Computer Communications 35 (2012) 1017–1028

Contents lists available at SciVerse ScienceDirect

Computer Communications

journal homepage: www.elsevier.com/locate/comcom

Team formation and steering algorithms for underwater gliders using acoustic communications ☆,☆☆

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ARTICLE INFO

Article history:
Available online 14 January 2012

Keywords:
Underwater acoustic sensor networks
Autonomous underwater vehicles
Underwater gliders
Team formation
Team steering

ABSTRACT

In order to take measurements in space and time from the undersampled vast ocean, it is necessary to employ multiple autonomous underwater vehicles, such as gliders, that communicate and coordinate with each other. These vehicles need to form a team in a specific formation, steer through the 3D region of interest, and take application-dependent measurements such as temperature and salinity. In this article, team formation and steering algorithms relying on underwater acoustic communications are proposed in order to enable glider swarming that is robust against ocean currents and acoustic channel impairments (e.g., high propagation and transmission delay, and low communication reliability). Performance of the proposed algorithms is evaluated and compared against existing solutions, which do not rely on underwater communications, using different ocean current models.

1. Introduction

In the recent years, underwater acoustic sensor networks (UW-ASNs) [2,3] have been deployed to study dynamic oceanographic phenomena such as variations of salinity and temperature, fish migration, and phytoplankton growth for environmental and disaster monitoring (e.g., climate change, tsunami and seaquakes, pollution). In order to enable these applications, it is necessary to take measurements in space and time from the undersampled vast ocean in such a way as to monitor the variations of these phenomena. For example, coral reef spatio-temporal variations are studied in [4] to assess the ability of coral reefs to cope with accelerating human impacts.

Current solutions for ocean sampling rely on existing integrated ocean observing infrastructure, which is comprised of static platforms such as subsurface moorings, ocean-bottom sensors, surface moorings, and mobile platforms. Static platforms will connect to the onshore sensing and high-performance computing resources through high-speed undersea cables, while mobile platforms will connect through satellite and terrestrial links from the ocean surface. These solutions are limited with respect to their application domain, their scalability, and their data quality (e.g., the accuracy of sensed data). These limitations can be removed by using multiple autonomous underwater vehicles (AUVs) that communicate and coordinate with each other and that swarm as a team. Moreover, as long-time measurement is generally needed to collect and derive the spatio-temporal distribution of the data, it is necessary that these AUVs operate over prolonged time periods. Hence, in this article we focus on underwater gliders – a class of energy-efficient propeller-less AUVs. These vehicles can operate over months as they use battery-powered hydraulic pumps to change buoyancy, which power their forward gliding along a sawtooth trajectory.

In order to efficiently take the measurements, it is necessary that these vehicles communicate and coordinate with each other to form a team in a specific formation and steer through the 3D region of interest. Specifically, given the number of gliders to form the team and the formation geometry, which depend on the monitoring application, the gliders need to decide and reach their positions in the specified formation; then, once the formation has been formed, they need to move through the region along a predefined trajectory while maintaining the formation. This problem can be split into two subsequent subproblems: *team formation* (Phase I) and *team steering* (Phase II). In this article, we focus on providing robust yet practical solutions to these two subproblems by proposing the use of underwater acoustic communications to facilitate the coordination of the gliders. In this work, *robustness* refers to the ability of the AUVs to maintain the specified formation in the presence of ocean currents and communication errors.

In the underwater environment, because of the high medium absorption, radio frequency (RF) waves can propagate only a few tens of meters and require high transmission power. Also, while optical transmissions do not suffer from such high absorption, they scatter and require precise pointing of the narrow laser beams,

☆ A preliminary shorter version of this article is in Proc. of IEEE Sarnoff Symposium, Princeton, NJ, April 2010 [1].
☆☆ This work was supported by the NSF CAREER Award No. OCI-1054234.
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doi:10.1016/j.comcom.2012.01.001

which makes them impractical for underwater communications. For these reasons, *acoustic technology is used for underwater inter-vehicle communications*. However, acoustic communications suffer from several impairments: they are influenced by path loss, noise, multi-path, Doppler spread, and high propagation delay. All these factors determine the temporal and spatial variability of the acoustic channel, and make the available channel bandwidth and data bit rates limited and dramatically dependent on both range and frequency.

The problem of underwater vehicle coordination is generally difficult due to its distributed nature and to the harsh communication environment. Decentralized algorithms that are robust enough to compensate for the communication errors caused by the acoustic channel impairments need to be designed so that the gliders can self organize into a team and maintain the predefined formation along the assigned trajectory. To support the coordination of multi-agent systems, *swarming intelligence* has been introduced. A swarm is typically made up of a number of agents interacting locally with one another and with their environment. Through swarm intelligence, the fleet of agents would be able to optimize the mission and achieve a mutual goal. Numerous swarming algorithms such as particle swarm optimization (PSO) [5] have been proposed for the coordination and control of the agents. However, many of these algorithms, several of which inspired by the biological swarms of ant colonies, bird flocking, bacterial growth, and fish schooling, assume a large number of agents and do not perform well when the number of agents is small, as is the case with expensive AUVs.

To address this problem, many solutions such as [6–9] have been proposed by underwater robotics researchers to steer a team of autonomous vehicles along a specified path and thus performing a mission such as adaptive sampling. For many of these solutions, inter-vehicle communications are assumed to be ideal (i.e., no packet loss, no delay, etc.) or are based on ideal graph theory models. Therefore, it is not clear how well they perform using real underwater communications. There are also some solutions such as [10] that rely on air communication techniques (e.g., satellite communications) to exchange inter-vehicle information. In this case, these vehicles have to surface, thus wasting more energy and time (not to mention the risk that – as it has happened – the vehicle is stolen by pirates or damaged by vandals).

To overcome the limitation of using theoretical communication models and relying on radio communication techniques, we introduce innovative coordination algorithms using underwater communication techniques to support swarming of a realistically limited number of underwater gliders (less than ten). Specifically, we propose: (1) a *team formation algorithm* to move the gliders into the specified geometry in minimal time and without collisions, and (2) an *attraction and repulsion swarming algorithm* to steer gliders while maintaining the formation. Underwater acoustic communication techniques are combined with these algorithms in order to improve the performance of vehicle coordination. For team formation, a packet type that performs well for long-range communications is used. For team steering, the relative locations of AUVs are estimated from the Doppler shifts extracted from ongoing opportunistic inter-vehicle communications.

The contribution of our solution is the following:

- Our team formation and team steering algorithms use real underwater acoustic modems and are combined with more realistic underwater communication models. Therefore our solution is closely integrated with realistic underwater communications.
- We design novel underwater acoustic communication techniques to improve the performance of inter-vehicle communications. For example, reliable short FSK-modulated packets are used for long-range communication during team formation.
- We propose a hybrid team steering scheme based on the Doppler shifts extracted from ongoing opportunistic inter-vehicle communications. These Doppler shifts are then used to estimate the relative locations of the AUVs, which are then fed back for distributed steering control.

Our communication techniques are biologically inspired in the following aspects: (i) long-range communication technique for team formation is inspired by the low-frequency long-haul vocalization used by kill whales, (ii) team organization consisting of rotating roles of a leader and multiple followers is inspired by migratory bird flocking, and (iii) Doppler-based relative velocity estimation to maintain the geometry by exploiting local communications is inspired by the echolocation adopted by bats.

The remainder of the article is organized as follows. In Section 2, we review the related work for UW-ASNs and AUV team formation and steering. In Section 4, we present the proposed algorithms for team formation and steering, while in Section 5 their performance is evaluated. Conclusions are then drawn in Section 6.

2. Related work

Cooperation of a team of AUVs to efficiently complete underwater missions such as adaptive sampling [11,10] has attracted many researchers. For example, a solution was proposed for cooperative control of multiple vehicles based on virtual bodies and artificial potentials [10]. However, the control is achieved through satellite communication, which is not available underwater. Periodically, these AUVs have to surface to update their global positioning system (GPS) location and mission plan. The control of the AUVs is not in real time, therefore team formation and steering error due to unpredictable events such as variations of ocean currents cannot be fixed in real time.

In [7], research work in the European Union project GREX, which focuses on the coordination and control of cooperating heterogeneous autonomous marine vehicles (AMVs) in uncertain environments, is summarized. A general architecture for cooperative AMV control in the presence of time-varying communication topologies and communication losses is proposed. The simulation results with the networked marine system simulator and the real sea-experiment results are presented and show the efficacy of the algorithms developed for cooperative motion control. Some theoretical and practical implementation issues have, however, been raised.

A leader–follower approach is proposed in [9] for multi-AUV coordination using underwater communications. Specifically, two control algorithms are designed for two scenarios using two AUVs. The effectiveness of both algorithms are verified only in simulations.

In [8], a solution is proposed to address the problem of steering a group of vehicles along given spatial paths while holding a desired geometrical formation pattern (i.e., the path following problem). The solution is built on Lyapunov-based techniques and addresses explicitly the constraints imposed by the topology of the inter-vehicle communications network. By decoupling the path-following and coordinated control system, the dynamics of each AUV can be dealt with by each vehicle controller locally at the path-following control level, while coordination can be achieved using a decentralized control law whereby the exchange of data among the vehicles is kept at a minimum. The effectiveness of the proposed solution is verified by simulations. However, as the communication impairments are based on ideal graph theory models, i.e., the network topology of the AUVs follows an ideal probabilistic graph without considering the performance of underlying acoustic communication techniques or hardware constraints, the proposed solution needs to be extended to handle stringent underwater communication constraints. Therefore, it is unclear how well the proposed solution performs in real underwater communication environments.

In [12], the problem of team formation from initial to target formation positions under the influence of external disturbances is studied. An event-based approach is proposed, which relies on an uncertainty model to trigger surfacing events so that AUVs can measure their own position and update their control signal. A method is also proposed to characterize the disturbance set using these events. Communications between AUVs are modeled with network adjacency matrix and are limited to the time when the AUVs surface. Numerical examples on relevant scenarios are also provided.

Many of the above approaches use ideal graph theory models for underwater acoustic communications without considering the different performance of underlying communication techniques or hardware constraints. Therefore, it is not clear how well these solutions perform in real underwater acoustic communications. Conversely, in this article, we propose a solution that is based on realistic underwater acoustic communication models and that uses real underwater acoustic modems. In this way, we are able to assess the impact of the impairments of underwater communications on the coordination of AUVs.

A few solutions using underwater acoustic communications have been proposed for coordination of AUVs. In [13], a leader–follower algorithm is proposed to control the formation. It is assumed that each vehicle follows a specific path and the formation algorithm changes the velocity of each vehicle to maintain a specified distance from the leader. The followers must adjust their velocity to maintain the desired distance to the leader according to a so-called force magnitude function that considers the velocity and displacement error. However, this algorithm is not suitable to keep the 2D or 3D formation if no external constraints are enforced (e.g., AUVs needs stay on their individual trajectories or depths accurately), as the AUVs only need to keep the relative distance to the leader, which is obviously not enough to keep the 2D or 3D formation and the effectiveness of the algorithm depends on the accuracy of the leader's position and the ability of the vehicles to stay on their planned trajectories/depths. Therefore, this algorithm is more suitable for the 1D linear formation control.

In [9], two coordination schemes using acoustic communications are proposed to keep the relative distance between two heterogenous vehicles. In the first scheme, called "wait on distance", when the leader finds the relative distance is over a threshold, it issues a message with position information to the follower and then waits until the follower catches up. In the second scheme, called "survey and patrol", a set of meeting points are calculated during the mission planning, the leader enters the wait state until the follower catches up. After receiving the confirmation message of the follower, the leader tells the follower the next meeting point and both vehicles move towards that point using this coordination scheme. These two schemes are proposed for the coordination of two heterogenous vehicles and hence is not suitable for the formation of 3 or more vehicles. Time division medium access (TDMA) is chosen for the simplicity of its implementation for medium access control to avoid packet collisions during acoustic communication.

In contrast to [13] and [9], our solution is a general one that works with more complicated formations and steering tasks (which may be needed to extract temporal and spatial correlation features from the sampled data). Moreover, our solution exploits acoustic communication techniques to improve the communication performance (e.g., 3 bio-inspired techniques are used and performance of different packet types is considered), while existing solutions pay little attention to this. They use simple acoustic communication functions so communication performance may not be optimized.

3. Network model

In this section we introduce the UW-ASN, which our solution is based on, and state the assumptions we make. Let us assume that the network is composed of a number of gliders that communicate with each other. Gliders are deployed in the ocean for long periods of time (weeks or months) to collect surveillance data. For propulsion, they change their buoyancy using a pump and use lift on wings to convert vertical velocity into forward motion as they rise and fall through the ocean. They travel at a fairly constant horizontal speed, typically 0.25 m/s [14]. Gliders control their heading toward predefined waypoints using a magnetic compass and may occasionally surface to acquire their location using GPS and communicate with their handlers using a cellular or satellite connection. When submerged, these gliders rely on localization methods – such as dead reckoning, long baseline navigation and short baseline navigation [15] – to determine their own positions.

The Urick model is used to estimate the communication transmission loss $TL(l,f)$[dB] as [16],

$$TL(l,f) = \kappa \cdot 10\log_{10}(l) + \alpha(f) \cdot l, \tag{1}$$

where l[m] is the distance between the transmitter/receiver and f[kHz] is the carrier frequency.

In (1), the first term accounts for *geometric spreading*,[1] which is the spreading of sound energy caused by the expansion of the wavefronts. It increases with the propagation distance and is independent of frequency. Usually spreading factor $\kappa = 2$ for spherical spreading, $\kappa = 1$ for cylindrical spreading, and $\kappa = 1.5$ for the so-called practical spreading. The second term accounts for *medium absorption*, where $\alpha(f_0)$ [dB/m] represents an absorption coefficient that describes the dependency of the transmission loss on the frequency.

The Urick model is a coarse approximation for underwater acoustic wave transmission loss. In reality, sound propagation speed varies with water temperature, salinity, and pressure (i.e., depth), which causes wave paths to bend. Acoustic waves are also reflected from the surface and bottom. Such uneven propagation of waves results *in convergence (or shadow) zones*, which are characterized by lower (or higher) transmission loss than that predicted by the Urick model due to the uneven energy dispersion. The variations of water temperature, salinity and pressure generally depend on location and time of year. Due to space limitation, we cannot give a detailed description, but more details can be found in [17]. A shadow zone scenario is shown in Fig. 1, where node 3 has very low signal power from node 1 than node 4, although node 3 is closer.

We adopt the empirical ambient noise model presented in [16], where a '*V*' structure of the power spectrum density (psd) is shown. The ambient noise power is obtained by integrating the empirical psd over the frequency band in use.[2]

4. Proposed solution

Solutions for both phases (team formation and steering) are designed considering practical constraints and limitations of real underwater acoustic modems. Our solution is based on the functionalities of Woods Hole Oceanographic Institution (WHOI) acoustic Micro-modem [18], which is a state-of-the-art low-power

[1] There are two kinds of geometric spreading: *spherical* (omni-directional point source, spreading coefficient $\kappa = 2$), and *cylindrical* (horizontal radiation only, spreading coefficient $\kappa = 1$). In-between cases show a spreading coefficient κ in the interval (1, 2), depending on water depth and link length.

[2] Note that, in underwater acoustics, power (or source level) is usually expressed using decibel (dB) scale relative to the reference pressure level in underwater acoustics 1 μPa, i.e., the power induced by 1 μPa pressure. The conversion expression for the source level SL re μPa at the distance of 1 m of a compact source of P watts is $SL = 170.77 + 10\log_{10}P$ [17].

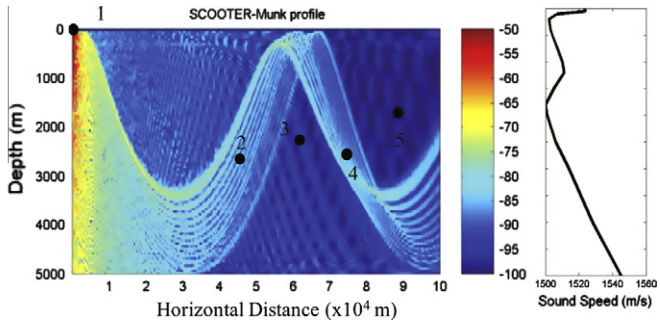


Fig. 1. Shadow zone scenario where acoustic signals are transmitted by node 1 that is located at the origin. The SCOOTER-Munk profile is the sound speed profile as shown in the right subfigure.

Table 1
Four types of packets used by WHOI acoustic micro-modem (Type 1 and 4 unimplemented yet).

Type	Modulation	Coding scheme	bps	Max. frames	Frame bytes
0	FH-FSK		80	1	32
2	PSK	1/15 spreading	500	3	64
3	PSK	1/7 spreading	1200	2	256
5	PSK	9/17 Rate Block Code	5300	8	256

compact underwater acoustic modem that can transmit four different types of packets at four data rates (Table 1) in four different bands from 3 to 30 kHz. Control of the modem is by NMEA commands [19].

4.1. Overview

In this article, we focus on how to form the team according to the given formation geometry when randomly scattered gliders are selected and on how to steer them along the trajectory while maintaining their formation. We assume that the gliders in the team have been selected from a pool of vehicles using a task allocation algorithm (e.g., [20]). As in Fig. 2, given (i) the number of scattered gliders, (ii) the corresponding geometry formation, and (iii) the target trajectory, two phases of operations are required to perform the monitoring mission: (1) the selected gliders need to be mapped into a specified geometric formation making sure that no collisions occur (Phase I); (2) after the first phase, the team needs to steer through the 3D region of interest along the predefined trajectory while maintaining its formation (Phase II). Note that swarming using a specified geometric formation is necessary not only in coordinated monitoring missions but also in many applications such as surveillance/tracking and collision avoidance in critical navigation missions.

In our solution, a glider is selected to play the role of *leader* in order to guide the other gliders, which will then act as *followers*. These are *logical roles* that do not depend on the physical position within the formation, i.e., the leader is not necessary ahead of the followers at all times. As the GPS does not work underwater, gliders can only receive GPS signals when at the surface; therefore, to calculate their positions while underwater they can only rely on localization algorithms. Moreover, accuracy of the location information decreases as the time in the water increases due to the accumulation of localization errors. Consequently, in order to take advantage of the GPS information, the last surfaced glider is chosen to be the *leader*. The aim of the leader is to let the team be on track along the target trajectory, while the aim of the other gliders, the so-called *followers*, is to maintain the formation according to the predefined geometry.

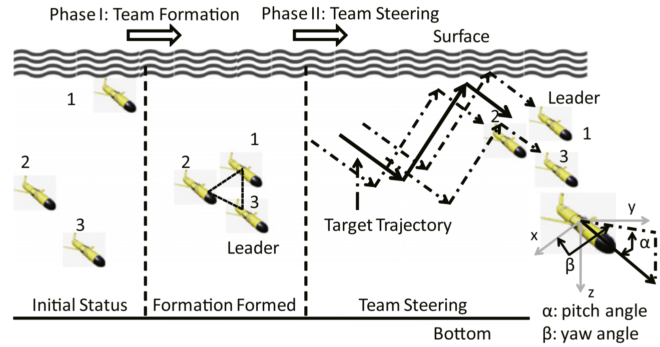


Fig. 2. Overview of the proposed solution for team formation and steering.

Every glider keeps a record of the current leader. The initial leader can be assigned manually to the one that surface last. When surfaced, if a glider discovers it is different from the current leader in its record, it advertises itself as the *'new'* leader by broadcasting a message that contains the surface time stamp. Upon receiving this message, the other gliders send a confirmation to the new leader using an acknowledgement packet (ACK) if the surface time stamp in the message is more recent. Here we assume the gliders are within the communication range of each other. In general the WHOI modem communication range can be up to about 7 km for packet error rate of 0.5. If the distance is greater than the one-hop range, reliable geocasting[3] protocols such as [21] can be used to route this message to all the gliders.

Our solution is based on the SLOCUM glider. SLOCUM glider control involves monitoring performance, adjusting glide angle by controlling pitch and/or buoyancy, and adjusting heading by controlling roll or rudder position. The gliders can use Precision Navigation TCM2 attitude sensors to sense heading, pitch and roll, and pressure sensors to measure depth and, from pressure rate, vertical velocity. Altitude is measured using an acoustic altimeter. A movable rudder gives the tightest turning radius (approximately 7 m) and allows turning without significant roll so that the acoustic altimeter, critical in shallow-water operations, remains accurate. When submerged, the SLOCUM glider uses dead reckoning for position estimation.

Our solution controls the *pitch angle* α and *yaw angle* β (see Fig. 2) to steer each glider and keep the team formation. The pitch α for a glider ranges in $[\alpha_{min}, \alpha_{max}]$ and determines the velocity of the vehicle (in fact, the horizontal velocity can be considered constant in the absence of ocean currents).

4.2. Team formation

To enable the communications between the scattered gliders, we propose a communication technique that emulates the vocalizations used by killer whales. These whales use low frequency whistles ranging from 0.5 to 40 kHz (with peak energy in 6–12 kHz) to communicate with each other. These low frequencies make long-range communication possible, as explained by the underwater communication theory: low-frequency tones undergo a lower medium attenuation and achieve a higher signal-to-noise ratio (SNR) [16] at the receiver. Moreover, the whistles are usually short, which is advantageous as they are less affected by multipath. This effect is similar to what happens in wireless communications: shorter packets experience a lower packet error rate (PER).

To apply this technique in our work, we first study the PER performance of different packet types used by the WHOI Micro-modem, which is measured in our testbed emulation [22] and plotted

[3] Geocasting is the transmission of data packet(s) to a group of nodes located in a certain geographic region. It is a specialized form of multicast network protocols.

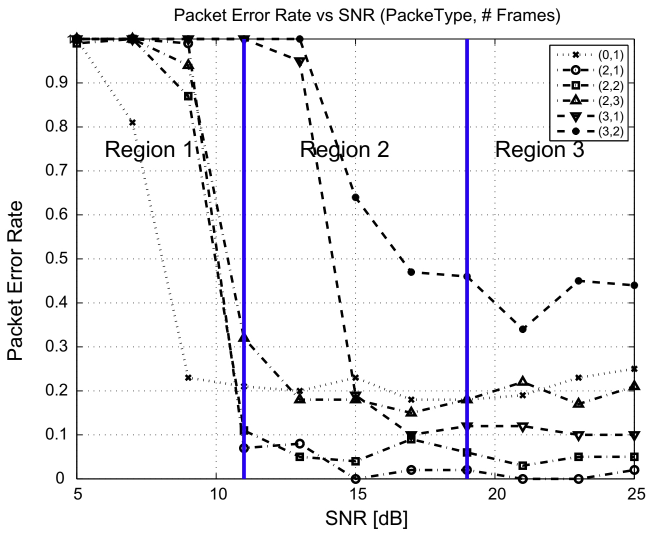


Fig. 3. Packet error rate (PER) for Type 0, 2, 3 packet.

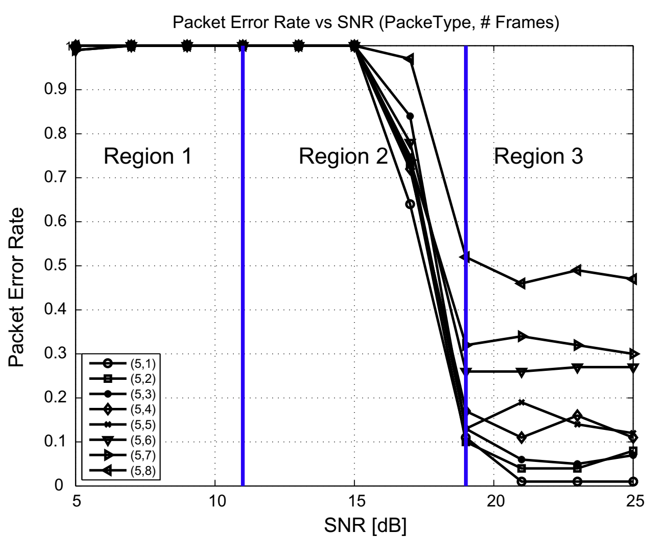


Fig. 4. Packet error rate (PER) for Type 5 packet.

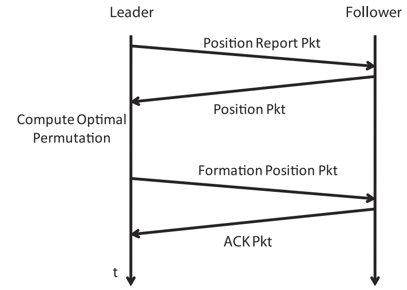


Fig. 5. Protocol for team formation (Type 0 packets).

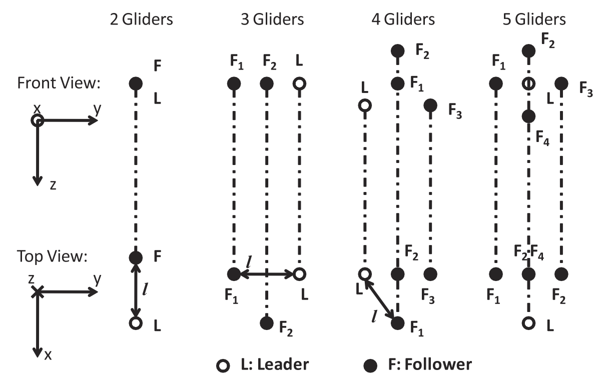


Fig. 6. Formation geometries for 2–5 gliders in front and top views, where the mission-specific inter-glider distance is l and the last surfaced glider is chosen as leader.

in Figs. 3 and 4. As presented in Table 1, there are four types of packets used by these underwater acoustic modems, each adopting a different combination of modulation and coding scheme, and a specific number of frames. As we can see in Fig. 3, in the low SNR region (Region 1: <11 dB), the PER relationship between different types are: Type 0 < Type 2 < Type 3. Note that: (i) as SNR > 11 dB (Region 2 and 3), Type 2 packet has lower PER than Type 0; Type 2 packet with 3 frames has about the same PER as Type 0, but its bit rate is much higher than Type 0; (ii) Type 3 packet with 1 frame has approximately the same PER as Type 0, but the bit rate is much higher. As for Type 5 packet (Fig. 4), when SNR < 19 dB (Region 1 and 2), its PER is higher than the other packet types. For SNR > 19 dB (Region 3), it has good PER performance with the highest bit rate of 5300 bps.

By comparing Figs. 3 and 4, it is clear that type 0 packets have the lowest PER when the SNR is low (<11 dB), which means that they perform the best for long-range communications. This is because type 0 is the shortest packet and the modulation it uses (FSK) is very reliable; this comes, however, at the price of low bit rates (80 bps). For these reasons, this packet type is a proper choice for long-range control message exchange to resemble long-haul whale vocalizations.

The communication protocol for team formation is depicted in Fig. 5. To calculate the ‘best’ formation position for each glider – with the objective of minimizing the formation time while avoiding collisions, the leader broadcasts a packet to collect the positions from the followers. Upon receiving the position packet from all the followers, the leader runs the formation mapping algorithm to find the best mapping (glider → vertex in the geometry); then, the leader informs each follower about its assigned formation position. The followers then acknowledge the reception of the message from the leader, and all the gliders start moving towards their assigned positions. All these control messages use short type 0 packets as their aim is to reach far apart gliders that are scattered in a wide region.

The gliders can move in regular formations as shown in Fig. 6. Different formation geometries can be used depending upon the number of gliders and the type of mission. Given the number of gliders forming the team and the corresponding geometry formation, the problem that we face is to map every glider to its position in the formation. Selecting a position in the formation for a glider depends upon factors such as the time for that glider to reach this position, the possibility of collision with other gliders, and the permutation of the gliders with the formation positions. We have to determine the optimum to minimize both *the time* and *energy* spent to attain the formation. We first optimize on time to find the mapping, and then on energy consumption, while deciding on the exact trajectory for the selected mapping.

The formation optimization problem, which aims at mapping the gliders to formation positions, finds – out of all the permutations that avoid collisions (the so-called *feasible solutions*) – the best permutation that minimizes the time to form the team formation. Specifically, given N gliders $1, 2, \ldots, N$, and the corresponding

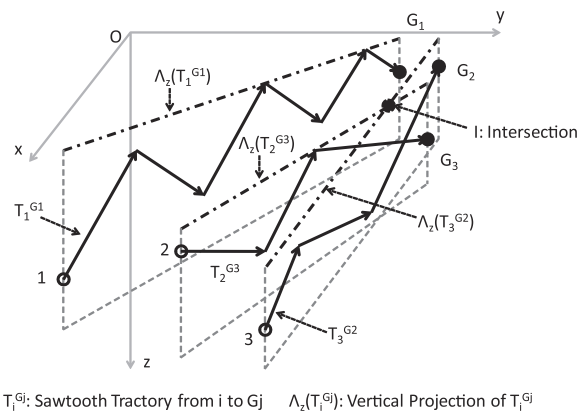


Fig. 7. Mapping gliders 1, 2, and 3 to geometry vertexes G_1, G_3, and G_2, respectively. Note that gliders 2 and 3 may collide as $\Lambda_z\left(T_2^{G_3}\right)$ and $\Lambda_z\left(T_3^{G_2}\right)$ intersect at point I.

formation points $G_1, G_2, \ldots, G_N$, we need to find a permutation $\pi \in \Pi$ such that the time spent by the gliders to form the formation is minimized while no collision occurs. Here, Π is the set of all $N!$ permutations.

For simplicity and because of the large inter-vehicle distances, in this article a glider is considered to be a single mass point. Note, however, that our solutions can be straightforwardly extended to account for the real dimensions of the gliders by adding marginal spaces between the points. To ensure no collision among gliders, the *sufficient and necessary condition* is that two or more gliders of the team do not meet at the same point *and* at the same time as they move along their trajectories. However, solving this problem in the 3D space is complex; also, the solution would be affected by the uncertainty of the velocities of the gliders caused by ocean currents. Therefore, we adopt a simpler conservative approach that relies on a *sufficient condition* to avoid collisions. Note that the fastest way for a glider to move to a point is to follow the sawtooth trajectory laying in the vertical plane containing the current glider position and the destination point. Hence, a sufficient condition to ensure no collision is that the projections of the glider trajectories on the x–y plane – segments describing the horizontal advance of the gliders – do not intersect (Fig. 7).

If we denote the initial position of glider i and formation point G_i as $\mathbf{P}_i^0 = (x_i^0, y_i^0, z_i^0)$ and $\mathbf{P}_{G_i} = (x_{G_i}, y_{G_i}, z_{G_i})$, respectively, given the constant horizontal speed s_H of the gliders, the formation mapping problem can be formulated as,

$$\textbf{Given}: \mathbf{P}_i^0, \mathbf{P}_{G_i}, s_H (\forall i = 1, \ldots, N)$$
$$\textbf{Find}: \pi^* \in \Pi$$
$$\text{Minimize}: \max\left(\sqrt{\left(x_i^0 - x_{G_j}\right)^2 + \left(y_i^0 - y_{G_j}\right)^2} / s_H\right)$$
$$\text{Subject to}: G_j = \pi(i); \tag{2}$$
$$\pi \in \left\{\pi : \forall i, m,\ i \neq m, \Lambda_z\left(T_i^{\pi(i)}\right) \cap \Lambda_z\left(T_m^{\pi(m)}\right) \equiv \emptyset\right\}; \tag{3}$$

where $T_i^{\pi(i)}$ is the vertical trajectory from i to its mapped point $\pi(i)$ and $\Lambda_z(\,)$ is the vertical projection to the x–y plane. Here, (2) is the mapping of glider i to G_j, and (3) ensures that the permutations incurring intersections of vertical trajectory projection, i.e., those unfeasible, not be considered.

When N is small – which is the case for our application, this optimization can be solved by first removing the permutations that incur intersections of vertical trajectory projection and then searching among the remaining permutations as the number of permutations is relatively small. Efficient algorithms – such as those that are heuristic and those that calculate the feasible permutations faster – can also be developed to narrow down the search space and we leave the development of such algorithms as future research direction.

4.3. Team steering

The team steering problem can be divided into two subproblems: (1) steering the team to follow the planned team trajectory, and (2) maintaining the formation. As the leader (the last glider that has surfaced) has the most accurate position information, it is selected to estimate the *team dislocation*, i.e., the deviation from the target trajectory. The leader calculates the adjusted sawtooth trajectory to steer the team back to the target trajectory. Depending on the application requirements, the leader can decide to either move back to the closest point on the target trajectory, or to head towards the final destination of the target trajectory. While the former strategy is more conservative, as it minimizes the time to go back to the target trajectory, the latter is more energy efficient when the goal is to reach the final destination. The other gliders, i.e., the followers, will then focus on maintaining the geometry of the formation, which also implies following the leader's path. Due to space limitation, in the following we focus only on this second subproblem.

We use a hybrid approach to keep the team formation depending on whether the position information is *absolute* or *relative*. Specifically, *absolute formation adjustment (AFA)* is used when absolute information such as gliders' position is available; whereas *relative formation adjustment (RFA)* is used when relative information such as inter-vehicle velocity is available. The reason for this hybrid approach is to reduce the communication overhead for position information dissemination. Using absolute positions, in fact, requires the exchange of location information, which introduces overhead. On the other hand, relative inter-glider velocity information can be estimated by each glider by measuring the Doppler shift of ongoing inter-vehicle communications. These relative velocities can then be used to control the trajectory of each glider in such a way as to keep the inter-distance between gliders constant. While this 'opportunistic' approach does not guarantee that the absolute geometry is maintained (e.g., rotations can occur), it does not introduce additional overhead as it may exploit ongoing communications. Consequently, in order to compensate for the errors due to formation rotations, the team periodically goes back to AFA to readjust the geometry using absolute positions.

The communication protocol for hybrid steering is presented in Fig. 8. Periodically, each glider runs AFA using the position information obtained from the localization algorithm. Then, RFA is run using relative information extracted from inter-vehicle

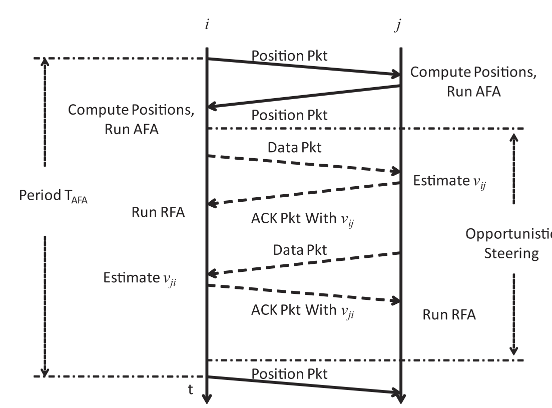


Fig. 8. Hybrid steering using acoustic communications.

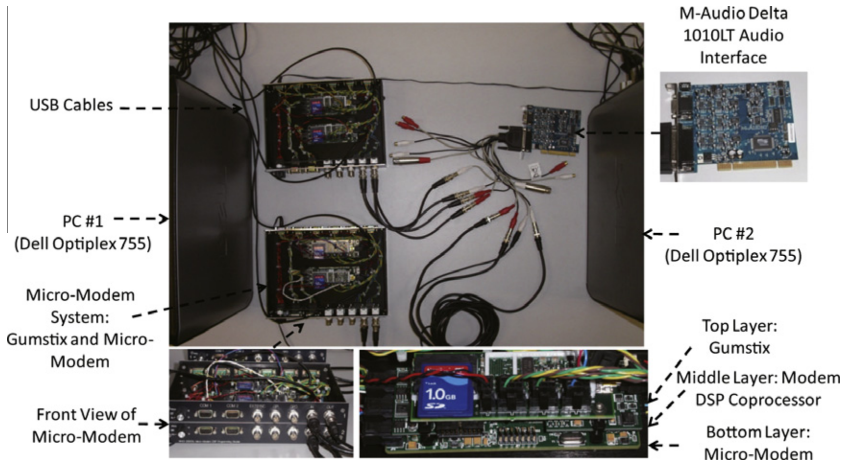


Fig. 9. Underwater communication emulator using WHOI micro-modems.

packets. Glider *i*'s relative velocity is estimated by *j* when an inter-vehicle packet is received. This information is then embedded into the reverse direction packet and fed back to *i*. At this point, the gliders are able to make adjustments according to their relative velocity. Finally, if the leader (or any other follower) assesses that the geometry is seriously compromised (i.e., if the team dislocation is greater than the dislocation associated with a new permutation), the leader can rerun the formation optimization problem and find the new best permutation (often involving only a subset of the vehicles) to reconstruct the geometry.

Intuitively, in order to keep the formation, two gliders need to move closer if the distance between them is longer than the initial specified distance, i.e., the equilibrium distance in the formation geometry. Conversely, they need to move farther if their distance is shorter than the equilibrium distance. In such a scenario, an *attraction and repulsion model (ARM)* is appropriate to implement the swarming behavior using local controls. Bio-inspired algorithms based on the ARM have been proposed and analyzed in [23,24]. Specifically, in [23] a class of attraction and repulsion functions for swarm formation is presented and their stability is analyzed, while in [24] a framework using artificial potentials and virtual leaders is proposed. Artificial potentials define interaction control forces between neighboring vehicles and an optimal inter-vehicle spacing is therefore enforced. Virtual leaders can be used to manipulate group geometry and direct group motion by means of additional artificial potentials. Closed-loop stability is proved and robustness to a single vehicle failure is shown.

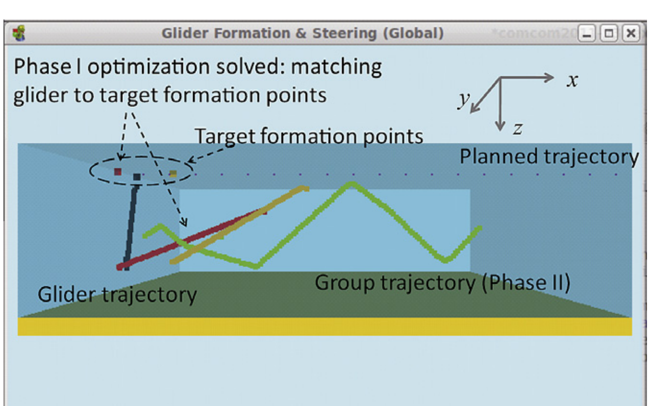


Fig. 10. Screenshot of the 3D visualization of our solution: global view of a team with 3 gliders.

In this article, we account for the physical constraints characterizing SLOCUM gliders and their energy-efficient acoustic WHOI Micro-Modems, and propose a novel distributed attraction and repulsion swarming solution integrated with the communication

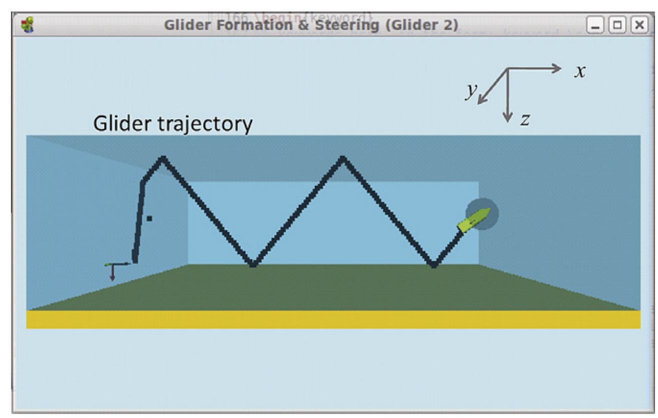


Fig. 11. Screenshot of the 3D visualization of our solution: individual view of glider 2. The transparent sphere (halo) at the glider head means that it is team leader.

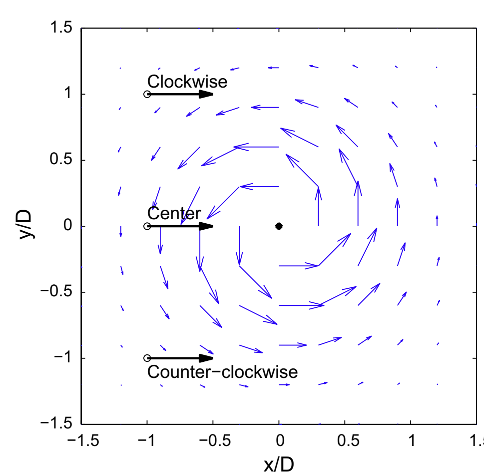


Fig. 12. Ocean current profile [27]. Each thin arrow indicates ocean current speed and direction at that point, while each thick arrow indicates the starting position and direction of the planned trajectory in Section 5.4. The position is relative to the gyre center and scales relative to reference distance *D*.

Table 2
Emulation parameters.

Parameter	Value
Initial deployment region	3000(L) × 3000(W) × 500(H) m^3
Interval Δ	30 s
Transmission power	10 W
Glider horizontal speed (relative)	0.3 m/s
Gliding depth range	[0,500] m
Pitch angle range	[10°, 35°]
Trajectory length	8000 m

mechanisms. As ARM is similar to a spring system in physics, we treat the team as such a system and we define a metric between i and j called *virtual potential energy*, $E_{ij} = \frac{1}{2}k_{ij}\Delta x_{ij}^2$, where k_{ij} is the virtual spring constant and Δx_{ij} is the displacement from the expected formation equilibrium between i and j. Virtual spring constant between the leader L and a follower F, and between followers, are denoted by k_{LF} and k_{FF}, respectively. To emphasize the role of the leader, which has more recent (and therefore more accurate) location information and is in charge of steering the entire team along the target trajectory, we enforce $k_{LF} > k_{FF}$ so that the dislocation from the leader will have greater influence than that between followers. This will imply that the 'rigidity' of the edges of the team structure will not be homogeneous; rather, it will depend on the logic role of the vehicles at the vertexes, being higher when one of the two gliders of an edge is the leader. Note that this is based on the ARM and artificial potential models, which have been proved to be stable in many papers on swarming or coordination control. So we feel there is no need to prove the stability again.

When glider i is in its equilibrium formation position, the total virtual potential energy between i and its neighbors, $E_i = \sum_{j\in\mathcal{N}_i} E_{ij}$, will be zero; otherwise, it will be greater than zero, where $\mathcal{N}_i$ is the set of neighbors of i. To keep the specified formation, i should adjust its pitch (α_i) and yaw (β_i) angles so that E_i can be minimized. For AFA, given the team glider positions $\mathbf{P}_j$ and directions α_j and β_j, with $j = 1,2,\ldots,N$, which are obtained by exchanging control packets, in a given interval δ[s] glider i will adjust its pitch and yaw by solving,

$$\textbf{Given}: \mathbf{P}_i, d_{ij}, s_H, \delta, \alpha_j, \quad \beta_j \ (\forall j \in \mathcal{N}_i)$$

$$\textbf{Find}: \alpha_i^* \in [\alpha_{min}, \alpha_{max}], \quad \beta_i^*$$

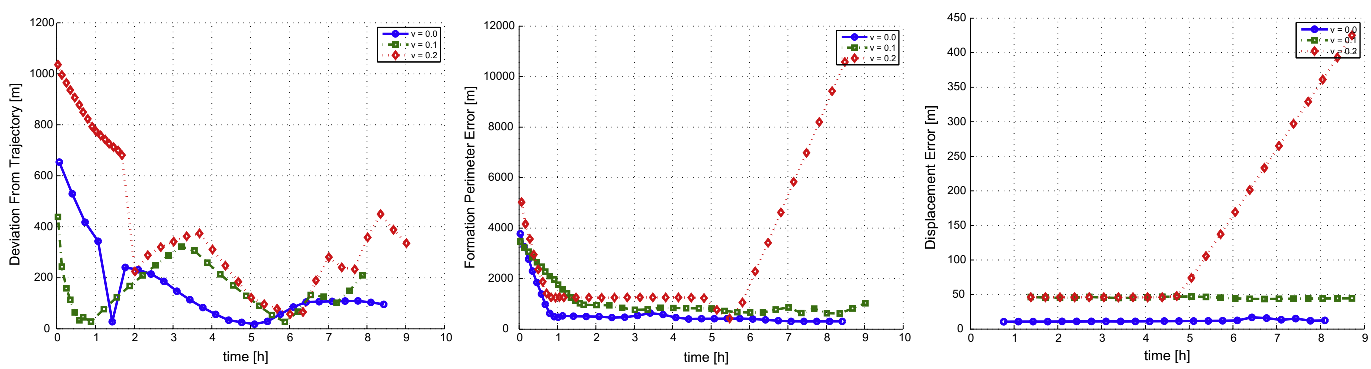
$$\text{Minimize}: E_i = \frac{1}{2}\sum_{j\in\mathcal{N}_i} k_{ij}\Delta x_{ij}^2$$

$$\text{Subject to}: \Delta x_{ij} = \|\overrightarrow{\mathbf{P}_i\mathbf{P}_j} + (\vec{\mathbf{v}}_j - \vec{\mathbf{v}}_i)\delta\| - d_{ij}; \tag{4}$$

$$\|\vec{\mathbf{v}}_i\| \cdot \cos\alpha_i = s_H; \tag{5}$$

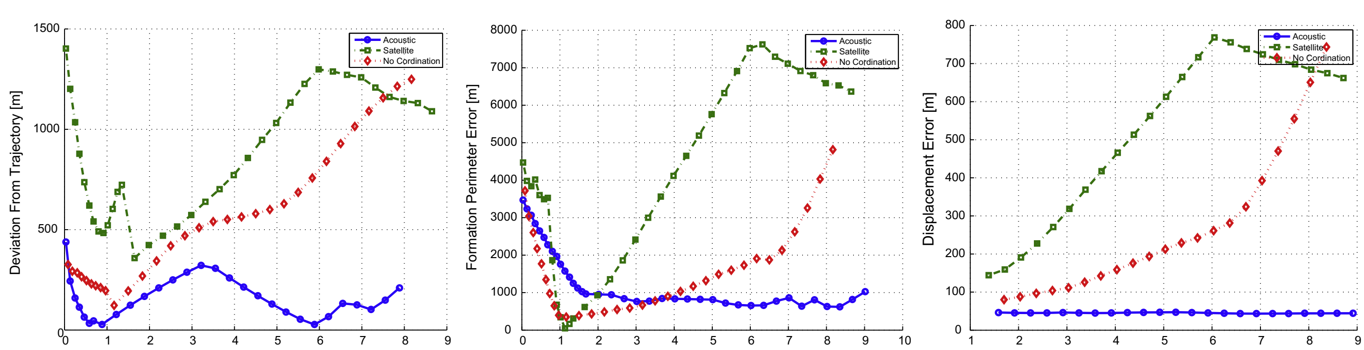
where d_{ij} is the equilibrium distance between i and j in the formation, $\overrightarrow{\mathbf{P}_i\mathbf{P}_j}$ is the location vector from i to j, $\vec{\mathbf{v}}_i$ is i's velocity, and $\|\cdot\|$ is the vector length. Note that the velocity of each glider $j \in \mathcal{N}_i$ can be computed at i as $\vec{\mathbf{v}}_j = (s_H \cdot \cos\beta_j, s_H \cdot \sin\beta_j, s_H \cdot \tan\alpha_j)$.

This problem can be solved by first converting it into an approximated discrete optimization problem. That is, we can discretize the continuous variables α_i and β_i into a finite number of equally spaced discrete values. It can then be solved using exhaustive search algorithm after the discretization. Depending on the computation capability of the onboard processor, appropriate number of discrete values can be used. Here we take the values with step



(a) Deviation from planned trajectory (b) Formation perimeter error (c) Displacement error during steering

Fig. 13. Performance of the proposed solution for ocean current profile 1 (speeds are in m/s).



(a) Deviation from planned trajectory (b) Formation perimeter error (c) Displacement error during steering

Fig. 14. Performance comparison of different solutions for ocean current profile 1 at v = 0.1 m/s.

size of 0.1. Further improvement of the solution can be done after converting it into appropriate optimization that can be solved efficiently and we leave this as future work.

For RFA, we adopt a bio-inspired communication technique that imitates the echolocation mechanism of the bat. A bat estimates the distance to an object by shouting and then measuring the acoustic echoing time from the object. Also, a bat relies on the Doppler effect, i.e., the frequency shift caused by the relative velocity, to sense an object's direction. Specifically, if the object is moving away from the bat, the returning echo will have a lower frequency than the original sound; conversely, the echo from an object moving towards the bat will have a higher frequency. When we do not rely to absolute position information, we use a similar technique to keep the swarm formation.

The WHOI Micro-modem can estimate the relative speed of the transmitter exploiting the frequency shift caused by the Doppler effect. Suppose that during steering glider i obtains its relative speed s_{ij} (*a scalar*) with respect to another glider j. This can be extracted from ongoing inter-vehicle communications without additional overhead: upon receiving i's packet, j can estimate the Doppler frequency shift Δf_{ij}; the relative speed s_{ij} of glider i to j along the line connecting the two gliders is then calculated from $\Delta f_{ij} = -s_{ij} \cdot f_0/c$, where f_0 is the current acoustic communication central frequency and c is the average underwater acoustic wave speed (1500 m/s). Glider j then sends s_{ij} back to i with its own location $\mathbf{P}_j$, which can be estimated using the leader's GPS position, and relative location and velocity. Both s_{ij} and $\mathbf{P}_j$ can be embedded in the ongoing communication packets to avoid additional overhead. In this way, i computes its relative speed vector with respect to j as $\vec{\mathbf{v}}_{ij} = s_{ij} \cdot \frac{\overrightarrow{\mathbf{P}_i\mathbf{P}_j}}{\|\overrightarrow{\mathbf{P}_i\mathbf{P}_j}\|}$.

Consequently, the expected virtual potential energy E_i after time δ can be estimated as $E_i = \frac{1}{2}\sum_{j\in\mathcal{N}_i} k_{ij}\|\vec{\mathbf{v}}_{ij}\delta\|^2$. Hence, the problem of steering i back into formation becomes the search for the optimal pitch and yaw to obtain a correction velocity $\vec{\mathbf{v}}_i$ such that E_i can be minimized,

$$\begin{aligned}
&\textbf{Given}: \vec{\mathbf{v}}_{ij}, s_H (\forall j \in \mathcal{N}_i)\\
&\textbf{Find}: \alpha_i^* \in [\alpha_{min}, \alpha_{max}], \beta_i^*\\
&\text{Minimize}: E_i = \frac{1}{2}\sum_{j\in\mathcal{N}_i} k_{ij}\|(\vec{\mathbf{v}}_{ij} + \vec{\mathbf{v}}_i)\delta\|^2;\\
&\text{Subject to}: \|\vec{\mathbf{v}}_i\| \cdot \cos\alpha_i = s_H.
\end{aligned} \tag{6}$$

This RFA optimization can be solved in a similar way to that of AFA. By solving this problem, glider i is able to fix its own steering so that the formation error, i.e., the virtual potential energy, can be minimized. Note that this is a distributed solution as only local information from i's neighbors is needed.

5. Performance evaluation

In this section, we first outline the objectives of our emulation and its setup; then, we discuss the results for representative scenarios.

5.1. Emulation overview and setup

We are interested in comparing the performance of our coordination algorithms (which use underwater acoustic communications) in terms of coordination errors with the solutions without using underwater communications or coordination algorithms. Specifically, our solution is compared with the following two solutions. The first one is the solution using satellite to exchange coordination information instead of using acoustic communications. In this solution, all gliders surface for satellite communications every 2 h, while underwater they do not exchange coordination information. Once they have exchanged the control information, they use the AFA algorithm to set their steering angles and then keep steering with the calculated angles until the next surface time. The second one is the solution where gliders do not coordinate at all. Each glider just steers itself to the destination without exchanging coordination information with other gliders. For convenience, in the following figures, we denote our proposed solution that uses acoustic communications, the solution using only satellite communications, and the solution without coordination as "Acoustic," "Satellite," and "No Coordination," respectively.

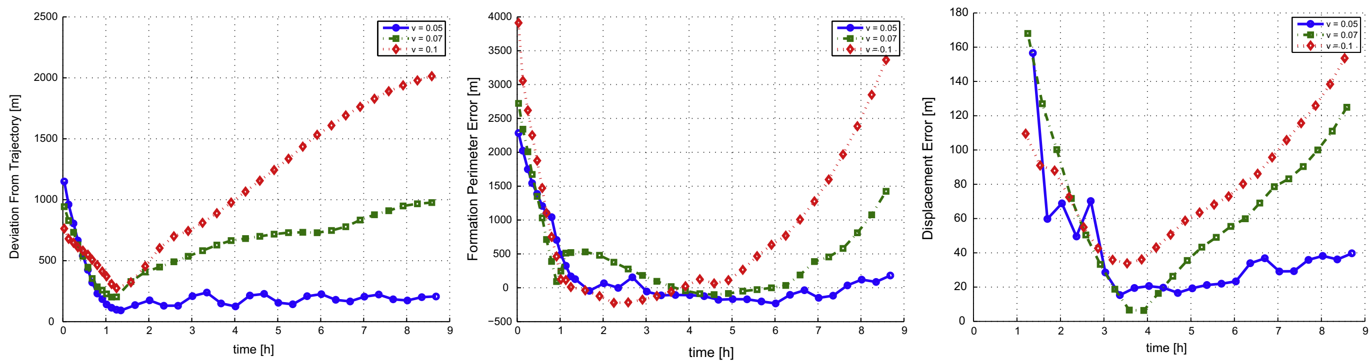
Note that the surfacing frequency should consider the tradeoff between the mission time, energy consumption and the localization error. The gliders should not surface too frequently as surfacing slows down the mission and consumes energy (as of current technology, surfacing takes up to tens of minutes to get a GPS fix and to communicate with satellites). On the other hand, large localization error may be introduced if a glider stays long underwater. Here we choose the surfacing time to be every 2 h for "Satellite", which is close to the time that is generally used nowadays by oceanographic researchers in real glider deployments. Also note that we do not compare our solution with solutions in [13] and [9] since these existing solutions can only deal with simple geometry formations or only two vehicles and are difficult to be extended to general solutions, as reviewed in Section 2. Therefore we do not feel appropriate comparing them with our solution.

The team formation and steering solution is implemented and tested on our hybrid underwater communication emulator [22] as shown in Fig. 9. This underwater acoustic network emulator is composed of four WHOI Micro-modems [18] and a real-time audio processing card to emulate the underwater channel propagation. With the help of softwares such as MATLAB and a Matlab-based audio processing package *Playrec* [25], the multi-input multi-output audio interface can process real-time signals to adjust the acoustic signal gains, to introduce propagation delay, to mix the interfering signals, and to add ambient/man-made noise and interference. Propagation delay is emulated by dividing the inter-vehicle distance by the underwater sound speed, while ambient/man-made noise is added to the acoustic signal using the noise models presented in [16]. Note that due to the limited number of Micro-modems and audio processing channels, we can only mix signals from up to 3 transmitters at the receiver modem. Therefore, we calculate, select for transmission, and mix with ambient noise, only the three most powerful signals the receiver will encounter. We leave the simulation of more than three simultaneously transmitted signals as a problem for further research.

We are interested in the performance of different solutions in the presence of ocean currents. A 3D visualization demo is also made during the implementation of our solution as shown in Figs. 10 and 11, so that the movement and trajectories of the gliders can be visualized. More details about the demo can be found at [26].

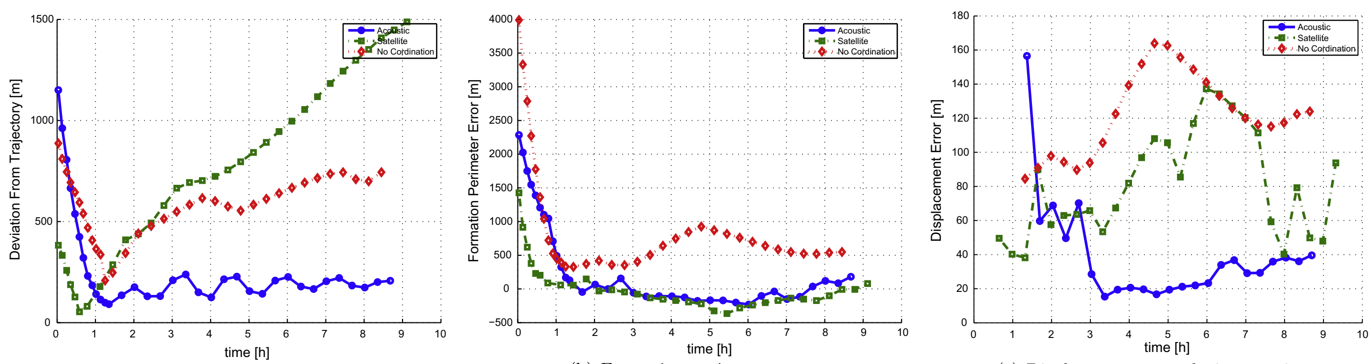
We simulated these solutions considering the following different ocean current profiles. (1) **Current Profile 1**: current along x direction with constant velocity; (2) **Current Profile 2**: current along y direction with constant velocity; and (3) **Current Profile 3**: ocean gyre current model as in Fig. 12, i.e., a circular eddy with counter-clockwise tangential velocity profile $s_H \cdot r \cdot \exp(-2r^2)$, where r is the ratio of the distance from a point to gyre center to a reference distance D [27]. We assume the current profiles are vertically constant, i.e., the current velocities are the same if the horizontal locations are the same. More realistic ocean models will be studied and solutions dealing with these models will be proposed in our future work.

Emulation parameters are listed in Table 2. The direction of the planned trajectory is *along the x-axis direction*. In the beginning,



(a) Deviation from planned trajectory (b) Formation perimeter error (c) Displacement error during steering

Fig. 15. Performance for ocean current profile 2 (speeds are in m/s).



(a) Deviation from planned trajectory (b) Formation perimeter error (c) Displacement error during steering

Fig. 16. Performance comparison of different solutions for ocean current profile 2 at $v = 0.05$ m/s.

gliders are randomly deployed in an initial 3D region. They are expected to form an equilateral triangle with inter-glider distance of 400 m and then steer along the planned trajectory.

We use the following three metrics to evaluate and compare performance. (1) **deviation from trajectory (DFT)**: the distance from the centroid of the team to the planned trajectory. This is used to characterize how well the algorithms work to keep the glider team on the planned trajectory; (2) **formation perimeter error (FPE)**: the difference between the actual formation perimeter and the perimeter of target formation geometry. This offers a way to estimate the distortion of the whole team's formation; and (3) **displacement error (DE)**: the average displacement distance of each glider from its expected location, i.e., the average distance from one glider's actual position to its expected position. This metric quantifies how well the gliders can maintain the expected formation.

Emulations are run and the above metrics versus the time from when the gliders are deployed are plotted in Figs. 13–18, which are discussed in the following. Note that different solutions and different ocean current models have different finish times. This is because different solutions or current models lead to different movement trajectories and, thus, different finish times. We stop the emulation when it is clear that getting to the end point of the planned trajectory is impossible and plot the metrics in intervals where another solution succeeds. Last, but not least, note that the plot of DE starts from Phase II as DE in Phase I is meaningless.

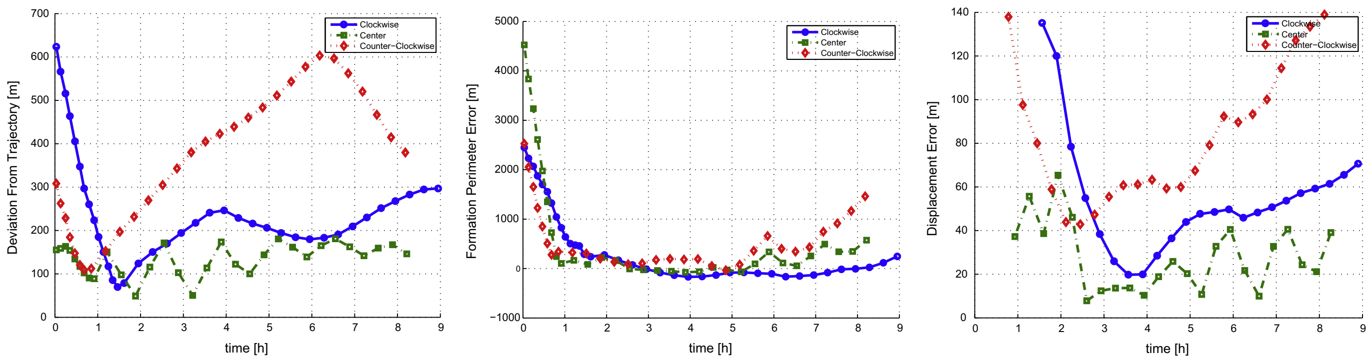
5.2. Performance using ocean current profile 1

In this case, the performance of our proposed solution is plotted in Fig. 13 for different velocities. As the ocean current speed v increases, DFT, FPE and DE all increase, which is not difficult to understand. After all, the greater the current speed is, the harder the team can stay in the expected position. From this figure, we can see that when the ocean speed is at 0 m/s and 0.1 m/s, the glider team using our proposed solution can stay close to the planned trajectory. Note that even at $v = 0$, these error metrics are not perfectly zero. This is because the physical constraints of the glider (such as sawtooth movement and pitch angle range) make it impossible to achieve perfect coordination. At a speed of 0.2 m/s, increase rate of FPE and DE becomes large when time is after about 5 or 6 h. This is because the team is pushed over the target trajectory end point by the strong current and this is difficult to compensate for.

As shown in Fig. 14, when compared to the other two solutions, our proposed solution achieves lower errors in terms of DFT, FPE, and DE. By exchanging the position information and extracting Doppler shifts from ongoing communications, our algorithms can adjust the gliding angles for error minimization in a timely manner. On the other hand, the "Satellite" solution only adjusts the angles of the gliders when they surface; hence, the error keeps accumulating during the long intervals between surfacing. Steering error is adjusted only when the gliders surface. For the "No Coordination" solution, though it has less error than the "Satellite" solution in the beginning, the error keeps increasing without a way to decrease it due to no coordination. In the end, it accumulates more error than the "Satellite" solution.

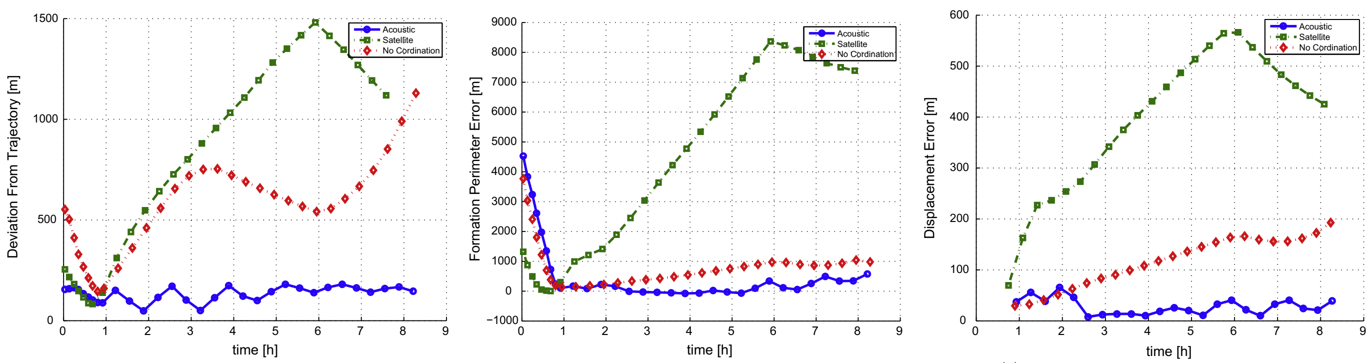
5.3. Performance using ocean current profile 2

In this case, the direction of the ocean current is perpendicular to the direction of the planned trajectory. Such an ocean current



(a) Deviation from planned trajectory (b) Formation perimeter error (c) Displacement error during steering

Fig. 17. Performance for ocean current profile 3.



(a) Deviation from planned trajectory (b) Formation perimeter error (c) Displacement error during steering

Fig. 18. Performance comparison of different solutions for ocean current profile 3 (“center” case).

pushes the gliders sideways and, therefore, away from the planned trajectory. As shown in Fig. 15, when the current speed is at 0.05 m/s, the proposed solution is able to keep DFT, FPE, and DE within a certain threshold. This verifies the effectiveness of our solution for team steering. As shown in Fig. 16, our solutions leads to the least error in terms of DFT, FPE, and DE among the three solutions. In fact, through extensive emulations we found that this is the maximum speed for which our solution is still effective.

Note that the ocean current speeds we use here are smaller than those for Profile 1. We have tried many simulations for different v's for both profiles. Our simulations show that the ranges of the current speed where the algorithms are effective are different for the two profiles, i.e., the capability of the algorithms to deal with currents of different directions is different. In other words, our simulations show that the proposed solution performs worse for Profile 2 – the metrics DFT, FPE and DE increase quickly when v is at 0.1 or 0.2 m/s. We plotted the curves when the algorithms are effective and ineffective so to make the figures more meaningful.

5.4. Performance using ocean current profile 3

Depending on the relative position of the team in the gyre current model, the performance of our proposed solution varies. As shown in Fig. 12, three cases, “counter-clockwise,” “center,” and “clockwise” are simulated for $D = 4000$ m. If the glider team moves counter-clockwisely around the gyre center (corresponding to “counter-clockwise” in Fig. 17), the vehicle and the current speeds add up together, leading to fast accumulation of error. Therefore, in this case the performance of our solution is worse than that in the “clockwise” case and that in the “center” case. In the “center” case, the team moves through the gyre via the center, where currents on opposite sides of the center tend to cancel the error as they move in opposite direction. Interesting enough, in Fig. 18 the performance of our solution is not much better than that of the “No Coordination”, which is because varying current speed makes it more difficult to coordinate.

Last, interestingly enough, as seen from all these figures, in the beginning our proposed algorithms are quite effective in reducing the DFT and DE, while after a certain time the algorithms become less effective, i.e., the DFT and DE may increase after this time. When the ocean current speed is within the range that the algorithms are able to deal with, our proposed algorithms is effective. Otherwise, the DFT and DE will keep increasing. It is also due to the dependence of our algorithms on accurate positions. Localization errors accumulate as the gliders stay submerged. As the localization errors accumulate for multiple AUVs (although some may get a position fix after surfacing), the algorithms will lose the ability to fix the errors. In this case all the gliders would need to get a position fix, either by surfacing so to acquire the GPS signal or by using more accurate localization methods.

In sum, our proposed solution is effective when the ocean current speed is within a certain threshold (which depends on the current model). Compared to the other two solutions, our solution leads to lower formation and steering errors.

6. Conclusion and future work

We proposed team formation and steering algorithms for gliders using underwater acoustic communications. These algorithms were shown to be robust against ocean currents and communication impairments. The advantage of our solution over the solution that only uses satellite communications for coordination and over the solution without coordination is verified by simulations using a hybrid underwater acoustic communication emulator.

Future work will involve a thorough theoretical analysis of the proposed algorithms, implementing and testing the proposed algorithms on our SLOCUM glider platform and perform real-world experiments off the coast of New Jersey, and improvement of the algorithms so that they can run efficiently and reliably in real gliders.

We will also consider to design an energy efficient solution for the coordination of AUVs. Energy consumption is an important issue to consider for prolonged operation of the AUVs. To incorporate energy considerations in the algorithm design, the application requirements on (1) path to be followed, (2) geometry for the formation, and even (3) the number of vehicles in the team, should be relaxed. In this case, adaptive sampling can be performed in a looser sense, e.g., gliders can take some decisions on their own real time not just to compensate for disturbances such as unpredicted ocean currents but to trade off data quality/quantity for energy saving. Our final goal is to enable underwater inter-vehicle communication and autonomous coordination solutions aimed at enhancing the capabilities of the existing ocean observing cyber-infrastructure.

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