP experiment was the "three-dimensional dynamics of the coastal upwelling frontal zone in Monterey Bay and the processes governing the heat budget of the 22 km $\times$ 40 km control volume during periods of upwelling-favorable winds and wind relaxations" [3]. An objective for the coordinated glider sampling was to be responsive to the dynamics of intermittent upwelling events.

Data were collected during the experiment from other sources as well as the gliders. These include a Naval Postgraduate School research aircraft, satellite imagery, high frequency radar, and several moorings, drifters deployed by the Monterey Bay Aquarium Research Institute (MBARI) and other ships and vehicles outside the control volume. Three different high-resolution ocean models regularly assimilated data: the Harvard Ocean Prediction System (HOPS) [95], the Jet Propulsion Laboratory implementation of the Regional Oceanic Modeling System (JPL/ROMS) [96] and the Navy Coastal Ocean Model/Innovative Coastal Ocean Observing Network (NCOM/ICON) [97]. Each model produced daily updated ocean predictions of temperature, salinity and velocity. A central data server at MBARI was used to run a virtual control room (VCR) and to make all observational data and model outputs available in near real-time. The VCR, developed for the 2006 ASAP field experiment, made it possible for participants to remain at their home institutions throughout the experiment but still be fully informed and connected team members [98]. There were a number of different panels on the VCR including those for team decision making and voting.

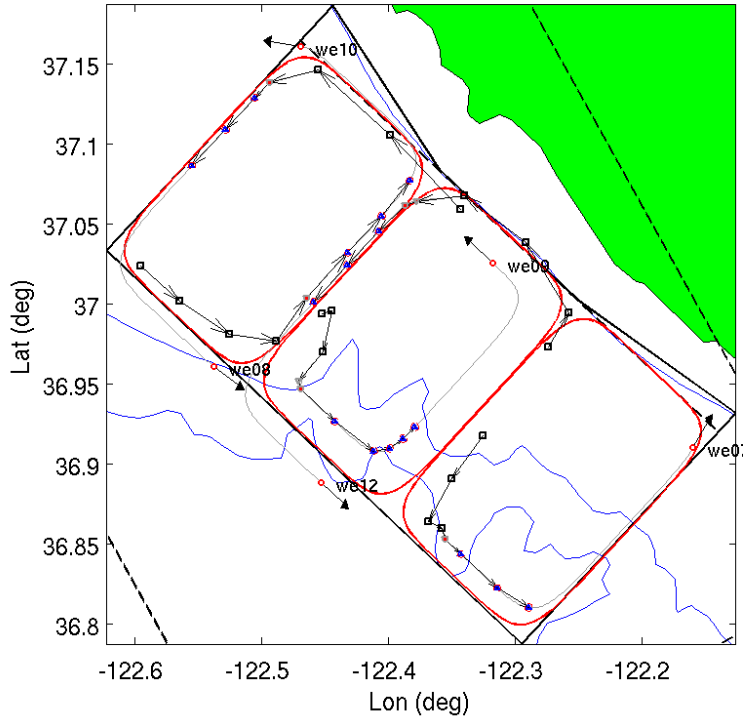
Virtual pilot experiments were run in advance of the field experiment to get experience with the coordinated control and adaptive sampling implementation. The virtual experiments were run as if they were real field experiments except for the replacement of real vehicles in the real ocean with simulated vehicles moving in the currents of a virtual ocean defined by a HOPS re-analysis of Monterey Bay in 2003. The simulation mode of the GCCS was designed to allow for virtual experiments with control of gliders, communication paths, and data flow exactly the same as what was used in the 2006 field experiment [90, 99].

For the ASAP experiment, the Slocum gliders were allocated to mapping the interior volume using automated coordinated sampling defined by motion patterns on a finite set of closed curves, with properties between measured paths inferred using interpolation. The automated feedback control laws for the Slocums were implemented with the GCCS. The Spray gliders were allocated to mapping the periphery of the volume. The boundary was divided up into segments and each Spray glider was assigned to move in an oscillatory manner along a segment of the boundary. A separate control law was implemented for this oscillatory behavior so the gliders were well distributed. The experiment started with a default coordinated motion pattern, and as the environment and operating conditions changed, the coordinated motion pattern was re-designed and updated.

The input file to the GCCS that defines a coordinated motion pattern is called a *glider coordinated trajectory* (GCT). As an example, GCT #2 used for the Slocum gliders in the ASAP experiment is illustrated in Figure 3(a). A GCT defines the curves that serve as tracks for the gliders as well as the synchronization of the motion of the gliders on and across the different curves. For example, the GCT #2 shown in Figure 3(a) defines a pattern in which a pair of gliders, denoted with red circles, moves around the red curve with maximal inter-vehicle spacing and is synchronized with another pair of gliders, denoted with green circles, that moves around the green curve with maximal inter-vehicle spacing. The glider planner status panel of the VCR on July 30 at 23:10 GMT, when GCT #2 was active, is shown in Figure 3(b). The glider planner panel for OA mapping error at roughly the same time is shown in Figure 2(b).



(a) GCT #2 active on July 30, 2006.



(b) GCCS planner panel, July 30, 2006 at 23:10 GMT.

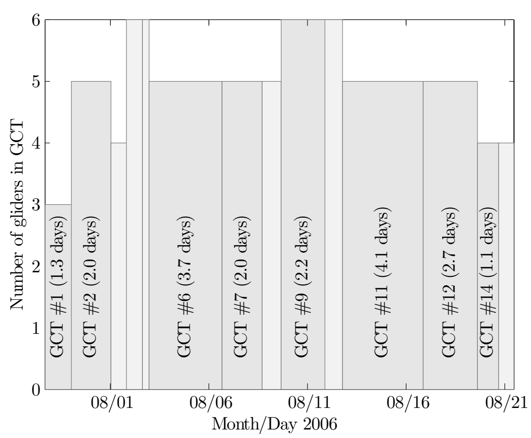
Figure 3: From [3]. (a) The coordinated pattern for four of five Slocum gliders already in the water at the end of July 2006, with the pair we08 and we10 to move on opposites of the north track, the pair we09 and we12 on opposites of the middle track and the two pairs synchronized on their respective tracks. Glider we07 should move independently around the south track (the sixth glider had not yet been deployed). The dashed lines show the superelliptical tracks, the circles show a snapshot of the glider positions and the color coding defines each glider's track assignment. The thin gray lines show the feedback interconnection topology for coordination (all but we07 respond to each other) and the arrows show prescribed direction of rotation for the gliders. (b) Several real-time status and assessment figures, movies and logs were updated regularly on the VCR. Shown here is a snapshot of one of the panels, which was updated every minute. It presents, for each glider, surfacings over the previous 12 hours (black squares), waypoints expected to be reached before the next surfacing (gray triangle), next predicted surfacing (gray circle with red fill), new waypoints over the next six hours (blue triangles inside red circles) and planned position in 24 hours (hollow red circle). Each glider is identified with a label at the planned position in 24 hours.

Pseudo-elliptical curves were selected for the Slocums since they had nearly straight long sides. The curves were oriented to ensure that the gliders would repeatedly cross over the shelf break, each time sampling a cross-section of the dynamic ocean processes that propagate parallel to the shelf break. The shelf break refers to the end of the continental shelf characterized by a markedly increased slope toward the deep ocean bottom. "By constructing a time sequence of cross-section plots, it would then be possible to reconstruct, identify and monitor ocean processes even before assimilating the glider profile data into an advanced ocean model" [3].

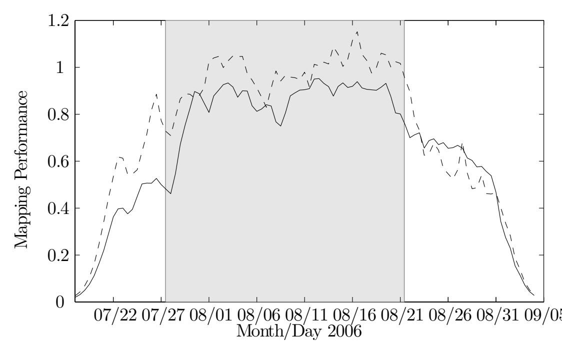
The distribution (synchronization) of the gliders relative to one another around the curves, as well as the dimensions and position of the curves, were selected to maximize the sampling performance metric. An on-line optimization tool was available for locally optimizing any candidate motion pattern. Additionally, candidate coordinated motion patterns were often pre-tested using the GCCS in simulation mode using one or more of the forecast ocean fields. Because the simulations of gliders moving in the forecast ocean could be run in faster than real-time, it was possible to obtain predictions of glider performance in the predicted real ocean.

To implement an adaptation to sampling plans, a new GCT was prepared to replace the existing GCT. This was initiated manually by briefly interrupting the GCCS, swapping the new GCT file for the old one, and then re-starting the GCCS. Over 24 days of the ASAP experiment, 14 different GCTs were used to adapt the Slocum glider plan (see Figure 4(a)). Some of the adaptations were made in response to changes in the ocean involving strong and highly variable flow conditions. Other of the adaptations were made in response to changes in scientific objectives, for example to add sampling over the head of the canyon and to chase an eddy moving offshore. The influence of these adaptations are reflected in the Slocum glider sampling performance, which is plotted as a function of time in Figure 4(b). In particular, poor coordination of gliders resulted in a decline in sampling performance. On August 6, during GCT #6, the sampling performance experienced its steepest decline as a result of flow conditions impairing coordination. Recovery of performance after a subsequent adaptation of motion pattern demonstrated the positive impact of coordinated control on sampling performance. Details on the ocean conditions, adaptations, and performance of the gliders during the field experiment are described in [3].

The methodology of [6] was successfully implemented in the challenging coastal ocean environment of Monterey Bay, CA in August 2006, demonstrating a new capability for ocean sampling. The implementation points to the feasibility and versatility of the method for adaptation of motion patterns and integrated human decision-making to address a complex multi-robot sensing task. The glider network coordination was autonomous and sustained with glider motion patterns adapted to meet the requirements of the changing ocean sampling mission and the changing dynamic state of the ocean. The methodology can be applied to collaborative robotic sensing in other domains.



(a)



(b)

Figure 4: From [3]. (a) Time of GCTs for Slocum gliders. (b) Slocum glider sampling performance over the interior of the sampling region (solid line) and along the boundary (dashed line). The sampling performance ramped up when the gliders entered the water and ramped down when the gliders came out of the water. The portion of the plot that is shaded gray corresponds to the period of time during which the GCCS was actively steering the Slocum gliders.

4 Recent Developments and Future Directions

Recent years have seen an acceleration of theoretical developments and field testing of cooperative vehicle environmental monitoring; these have both motivated and leveraged advances in sensors, energy efficient and versatile mobile sensing platforms, communications, environmental modeling and estimation techniques, and control theory for cooperative exploration by networked mobile agents. It has become clear that robotic vehicles are especially useful for monitoring in remote and hostile environments and that their potential is much enhanced when they perform in cooperative teams [100]. A recent survey of robotics for environmental monitoring, including a discussion of cooperative systems, is provided by Dunbabin and Marques [101]. Redfield surveys works on cooperative underwater vehicles in [102]. Many of the recent advances are opening up further opportunities and avenues for continued research.

Further, new infrastructure developments, such as the cabled ocean observatories, provide significant resources that could potentially enhance the versatility of cooperative autonomous vehicles, most particularly with respect to data, communication and power. For example, the NEPTUNE regional cabled ocean observatory boasts continuous high power and high-bandwidth data transfer in real-time between a large expanse of the ocean sea floor and the shore. Without having to surface, any autonomous vehicle could make use of sea floor nodes to send its data back to shore, or to share its location and data with other vehicles in the team, which would improve coordination among vehicles. A vehicle could also use the infrastructure to calibrate its location for its on-board deduced reckoning and to leverage the data collected in the cabled observed for its on-board (and thus collective) decision-making. Further, if docking stations were available, autonomous vehicles could recharge their batteries. Leveraging cabled observatories in this way would be most advantageous if dynamic sampling coverage were needed to complement the existing coverage from the sea floor nodes. Otherwise, there would be a tradeoff for the autonomous vehicles between moving into areas already well covered and exploring new areas where no cabled observatory exists.

Examples of recent field tested methodologies for cooperative vehicle environmental monitoring include a decentralized strategy for coordinated harbor patrol using the theory of Gaussian processes implemented on three AUVs in Lisbon harbor by Marino et al. [103]. Schofield et al. [104] describe a number of field tests including a test of remote coordination of an array of acoustically networked AUVs and the coordinated sampling of underwater gliders and the space-based Hyperion imager flying on the Earth Observing-1 spacecraft. Using decentralized data fusion and control, two unmanned aerial vehicles (UAVs) were used to demonstrate cooperative localization of ground-based features by Cole et al. [105]. Techy et al. [106] implemented a strategy for coordination based on speed modulation to synchronize two autonomous UAVs for tracking long-distance movement of plant pathogens above crop fields. Maczka et al. [107] demonstrated an efficient method for cooperative navigation of underwater vehicles from time-synchronized acoustic data transmissions. Hollinger et al. [108] demonstrated on a single AUV in the Southern California Bight a probabilistic planner that uses uncertainty in ocean current prediction based on an interpolation variance. Merino et al. [109] presented a cooperative perception system for multiple UAVs with different kinds of sensors and showed experimental results of forest fire detection with cooperating UAVs. Alvarez et al. [110] described methodology that estimates volumetric distribution of the geostrophic current field from glider measurements merged with satellite altimetry data; this methodology was validated using data collected from three Slocum gliders and one Spray glider moving along predefined paths during a field experiment in August 2010 in a coastal region of the Ligurian Sea. Alvarez and Mourre [111] examined optimal sampling strategies for a single underwater glider sampling in the presence of a mooring.

Lekien et al. [112] presented a method that uses Lagrangian coherent structures to coordinate vehicles robustly in the presence of very strong currents. Other methods to coordinate gliders and AUVs to maximize information in the data collected, taking explicit account of challenging ocean currents have been studied, e.g., by Lynch et al. [113], Baumgartner et al. [114], Munafò et al. [115], Liang et al. [116], and Davis et al. [117]. Strategies for coordinated sampling that optimize information-based metrics have also been further explored, e.g., [118, 119, 120, 121, 122, 123, 124].

Advances have been made in decentralized cooperative control strategies that improve or leverage the communication network structure of mobile robotic teams. These include new algorithms that use graph theoretic approaches [125] for computing, maintaining or maximizing connectivity [126, 127, 128], controllability [129], and robustness of coordinated motion to uncertainty [130]. Techniques from algebraic topology have also been applied to problems in multi-vehicle sensing [131]. Advances in cooperative routing and motion planning for multiple autonomous vehicles have been extensive, see for example [132, 133].

Another source of inspiration for cooperative control design comes from mechanisms of collective behavior in animal groups such as fish schools and bird flocks. In these animal groups, remarkable collective behaviors result without centralized direction from relatively simple individuals who sense and respond to their local environment, including the relative position, heading or speed of "neighbors" in the group [134, 135, 136, 137]. Mathematical models have been used to explain individual decision-making and interactions that lead to high-performing group behaviors [138, 139, 140, 141, 142]. These models can potentially be used to design provable decision-making feedback laws for individual robotic vehicles so that robotic teams inherit some of the critical group-level properties observed in nature, e.g., the ability of the group to forage efficiently (for information) despite individual-level limitations on sensing and communication and significant uncertainty in the environment. For example, Torney et al. [143] showed how animal groups could apply a performance-dependent interaction to efficiently move to the source of a chemical gradient in a turbulent environment, and Wu et al. [144] turned this into a provable algorithm for efficient cooperative search in a noisy distributed field. In [145], Young et al. applied system-theoretic techniques to understand interactions in starling flocks that yield robustness of consensus to uncertainty, and used these in [130] to design decentralized feedback laws that enable networks of vehicles to improve their robustness to uncertainty.

Design of dynamics of decision-making teams of robots and humans is yet another important direction of research that has the potential to impact the success of cooperative vehicles in complex tasks. Humans are capable of intelligent and adaptable decision-making in response to reasoning about real-world information in real-time, and robotic systems are capable of significant computational speed and memory. Challenging problems in complex settings, e.g., with multiple scales and significant uncertainty, can be well served by solutions in which humans and robotic systems participate in complementary ways. Benefits and possible pitfalls of such human and robot collaboration were evidenced in the AOSN II and ASAP experiments. Indeed, with the data visualization tools, computational aids, and communication mechanisms accessible through the GCCS and ASAP's virtual control room, the ASAP field experiment demonstrated collaboration between a distributed team of humans and an automated group of underwater robots to perform adaptive ocean sampling in an uncertain environment with multiple objectives subject to a variety of safety and operational constraints. While the autonomous vehicles moved continuously in coordinated patterns, the human participants contributed in ways the automated system could not by making rapid decisions in response to critical environmental changes (e.g., sudden excessively strong currents or unanticipated shallow water) and operational failures. The human team also made important longer-term decisions in response to observed or predicted indications of change in the environment, such as new features or locations of interest, or decline in performance with respect to one or more performance metric. And yet, opportunities may have been missed when the human participants had difficulty assessing the likelihood of risk in proposed scenarios or balancing the many competing objectives. Likewise, human supervisory strategies may have been less than optimal given that the autonomous robots had no opportunity to provide direct feedback to their human supervisors.

In this vein, progress has been reported on humans and robots in exploration [146, 147, 148, 149, 150] and on humans working together in search tasks [151, 152, 153, 154]. Progress has also been made on algorithm development using what cognitive scientists understand about human decision-making. For example, decision-making algorithms with provable performance in search tasks were derived in [155], drawing on research on the heuristics humans use to trade off between exploiting well-known alternatives and exploring uncertain but possibly better alternatives. It has been shown in [156] that humans use their ability to learn correlation structure when it exists among decision alternatives, as in the case of alternatives representing different locations in a spatially distributed resource, and the knowledge of correlation structure has been shown to be critical to enhancing performance in the search algorithms of [155]. This suggests approaches to systematize means for robots to benefit from humans input, e.g., by using observations of human choices to estimate correlation structure and updating decision-making strategies accordingly. Further work that builds on research on human decision-making and behavior may allow derivation of engineering models and provable strategy design for well integrated human-robot teams in complex missions such as cooperative vehicles for environmental monitoring.

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