Task Allocation for Networked Autonomous Underwater Vehicles in Critical Missions

Indraneel S. Kulkarni, *Student Member, IEEE,* Dario Pompili, *Member, IEEE*

***Abstract*—Underwater Acoustic Sensor Networks (UW-ASNs) consist of stationary or mobile nodes such as Autonomous Underwater Vehicles (AUVs), which may be classified as propeller-driven vehicles and gliders, that are equipped with a variety of sensors for performing collaborative monitoring tasks. The missions entrusted to the AUVs in this work are critical to human life and property, are bound by severe time and energy constraints, and involve a high degree of inter-vehicular communication. In this work, a task allocation framework for networked AUVs that participate as a team to accomplish critical missions is developed. The team formed as a result of this task allocation framework is the subset of all deployed AUVs that is best suited to accomplish the mission while adhering to the mission constraints. Research specific to this area has been limited, hence a task allocation framework for networked AUVs to accomplish critical missions is proposed.**

***Index Terms*—Underwater Acoustic Sensor Networks, Autonomous Vehicles, Task Allocation, Gliders.**

I. Introduction

UNDERWATER Acoustic Sensor Networks (UW-ASNs) consist of stationary or mobile nodes such as Autonomous Underwater Vehicles (AUVs), which comprise of Propeller Driven Vehicles (PDVs) and gliders, that are equipped with a variety of sensors for performing collaborative monitoring tasks. UW-ASNs are envisioned for critical missions like tsunami and seaquake warning, surveillance of leakage in underwater oil and gas pipelines and data cables, mine reconnaissance and submarine rescue. Failure of these missions would pose a threat to human life and property [20]. Missions involving safeguarding of life and property are essential for the safety, security, and economic vitality in a complex world characterized by uncertainty. Success of these missions is based on reliable and timely response by the rescue team of AUVs to an untoward situation.

The focus of this work is to develop a task allocation framework to select in a localized manner a team of AUVs for critical missions. The fundamental requirement in critical missions is the ability to accomplish the required tasks with reliability and in allotted time. The team formed as a result of the task allocation algorithm is the optimal subset of the deployed AUVs that can reliably and efficiently complete the mission. If all the deployed AUVs were selected as a team, the mission may or may not be feasible to accomplish, and even if it could be accomplished successfully it may be inefficient in terms of resources. Hence, task allocation is required to choose the best possible subset of vehicles in such as way as to reliably accomplish the mission with high time and energy efficiency.

Critical missions involving multiple AUVs become feasible only if the vehicles communicate with each other effectively, as it is not possible for a team to collaborate otherwise [15], [22]. Communication is often the critical link on which the success or failure of the mission depends. Missions like rescue of a drowning nuclear powered submarine would require an immediate response from a team of AUVs to find out the location of drowning, to detect any leakage of radioactive substances from it, to temporarily stop the leakage if possible, and to continuously monitor the hazard level of the spillage in order to asses the damage to the marine environment. An optimal response team for such missions based on task allocation for networked AUVs is envisaged in this work.

There are two categories of vehicles that can operate as AUVs, Propeller Driven Vehicles (PDVs) and gliders. PDVs are propeller driven, battery operated vehicles with high maneuverability and variable speed. Underwater gliders are buoyancy-driven vehicles that alternately reduce and expand displaced volume to dive and climb through the ocean [19], [8]. These vehicles are designed to glide from the ocean surface to its bottom and back while taking different measurements along a sawtooth trajectory through water [11]. Underwater gliders offer a solution for exploring the ocean with much higher resolution in space and time than is possible with techniques reliant on ships and moorings. Gliders cannot vary their speed substantially and are less maneuverable as compared to PDVs. However, although PDVs are time-efficient means of ocean exploration due to their variable speed, they have a mission length limited to a few days due to high energy consumption. There are two distinct advantages of speed and energy efficiency offered by PDVs and gliders, respectively. In critical missions, in fact, PDVs may act as *primarily responders*, whereas gliders may act as *sentinels*. As a team the AUVs need to perform various tasks and measure different quantities for which they are fitted with a variety of sensors. Space, weight, energy consumption, and other design constraints of AUVs limit the number of sensors a single AUV can carry. Hence, in order to take full advantage of the different design characteristics of PDVs and gliders, fitted with a variety of sensors, we envisage the use of a heterogenous team involving both types of vehicles.

The remainder of the article is organized as follows. In Sect. II, we focus on the related work. In Sect. III, we describe the basic model assumptions. In Sect. IV, we present

Manuscript received 1 April 2009; revised 1 November 2009. A preliminary shorter version of this paper was presented in the Proc. of *ACM International Workshop on UnderWater Networks (WUWNet)*, San Francisco, CA, September 2008 [14].

The authors are with the Department of Electrical and Computer Engineering at Rutgers, The State University of New Jersey, 94 Brett Road, Piscataway, NJ 08854 (e-mails: neelk@eden.rutgers.edu, pompili@ece.rutgers.edu).

Digital Object Identifier 10.1109/JSAC.2010.100609.

the mission critical networking required for formation of the optimal response team. In Sect. V, we cast the problem for the networked AUVs. In Sect. VI, we present performance evaluation based on the comparison of results obtained from models developed for gliders, PDVs, and a heterogeneous team. Finally, in Sect. VII, we draw the main conclusions.

II. Related Work

The research done in the field of multi AUV coordination for critical missions has been limited. In [20], the authors study how a team of AUVs can act as a recoverable, reconfigurable array or form a polyhedral structure for monitoring a region of interest in time and space. In [3], the authors present a model for decentralized control of platoons and emphasize the need for efficient communication among participating AUVs. In [4], the authors propose a coordination framework based on estimation theory and potential distribution for directing the robots to target locations. In [7], the authors propose multi AUV control based on Virtual Bodies and Artificial Potentials (VBAP). In [18], the authors propose an acoustic network for communication, control, and navigation of gliders. We observe that none of the above mentioned work considers the criticality of the mission in the sense of time and reliability; most of the research until date has focused, in fact, on passive monitoring and sampling missions. We also observe that no work until date considers PDVs and gliders to form a heterogeneous team.

Extensive research has been done on the area of localization, coordination, and task allocation for terrestrial robots [24], [9], [1], [21], but the work has been very limited for AUVs. In [25], the authors propose a decentralized coordination approach based on individual prioritization schemes. In [6], the authors propose a probabilistic coordination approach that simultaneously considers cost to reach the target point and utility of the target point. It was observed that coordination algorithms for terrestrial robots are communication intensive, i.e., require large bandwidth, and heavily rely on GPS tracking. Compared to terrestrial environment, underwater the available bandwidth is low, channel is noisy, bit rate is very low, packet loss is high, and GPS tracking is available only at the surface [2]. Hence, AUVs need specially designed algorithms that strictly adhere to the limitations and impairments of underwater acoustic communications.

III. Basic Model Assumptions

The task allocation framework proposed in this work is based on certain basic assumptions. The assumptions are: 1) it is assumed that the object about which information is to be obtained is present in the region of interest; 2) a virtual sphere known as the *object sphere* of radius r [m], as shown in Fig. 1, is assumed around the target object; 3) a concentric virtual sphere known as *constellation sphere* of radius R [m] is assumed around the object such that $R > r$; 4) the radius of the constellation sphere is limited by the maximum distance from which the sensors fitted on the AUVs can acquire data efficiently, which is denoted as R_{max}; note that the minimum distance is the distance that should be maintained between the AUV and the object to avoid collision; 5) all the AUVs in the constellation form a symmetric polyhedral structure known as *constellation polyhedron*, as shown in Fig. 1; all the vertices of the polyhedron lay on the constellation sphere such that they are evenly distributed on the surface; 6) each AUV is assigned a unique *optimum position* on the constellation sphere so as to avoid collision between any two AUVs; 7) each AUV is equipped with acoustic modems for underwater wireless communication; 8) each AUV has enough computing power and memory to solve the optimization problem; 9) a Mission Observer Ship (MOS), which is capable of i) collecting and relaying the acquired information to the base station and ii) communicating with the deployed AUVs using acoustic underwater communication, is assumed to be present near the deployment region, as shown in Fig. 2; or, the AUVs are assumed to have knowledge about the mission and are waiting for an event to occur; 10) the base station is assumed to be located far from the region of interest and can communicate only with the MOS via satellite communications; 11) each AUV taking part in the mission knows its approximate distance from the target object.

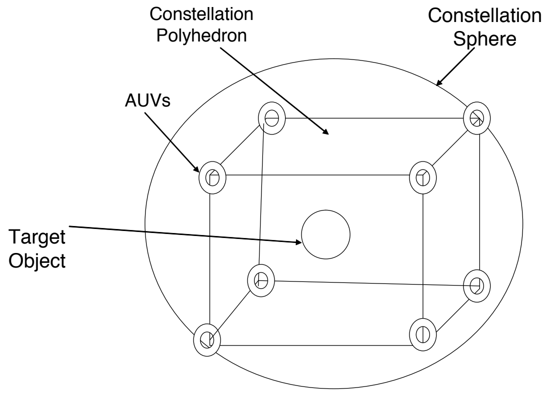

Fig. 1. Constellation formation to capture object information.

IV. Mission Critical Networking

The success or failure of the mission depends on sharing the time-critical information between the AUVs deployed. The task allocation and team formation process involve sharing of information about the positions of AUVs, ocean currents, available energy, onboard available sensors, type of vehicle, i.e., PDV or glider. This critical information, mandatory to form the team, is shared using underwater acoustic communication.

Formation of an optimal team to accomplish the mission involves five phases: Phase I involves MOS broadcasting mission details to the AUVs deployed near the target object based on geocasting mechanism; Phase II is the election of a collector AUV from AUVs deployed near the target object based on geocasting of the data; Phase III consists of finding the AUVs available to be part of the team; Phase IV involves solving the optimization problem; Phase V consists of geocasting the output of the optimization problem in order to inform the AUVs in the geocasting region of their selection as part of the optimal team; Phase VI aims at achieving vehicle self-localization via exchange of position information. The timing diagram for the first five phases is shown in Fig. 3.

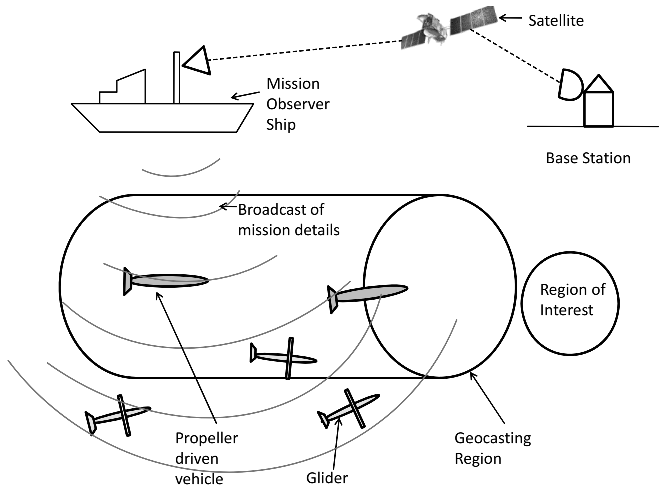

Fig. 2. MOS receiving mission details from base station via satellite and broadcasting these mission details to the deployed AUVs.

As localization is assumed to be a part of trajectory planning problem, it is not considered in the timing diagram.

Phase I: Broadcast of mission details to deployed AUVs. Objective and requirements of the mission are conceived at the base station. The data is relayed to the MOS via satellite communications, as shown in Fig. 2. MOS broadcasts the message in the region where the AUVs are deployed, as shown in Fig. 2. The time taken by the broadcast message containing the mission details to reach the AUVs is dependent on the propagation delay $T_p = d_{sd}/c$ [s] and the transmission delay $T_r = l_{pkt}/X_{sd}$ [s], as shown in Fig. 3, where d_{sd} [m] is the distance between the sender and the receiver, c [m/s] is the velocity of sound underwater, l_{pkt} [bits] is the length of the packet, and X_{sd} [bps] is the transmission rate. The underwater channel presents communication challenges such as limited bandwidth, heavy multipath and fading, propagation delay that is five orders of magnitude higher than in terrestrial radio frequency communication and variable, high bit error rate and temporary loss of connectivity [2]. Transmission loss in an underwater channel is described by the Urick's propagation model, $TL^D(d, f_o) = 20 \cdot \log(d) + \beta(f_o) \cdot d$ [23], where $TL^D(d, f_o)$ [dB] is the deterministic transmission loss of a narrow band acoustic signal with a center frequency of f_o [kHz] experienced along a distance d [m] and $\beta(f_o)$ [dB/m] represents the medium absorption coefficient and quantifies the dependency of transmission loss on frequency band. The statistical transmission loss model of the channel is developed in [16]. To model the statistical loss $TL_{ij}(t_k) = TL_{ij}^D \cdot \rho_{wh}^2$, the water body where the AUVs are deployed is assumed to be a parallelepiped and is divided into cubes w, h, etc., each with side S_c $[m]$, which is taken as coherence distance. A matrix $\Psi(t_k) = [\rho_{wh}]$ is formed, such that it stores the value of random variable ρ with unit-mean Rayleigh distribution, to account for statistical attenuation in the channel from cube w and h. The subscripts i and j are sending and receiving AUVs respectively, w and h are the cubes where i and j are located respectively, while ρ is an element in the matrix Ψ at time t_k that is recomputed every T_c [s], which is the coherence time of the channel. Special properties of matrix Ψ are: i) $\rho_{ww} = 1$ (transmission loss within the coherence distance), ii) $\rho_{wh} \neq \rho_{hw}$, i.e., link asymmetry, iii) Ψ is memory less, i.e., $\Psi(t_{k+1})$ does not depend on $\Psi(t_k)$. This model takes into consideration the spatio-temporal variation and link asymmetry, which are peculiar characteristics of the underwater acoustic channel, and accounts for the worst-case scenario where the channel is in 'saturated conditions', i.e., it is affected by heavy multipath (e.g., in shallow water - where the depth is less than 100m).

Phase II and III: Election of collector and selection of the available set of AUVs to be used as input in the optimization problem. A collector AUV, selected from the deployed set, collects the information from all the other deployed AUVs and solves the optimization problem to select the best possible team for the mission. Once an AUV receives the mission details from the MOS, it starts a *hold-off* timer, after the end of which it will broadcast a message to inform all the other AUVs deployed in the region of its role as collector, as shown in Fig. 2. The concept of neighbor is defined statistically. If an AUV receives 85% of the packets from another AUV, the latter is assumed to be its one-hop neighbor [16]. The collector election is implemented by the geocasting mechanism. The collector once elected starts collecting information required to solve the optimization problem by geocasting *CollectorInfoPkt* to all the AUVs present in the geocasting region.

Geocasting in wireless sensor and adhoc networks is the delivery of a message from a source to all the nodes in a geographical region [12], [13]. Dissemination of query inside the geographical region is defined by the sender. Geocasting can be achieved by 'selectively' flooding the network so as to reach all the nodes in the geocast region. In the proposed geocasting protocol, we leverage the shape of the geocast region using the information included in the transmitted query packet. Assuming the geocast region to be cylindrical, the surface station includes the following information about the geocast region in the query packet: the geographical coordinates of the center 'C_g' of the geocast region, vector $\overrightarrow{L}$ along the longest side of the geocast region and passing through the center, radius 'r_g' of the cylindrical region, as shown in Fig. 4. If $\overrightarrow{si}$ is the vector from the sender 's' to the receiver 'i' of the *CollectorInfoPkt* packet, the projection of the vector $\overrightarrow{si}$ along vector $\overrightarrow{L}$ is given by,

$$d_{si} = \overrightarrow{si} \cdot \frac{\overrightarrow{L}}{\|\overrightarrow{L}\|} \tag{1}$$

A node receiving the query packet determines if it resides in the geocast region, with the help of the above information transmitted in the query packet, and knowledge of its own geographical location. Every node inside the geocast region that receives the packet will follow this protocol for query dissemination inside the region. Conversely, if a node resides outside the geocast region, it discards it.

Consider the shape of the geocast region as shown in the Fig. 4. Let us assume that the query packet enters the geocast region through node A. Node A will then broadcast a short ENFORCE packet; immediately after, node A will transmit the query packet. The ENFORCE packet alerts the nodes that a query packet is to be expected after a certain interval of time; due to this, the nodes that want to transmit data defer their

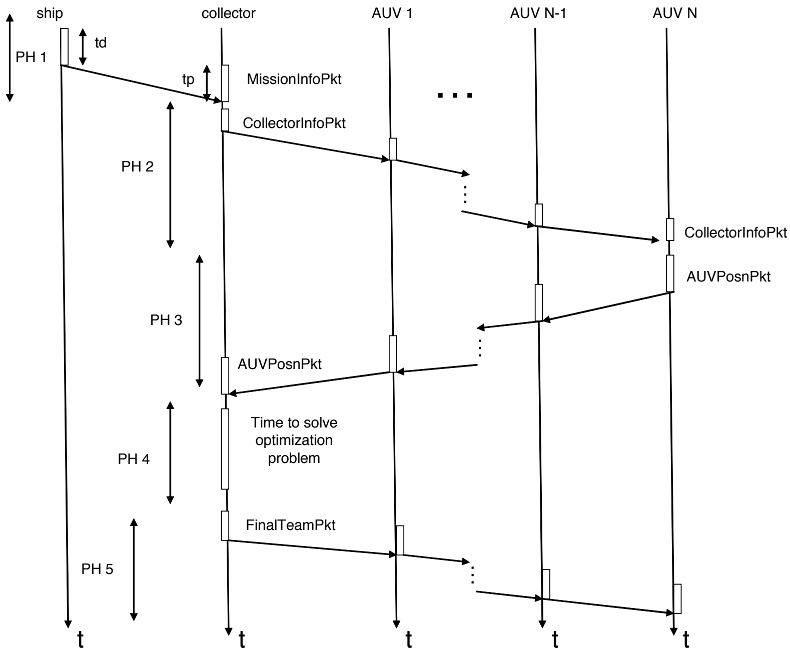

Fig. 3. Time critical networking for the formation of optimal team of AUVs.

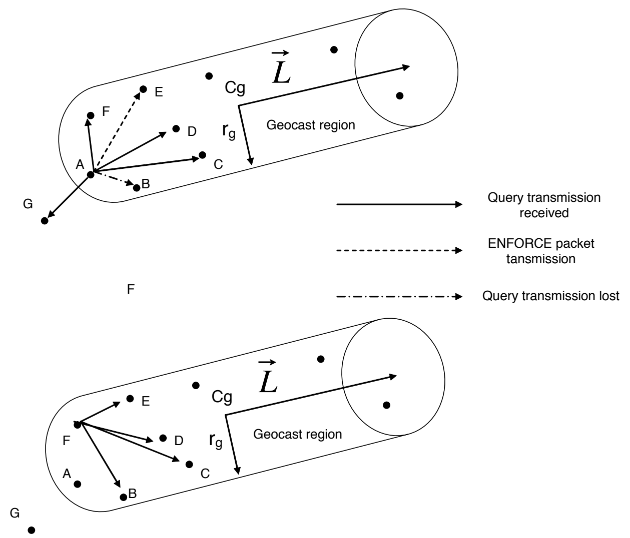

Fig. 4. Broadcast in the geocast region.

transmissions accordingly. Also, as the ENFORCE packet is short, the probability of packet collision is low. On receiving the query packet for the first time, nodes E, D, C, and B start a hold-off timer, $T_{hold}^{geocast}$, a uniform random variable in $[0, 2T_{hold-mean}^{geocast}]$, where $T_{hold-mean}$ is given by,

$$T_{hold-mean}^{geocast} = (1 - \frac{d_{si}}{R_max} \cdot \tau + \frac{\phi_{si}}{c}), \tag{2}$$

$$\Phi_{si} = \begin{cases} R_{max} - d_{si} & \text{if } R_{max} \geq d_{si} \\ 0 & \text{if } R_{max} < d_{si}, \end{cases}$$

where d_{si} is the projection of the vector $\overrightarrow{si}$ along the vector $\overrightarrow{L}$ passing through 's'. The idea is to give higher priority to nodes having a greater value of d_{si} so that the query packet quickly penetrates the length of the geocast region. From Fig. 4 one can see that node C will have the smallest hold-off timer as compared to other receiving nodes. Once node C's hold-off timer expires, it broadcasts the packet. A node, while still being in the hold-off state, will wait to overhear transmissions from all directions except from the sender's direction. The node that fails to overhear from any one of these directions will decide to be a forwarding node. A non-forwarding node simply stops its hold-off timer, whereas forwarding node broadcasts the packet once the hold-off timer expires.

A node that does not receive the query packet, but receives the ENFORCE packet, informs other nodes that it did not receive the query packet by sending a short NACK packet. Before transmitting a NACK, the node waits for a duration of NACK-hold-off timer given by,

$$T_{NACK-hold-off}^{geocast} = T_{hold-max}^{geocast} + \frac{R_{max}}{c} + t_d^Q, \tag{3}$$

where t_d^Q is the transmission delay for the NACK.

In Fig. 4, it can be seen that node F will transmit a NACK. The NACK hold-off timer ensures that node F waits long enough to overhear the transmission from a forwarding node in the neighborhood - if any. If node F is not able to overhear before the NACK-hold off timer expires, it will transmit the NACK and start a NACK-timeout timer given by,

$$T_{NACK-timeout} = 2\frac{R_{max}}{c} + T_r^Q. \tag{4}$$

A node that receives the NACK will respond with probability $P(N) = \frac{n}{n+2}$, where 'n' is the number of NACK's received. A node that receives the highest number of NACKs will have a higher probability to respond. If a node does not get the packet during the NACK timeout period, it will retransmit the NACK.

This geocast protocol is used by the collector AUV to acquire data from all the other AUVs deployed in the geocast region. The center of the geocast region is the same as the center of the target object when underwater currents are not considered. In the presence of underwater currents, the geocast region can be shifted in the direction opposite to direction of current so as to include maximum number of AUVs traveling in the direction of current, which may lead to a more energy-efficient solution. If one- or two-hop neighbor knowledge is considered, the time for data collection at collector can be reduced drastically; finding out the optimality of the protocol assuming one- or two-hop neighbor knowledge is left for future research.

Phase IV and V: Solving the task optimization problem and geocasting mission details. The optimization problem formulated in Sect. V is solved by the collector AUV. The optimization problem chooses the best possible set of networked AUVs to accomplish the critical mission. As the optimization problem is substantially complex and involves many variables, the time to solve it depends on the processing power of the AUV. The computing power available on the AUV is limited as it is shared for controlling the AUV, processing sensor information, and solving the optimization problem. Hence, it may take more time to solve the problem than on a computer dedicated for such a task. After the optimization problem is solved the AUVs selected in the team are informed about the mission details, which are geocast by the collector AUV. If an AUV that is not selected in the team receives the message, it discards it.

Phase VI: Localization. Once selected in the team, the AUVs localize themselves with respect to the rest of the team. A simple localization approach based on dead reckoning and acoustic communication is used in this work. Dead reckoning is a navigation system that uses readings from compass, depth sensor, and speed sensor together to calculate the current position with respect to the initial position where GPS information was available. It is prone to error due to the drift caused by underwater currents and it adds cumulatively with time. To improve the accuracy of dead reckoning we propose a simple geocasting-based feedback mechanism. The AUV geocasts a query asking for the coordinates of the adjacent AUVs selected as a part of the team. Response from at least one neighbor is required for team size greater than one. Based on the response time and velocity of sound in water, the broadcasting AUV knows its distance from the responding AUV. Broadcasting AUV uses this distance and coordinates of the responding AUV obtained in the response to the query to find its coordinates using standard Euclidean distance. The broadcasting AUV compares this position with its dead reckoning system reading and computes the error, which is fed back to dead reckoning calculator to increase its accuracy.

Note that the time taken to implement Phase I to Phase V reduces the *actual time* available for the mission. Hence, selecting a large geocasting region is not always a good choice as more time may be spent on communication and solving the task allocation problem, which may make accomplishing the mission impossible in the allotted time.

V. PROBLEM FORMULATION

In this section we formulate the mathematical models for the formation of the optimal team to accomplish the mission. The objective function has the aim to either *optimize energy* or to *optimize time* depending on the mission requirements. The objective function for *optimizing energy* has three subcategories: i) maximize the available energy of the team of AUVs after the mission, ii) minimize the energy required by the team of AUVs to complete the mission, and iii) maximize the minimum available energy of AUV that is part of the team, which in turn maximizes the life time of the team, while respecting the time bound δ [s] for the mission. Conversely, the objective function to *optimize time* aims at minimizing the time required to complete the entire mission even at the cost of a higher energy expenditure. In this section, we first formulate the problem for only gliders, then for only PDVs, and finally for both PDVs and gliders together (heterogenous team). The optimization problem proposed in this work is focused on maximizing the available energy of the team after the completion of mission as the energy saved can be used to transmit the data collected from the target object to the MOS.

A. Effect of Underwater Currents on Optimization Problem

Underwater currents are caused due to small streams and rivulets inside the water body. Due to underwater currents the solution of the optimization problem is affected drastically. The problem, in fact, cannot be considered localized in the presence of underwater currents. Underwater currents can make involving an AUV that is aligned with the direction of current but far from the target object beneficial; conversely, an AUV close to target object but facing opposite to current may be not the best choice to be part of the team. The drift would push the AUV aligned with the current forward, and it would need same or lower energy to travel at an increased speed. In contrast, an AUV traveling opposite to the current has to spend more energy to overcome the force of current, even to travel at its normal speed. It is assumed that under ideal case ocean current does not change with depth and are present only in the horizontal plane [17]. The force $\overrightarrow{F}_c$ acting on an AUV due to underwater current is given as,

$$\overrightarrow{F}_c = C_c \sigma A_{AUV} \cdot (\overrightarrow{V}_c - \overrightarrow{V}_{AUV}), \quad (5)$$

where $\overrightarrow{V_c}$ $[\mathrm{m/s}]$ is the horizontal velocity of underwater current, $\overrightarrow{V}_{AUV}$ $[\mathrm{m/s}]$ is the horizontal velocity of the AUV, A_{AUV} $[\mathrm{m}^2]$ is the cross-sectional area of the AUV, σ is a constant dependent on the shape of the AUV through $C_c = 721.1$ $[\mathrm{Ns/m}^3]$.

B. Buoyancy-driven Gliders

In this section we consider that the AUVs deployed are only gliders. The optimization problem is formulated to maximize the available energy for the team of gliders. Based on the assumptions in Sect. III, the aim is to find the optimal number of gliders to form a team based on the objective function to accomplish the mission respecting the time bound δ [s].

We also analyze the dynamics of the glider and evaluate the effect of ocean currents on the task optimization problem. From Sec. V-A, it is assumed that under ideal case ocean currents do not change with depth [17], and gliders move in

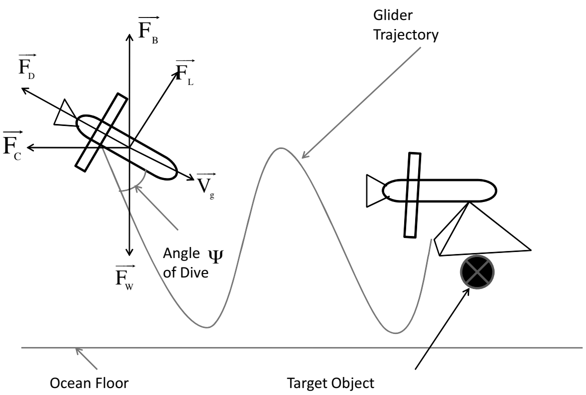

Fig. 5. Sawtooth trajectory of the glider.

a sawtooth trajectory as sketched in Fig. 5. The forces acting on the glider, as shown in Fig. 5, are

$$\overrightarrow{F}_{total} = \overrightarrow{F}_w + \overrightarrow{F}_b + \overrightarrow{F}_c + \overrightarrow{F}_{drag} + \overrightarrow{F}_{lift}, \quad (6)$$

where $\overrightarrow{F}_w = \rho_{glider} vol_{glider} \cdot \overrightarrow{g}$ is the weight force, which depends on the density ρ_{glider} [kg/m^3] and volume vol_{glider} [m^3] of the glider and on the terrestrial gravitation g [m/s^2][10]; $\overrightarrow{F}_b = \rho_{water} vol_{glider} \cdot \overrightarrow{g}$ is the buoyant force due to Archimedes' principle, which is equal to the weight of the displaced fluid by the glider, where $\rho_{water} = 1050$ [kg/m^3] represents the average density of salty water, $\overrightarrow{F}_c = C\sigma A_g \cdot (\overrightarrow{V}_c - \overrightarrow{V}_g)$ is the force of current as defined in (5), $\overrightarrow{V}_g$ is the horizontal velocity of the glider and A_g is the cross sectional area of the glider, $\overrightarrow{F}_{drag} = \frac{1}{2}\rho_{water} C_{drag}(\theta) A_g \cdot \overrightarrow{V}_g^2$ is the drag force, and $\overrightarrow{F}_{lift} = \frac{1}{2}\rho_{water} C_{lift}(\theta) A_g \cdot \overrightarrow{V}_g^2$ is the lift force; these forces are proportional to the square of velocity of the glider $\overrightarrow{V}_g$ [m/s], cross-sectional area of the glider A_g [m^2], and the density of the salty water through the constants C_{drag} and C_{lift}, respectively, which are dependent on the angle of dive θ.

The power required to move the glider is equivalent to the product of force required to counterbalance the force in (6) and move at velocity V_g. The glider moves in a sawtooth trajectory, which is unique as compared to other underwater vehicles. This has the advantage of conserving engine power as it needs energy only to climb, but it makes the model very complicated. Glider requires more power to climb as compared to dive, as it has to pump out water to travel at velocity V_g. Hence, in the mathematical model we consider only the power required to climb. It is assumed for simplicity that the glider dives at a constant angle, hence, the horizontal distance covered in one dive or climb can be calculated using $dist_{cov} = \tan(\theta) \cdot (depth_{fl} - depth_{gl})$, where $dist_{cov}$ is the horizontal distance covered by the glider diving at an angle θ and is present at depth $depth_{gl}$ with respect to the surface, and $depth_{fl}$ is the average depth of the sea floor in the given region. It is assumed that the glider starts and ends the mission with a dive. Depending on the horizontal distance the glider is required to cover, the number of dives and climbs can be calculated using $N_{climbs} = \frac{1}{2}\frac{dist_{trav}}{dist_{cov}}$, where N_{climbs} is the number of times the glider climbs in traveling a total distance of $dist_{trav}$ [km]. The glider engine is on for the time T_{pump} required to pump out the water, which is of the order of minutes. From N_{climbs}, the number of times the glider climbs is known and, hence, the total time for which the engine is 'on' can be calculated using $T_{on} = N_{climbs} \cdot T_{pump}$, where T_{on} is the total time for which the pump operates during the mission and T_{pump} is the time the pump needs to be on for one climb at velocity V_g.

In the following, for the sake of clarity, we introduce the notations for construction of our mathematical model for gliders. $Pos_g^i(x_g^i, y_g^i, z_g^i)$ is the *initial position* of glider g in the deployment region, $Pos_g^f(x_g^f, y_g^f, z_g^f)$ is the optimum position f on the *constellation sphere* of the glider g around the target object, $C_o(x_o, y_o, z_o)$ is the center of the *object sphere* with radius r and z_{fl} [km] is the depth of the ocean floor from the surface assuming the sea bed to be uniform. P^M [W] is the power required to run the buoyancy engine. $\mathcal{G}$ is the set of gliders deployed in the region; every glider g is its element and X_g is a binary vector determining which gliders are selected in the team for the mission. T_g^M [hr] is the time glider g requires to move a certain distance at horizontal velocity V_g^{eff} [km/hr], T_g^Ω [hr] is the time required to collect data from the target object by the respective glider, T_{on} [hr] is the time for which the buoyancy engine is 'on' and it is determined by the velocity V_g of the glider, T_{pump} [hr] is the time for which the buoyancy engine is 'on' for one climb and T^{Total} [hr] is the time the team of gliders will take to complete the mission. E_g^M [J] is the energy required by the glider g to move from initial position to the optimum position, E_g^Ω [J] is the energy required by the glider to move around the target object to acquire data and E_g^{Av} [J] is the energy available to the glider before the start of the mission. δ [hr] is the total time bound to complete the mission. α [degrees] is the angle that a glider makes with the direction of underwater current.

Now, we introduce a specific framework that presents a mathematical model that takes into consideration the initial position of the deployed gliders, optimum position of the gliders in the constellation, size of the object, time bound for the mission, energy of the gliders participating in optimization problem before the start of mission, and the angle made by each participating glider with the direction of ocean current. The velocity of gliders has a very limited range of variation as compared to that of PDVs; hence, in this mathematical model we assume the velocity of all gliders to be constant.

The problem is formulated as a *Mixed Integer Non Linear Program (MINLP)*. The objective of the problem is to maximize the available energy after the completion of the mission while respecting the time bound δ.

Multi-glider Task Optimization Problem

Given : $Pos_g^i, C_o, \mathcal{G}, P_g^M, R_{min}, R_{max},$
$\delta, V_g, T_{on}, F_{total}, \alpha, E_g^{AV}, T_{pump}, V_c$

Find : $Pos_g^{f*}, X_g^*, R^* \epsilon [R_{min}, R_{max}]$

Maximize : $\sum_{g\epsilon\mathcal{G}} [E_g^{AV} - (E_g^M + E_g^\Omega)] \cdot X_g$

Subject to :

$$E_g^M = P^M \cdot T_{on}^M; \quad (7)$$

$$P_g^M = F_{total} \cdot V_g^{eff}; \tag{8}$$

$$V_g^{eff} = |V_g \cdot cos(\alpha)| + |V_c|; \tag{9}$$

$$T_{on}^M = \frac{\sqrt{(x_g^f - x_o)^2 + (y_g^f - y_o)^2}}{\tan(\theta)(z_{fl} - z_o)} \cdot T_{pump}; \tag{10}$$

$$T_g^M = \frac{\sqrt{(x_g^f - x_o)^2 + (y_g^f - y_o)^2}}{V_g^{eff}}; \tag{11}$$

$$E_g^\Omega = P_g^\Omega \cdot T_{on}^\Omega; \tag{12}$$

$$T_{on}^\Omega = \frac{2 \cdot \pi \cdot R}{\tan(\theta)(z_{total} - z_o)} \cdot T_{pump}; \tag{13}$$

$$T_g^\Omega = \frac{2 \cdot \pi \cdot R}{V_g^{eff}}; \tag{14}$$

$$T^{Total} = \frac{1 + \sum_{g=1}^{|\mathcal{G}|} (\frac{T_g^M}{T_g^\Omega}) \cdot X_g}{\sum_{g=1}^{|\mathcal{G}|} \frac{X_g}{T_g^\Omega}} \leq \delta; \tag{15}$$

$$[(x_g^f - x_o)^2 + (y_g^f - y_o)^2 + (z_g^f - z_o)^2] \cdot X_g = R^2; \tag{16}$$

$$\sum_{g \epsilon \mathcal{G}} X_g \geq 1; \tag{17}$$

$$\sum_{g \epsilon \mathcal{G}} X_g \leq |\mathcal{G}|. \tag{18}$$

Eq. (7) determines the energy the glider requires to operate its buoyancy engine while pumping out the water and to travel at a horizontal velocity V_g^{eff}, where V_g is assumed to be constant as it does not vary over a wide range as compared to AUVs. Eq. (8) determines the power required to operate the buoyancy engine and to generate a total force equivalent to F_{total} so to maintain a horizontal velocity V_g^{eff}. Eq. (9) determines the effective horizontal velocity of the glider V_g^{eff} when the glider makes an angle α with the direction of underwater current. Constraint (10) determines the total time for which the buoyancy engine will operate when the glider moves from its initial position to its optimum position. This is calculated as a product of N_{climbs} and T_{pump}. Eq. (11) determines the time required by the glider to travel from its initial position to its optimum position at velocity V_g^{eff}. Eq. (12) determines the energy that the glider requires to move when it is acquiring the target object data. As the energy to operate the sensors and collect data is small compared to the energy to move, the dominant energy to move around the object is considered. Eq. (13) determines the total time for which the buoyancy engine will be on during the data acquisition from the target object. Eq. (14) determines the total time required to acquire the data from the object by a single glider; this is the time the glider would need to acquire the data as it will hop from one *optimal position* to another on the *constellation polyhedron*. Constraint (15) determines the total time the team of gliders will take to complete the mission and assures that this time be less than or equal to the given time bound δ; this is a very important constraint as it is a modification of the assumption that all gliders start scanning the object simultaneously. In this task allocation framework, we consider that if a glider arrives at the object it will start acquiring data - even before the other gliders in the team arrive; hence, the actual work to be done for the joining gliders is less than what they would have shared if all of them had arrived simultaneously. This constraint is the backbone for critical missions as it ensures that even if the focus is on minimizing the available energy there will be no compromise on time to complete the mission. For derivation of constraint (15), see the appendix. Constraint (16) puts bounds on the distance between the center of the *object sphere* and the *optimal position* of the gliders selected in the team such that all gliders lay on the *constellation sphere*. Constraint (17) assures that at least one gliders is always selected to form a team for the mission. Constraint (18) assures that the total number of gliders selected for the mission does not exceed the cardinality of the set $\mathcal{G}$.

C. Propeller-driven AUVs (PDVs)

There is a fundamental difference in the operation of PDVs and gliders. While gliders travel in sawtooth trajectory, there is no constraint on the trajectory of PDVs, i.e., they can travel in straight line, circular path, or a sawtooth trajectory. PDVs are capable of changing their velocity over a broad range but at the cost of some extra energy; hence, they are considered in this work to have variable velocity. The sum of forces $\overrightarrow{F}_{total}$ acting on the PDV are same as those acting on a glider, as given in (6). The task optimization model for PDVs and gliders is same except for one constraint, which is the power needed to move. We replace the power to move in (8), in the optimization problem for gliders, with the following,

$$P_a^M = [\zeta F_{total} \cdot V_a^{eff} + P_{min}^M]. \tag{19}$$

Eq. (19) determines the power required for a PDV to propel itself. Unlike gliders, PDVs require their propellers to be on for the full length of the mission. The power consists of two terms, P_{min}^M [W], which is the power required by the onboard electronics and the propeller control system, and $\zeta F_{total} \cdot V_a^{eff}$ [W], which is a nonlinear term that varies according to velocity V_a^{eff} of the PDV.

D. Heterogenous Set of Vehicles (Gliders and PDVs)

In this section we assume that the deployed set of AUVs consist of PDVs and gliders. This makes the optimization problem more complex as the energy consumed by gliders is less than that of PDV; on the other hand, PDVs can move faster than gliders. There is a speed/energy tradeoff between PDVs and gliders, respectively. The notation and mathematical models have been already introduced for the gliders in Sect. V-B and in Sect. V-C for PDVs. For heterogenous deployment, the constraints that change are the total time for the mission, the minimum size, and the maximum size of the team given by,

$$T^{Total} = \frac{1 + [\sum_{g=1}^{|\mathcal{G}|} (\frac{T_g^M}{T_g^\Omega}) \cdot X_g + \sum_{a=1}^{|\mathcal{A}|} (\frac{T_a^M}{T_a^\Omega}) \cdot X_a]}{[\sum_{g=1}^{|\mathcal{G}|} \frac{X_g}{T_g^\Omega} + \sum_{a=1}^{|\mathcal{A}|} \frac{X_a}{T_a^\Omega}]} \leq \delta, \tag{20}$$

$$\sum_{g\epsilon\mathcal{G}} X_g + \sum_{a\epsilon\mathcal{A}} X_a \geq 1, \tag{21}$$

$$\sum_{g\epsilon\mathcal{G}} X_g + \sum_{a\epsilon\mathcal{A}} X_a \leq |\mathcal{A}| + |\mathcal{G}|. \tag{22}$$

Constraint (20) is a combination of constraint (15) for gliders and an equivalent constraint for PDVs. It assures that time taken by the gliders and PDVs together to complete the mission will be less than the time bound δ. Heterogenous team is the most practical case for time and energy critical missions like rescue of drowning nuclear powered submarine. Gliders have the advantage of being energy efficiency, while PDVs offer the advantage of high speed and maneuverability. Together the two types of vehicles form a potent and flexible combination to accomplish critical missions efficiently in terms of both time and energy. The PDVs act as the action force or first responders, while the gliders act as sentinels and provide peripheral functionalities. Constraint (21) assures that the minimum number of AUVs in the heterogenous team is one. In extreme case, the AUV chosen may be either a glider or a PDV. Constraint (22) assures that the maximum number of AUVs chosen is less than or equal to the total available AUVs, i.e., the number of PDVs plus gliders deployed.

VI. Performance Evaluation

In this section, we evaluate the performance of the proposed framework. The optimization problem is implemented using $MATLAB^{®}$ and solved using *fmincon* non-linear optimization solver. The AUVs are initially randomly deployed in the 3D underwater region. The parameter values for the glider are set as: the power to operate the buoyancy engine of the glider is 940 W, velocity of the gliders is 6.4 km/hr, C_n has a value of 4, the time for which the buoyancy engine needs to be on to move at a horizontal velocity of 6.4 km/hr is 0.15 hr [20]. The parameter values for the PDVs are set as: the power to operate the propeller engine is 2000 W, velocity varies from 2 to 10 km/hr [5]. The velocity of PDVs is dependent on various non-linear factors like drag force, friction of the motor, etc.; hence, the value of non-linear component ζ is set to 0.005. We consider a $10 \times 10 \times 0.2$ km^3 3D underwater region for the deployment of the gliders and AUVs, which is similar to the region off the coast of New Jersey. The object is placed in the center of the region whose coordinates are $(5, 5, 0.1)$ km and diameter of 0.08 km.

In Sect. VI-A, we evaluate the tradeoff between the size of geocasting region and optimality of the solution and its effect on mission critical networking. In Sect. VI-B, we analyze how underwater currents affect the choice of geocasting region. In Sect. VI-C, we analyze how underwater currents affect the localized nature of the optimization problem. Finally, In Sect. VI-D, we compare the energy efficiency of a team of gliders with a team of PDVs for a given mission length δ.

A. Tradeoff Between Size of Geocast Region and Optimality of the Solution

In this section, we compare the size of the geocast region from which the AUVs are selected with respect to the time required for inter-vehicular communication. The

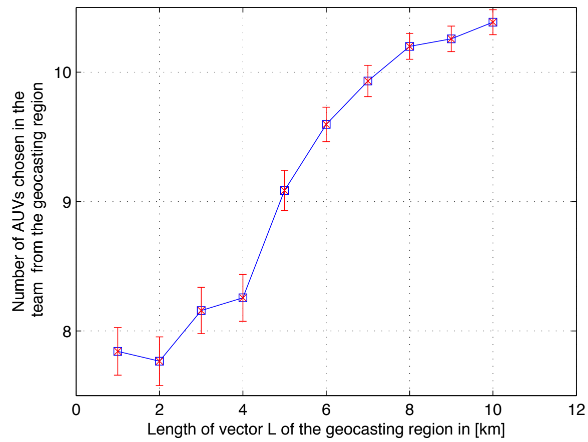

Fig. 6. Number of vehicles available to take part in optimization problem is shown against length of vector L of geocasting region.

collector needs to collect information from all the AUVs present in the geocast region. The AUVs that are successful in establishing communication with the collector are selected to participate in the optimization problem. Communication involves exchange of information about the position, available energy, their orientation with respect to underwater current, and velocity of underwater current at each AUV. This inter-AUV communication time for exchanging information in turn reduces the total time available to accomplish the mission. The communication is implemented based on the geocasting protocol described in Sect. IV. For missions with small time bound this communication overhead can make accomplishing mission impossible.

To observe the actual effect of the size of the geocast region on the optimization problem, underwater currents are not considered in this section. As the size of the geocasting region goes on increasing, more AUVs are available for the mission and this increases the time for collecting the data and solving the optimization problem at the collector. In Fig. 6, we observe that the the number of AUVs available to take part in the optimization problem increases with the size of geocasting region. From Fig. 7, we observe that the time required for the AUVs to communicate with the collector increases with the size of the geocasting region.

From Fig. 8, we observe that the available energy of the team after the mission is the highest when the number of vehicles in the team is five. Now, when the team size is six, suddenly the mission is not feasible. This is due to the fact that time for collecting information from six AUVs causes a communication overhead, which reduces the time available for the mission. It also increases the time required for solving the optimization problem, which in turn reduces the time available for completing the mission and suddenly - even with higher number of vehicles sharing the workload - the mission becomes infeasible.

Hence, choosing a larger region is not always the best solution as it causes a large communication overhead, increases the time to solve the optimization problem, and can make finding the solution to the problem impossible due to insufficient time to complete the mission. Depending on the urgency and time limit for the mission, the algorithm proposed in this

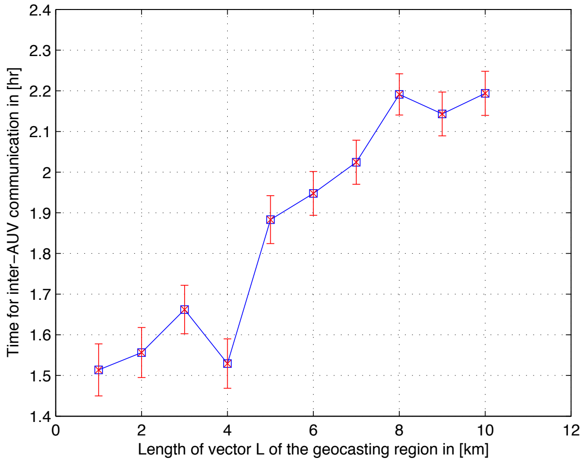

Fig. 7. Time for communication is shown against length of vector L of geocasting region.

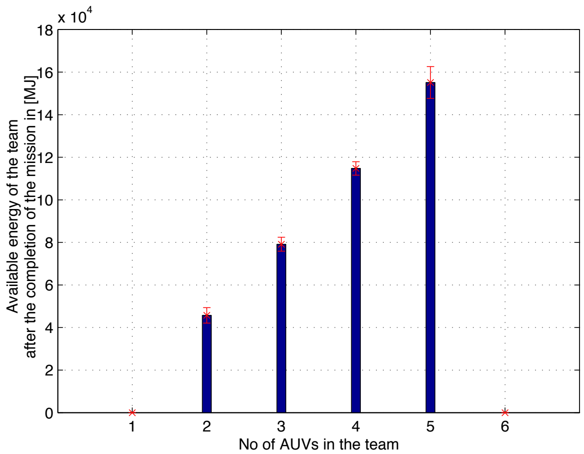

Fig. 8. Available energy of the team of AUVs after the completion of the mission against the team size.

work chooses an appropriate number of AUVs in the given geocasting region to find a feasible and an optimal solution. Other important factor dictating the choice of geocasting region is the effect of underwater currents, which is considered in Sect. VI-B.

B. Effect of Underwater Currents on Choice of the Geocasting Region

In this section, we analyze how underwater currents affect the choice of the geocasting region. As mentioned in Sect. IV, the ideal center for choosing the geocasting region is the center of target object. The geocasting region is chosen symmetrically about the target object in absence of underwater currents; however, when underwater currents are considered, this is not the most efficient choice. From Fig. 9, we observe that a higher number of AUVs facing the direction of current, i.e., deviating by a small angle α from the direction of underwater currents, are chosen to be a part of the team. Energy is conserved by these AUVs, as they use the force of current to drift along with it, at an increased speed, increasing the energy and time efficiency of the mission. Hence, it is beneficial to chose a geocasting region on that side of the target object from where the current is flowing rather than choosing it symmetrically about it.

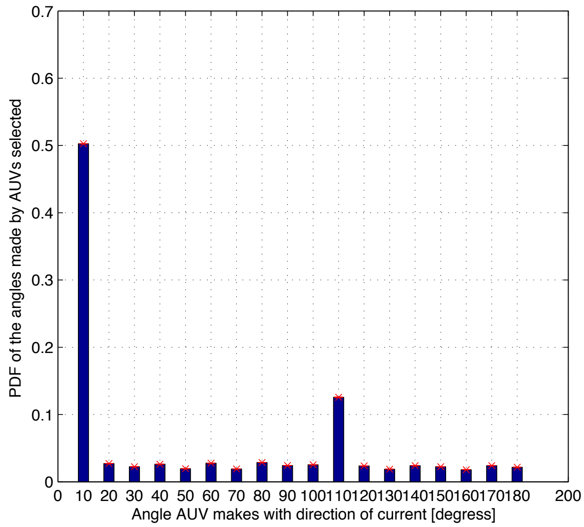

Fig. 9. PDF of AUVs chosen against the angle α made by them with the under water current.

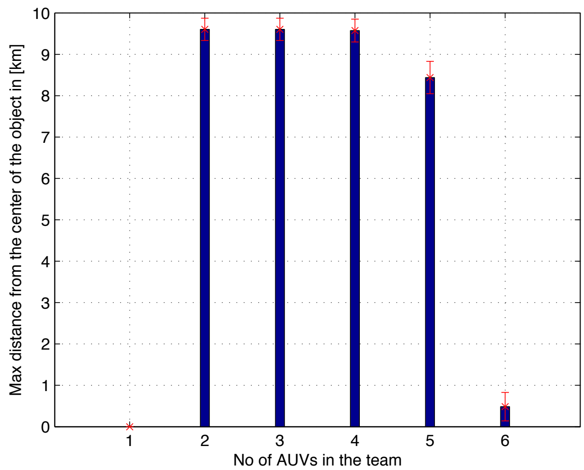

Fig. 10. Maximum distance from which AUVs are selected in the team is plotted against the size of the team.

C. Localized Nature of the Task Allocation Problem

The task allocation problem is localized when underwater currents are not considered. In absence of underwater currents the medium is uniform and all the AUVs have same forces acting on them. Hence, all the AUVs spend same amount of energy to overcome this force. From Fig. 10, we observe that the value of the maximum distance from which an AUV is selected to form an optimal team is almost constant as the size of the team goes on increasing.

In contrast, we can observe in Fig. 11 that in the presence of underwater currents the distances from which the AUVs are selected are not constant and vary according to the deployment and underwater current patterns. In Fig. 9, we see that most of the AUVs selected in the team are the ones that have the lower value for angle α. Thus, it can be inferred from the results that the optimization problem in presence of underwater currents is not a localized problem. Hence, the solution of the

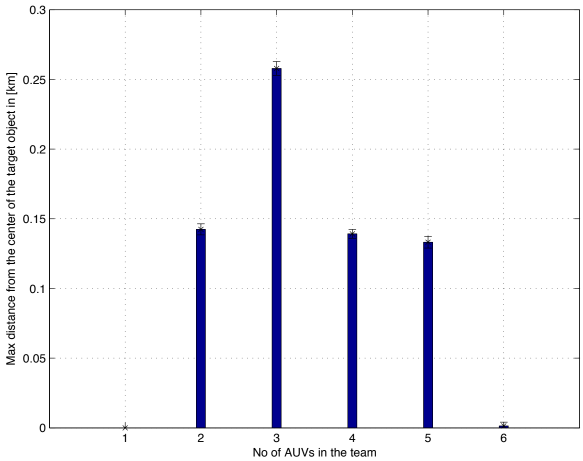

Fig. 11. Maximum distance from which a AUV is chosen against the size of the team in presence of underwater currents.

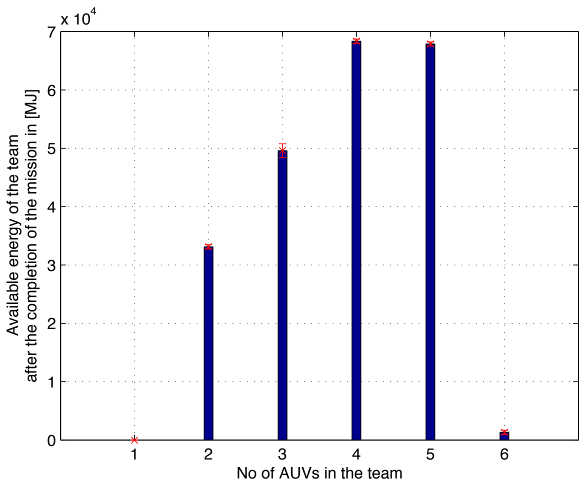

Fig. 12. Energy of the team of AUVs against the size of the team in presence of underwater current.

optimization problem obtained by considering only a subset of AUVs out of all the deployed AUVs is always suboptimal. In Sects. VI-A and VI-B, we have seen that it is not always possible to consider the entire region of deployment for the optimization problem as it can make the problem infeasible to solve. Hence, the framework proposed provides a solution that is suboptimal but always feasible.

In Fig. 12, we observe that the available energy for the team of AUVs does not have linear relationship with the size of the team when underwater currents are considered, as in the case of no underwater currents shown in Fig. 8. This can be attributed to the fact that, when moving along with the underwater current, the AUVs tend to use the force of the current to propel themselves at a higher speed but using lower energy. This reduces the energy consumption drastically. Hence, in a real scenario where underwater currents are present, the team with maximum feasible number of AUVs is not always the best one.

D. Energy Comparison Based on Time Bound for the Mission

In this section, we analyze how the available energy of the team of gliders and PDVs varies with the time bound

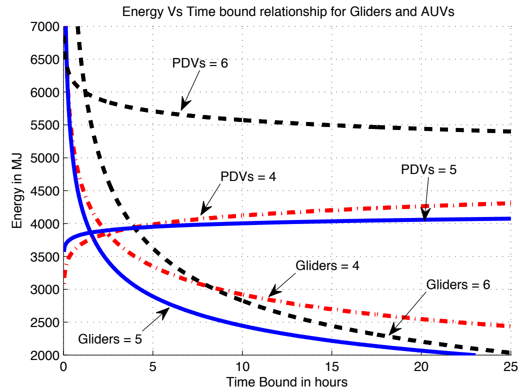

Fig. 13. Comparison between the energy in MJ of gliders and AUVs vs. the time bound for the mission δ.

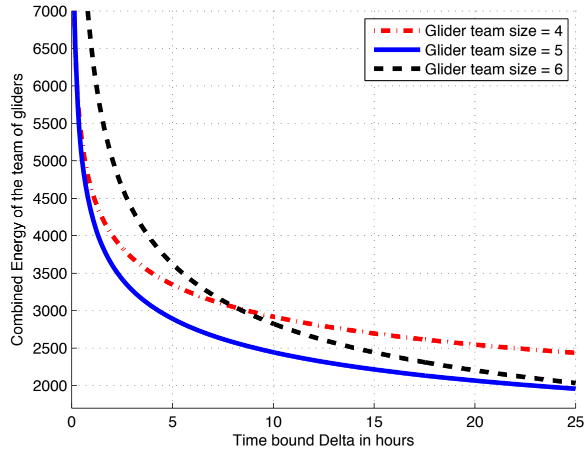

Fig. 14. Relationship between the energy in MJ of gliders vs. the time bound for the mission δ.

δ. In Fig. 13, we observe that, as the length of the mission goes on increasing (time bound), the energy required by the team of only gliders and only PDVs for the same mission differs. Specifically, the energy of the team of only gliders is comparatively less than that required by the team of only PDVs. PDVs are time efficient as compared to the gliders as we can see from the graph the *infeasible region* for team of PDVs is much smaller than the infeasible region for team of gliders. As the time bound goes on increasing and approaches the feasible region of gliders, the energy difference between the glider team and PDV team is drastic. As seen from the graph, the energy required by the team of 4 PDVs is about 2500 MJ more than that for a team of 4 gliders. Also, a team of 5 PDVs can perform the same work as a team of 6 gliders in less time, but it consumes a greater amount of energy, around 3500 MJ more than the team of 6 gliders. Hence, we can infer from the plot that, as a mission length increases, the team of gliders becomes much more energy efficient than the team of PDVs in terms of energy.

From Fig. 14, it is observed that, as the mission length goes on increasing, the energy of a team of gliders goes on decreasing. This indicates that, as the mission length goes on increasing, a larger team of gliders has almost the same energy consumption as a smaller team (or even less). From Fig. 15, it is observed that, as the mission length increases, the energy

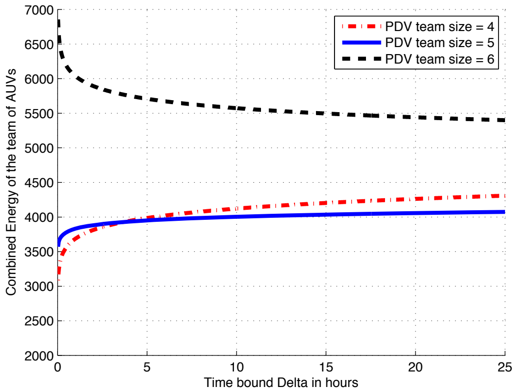

Fig. 15. Relationship between the energy in MJ of AUVs vs. the time bound for the mission δ.

for the team of PDVs reaches a constant value. This is the minimum energy required to keep the PDVs afloat and move. Similar to the team of gliders, the energy difference between the larger and the smaller team of PDVs differs by a marginal value. In Fig. 13, we observe that the energy of the team of gliders stabilizes at much lower level than that of the team of PDVs. As the energy to scan is much less than that to travel, we conclude that PDVs spend more energy in traveling and keeping themselves afloat at a particular level than gliders. In the case of gliders, the energy to scan is more dominant. This implies that the PDVs as a team consume a very large amount of energy as compared to a team of gliders to travel towards the object. This is where the energy efficiency of gliders has its advantage over PDVs in saving energy and cost. Ideally for an infinite time bound, only a single glider would be selected, so that the energy of team would be minimum. The optimization algorithm is run centrally on the computer of one of the glider or a PDV. As the time bound goes on decreasing, the solution of the optimization problem involves more and more vehicles in the proximity of the target object. Hence, an heterogenous team consisting of PDVs and gliders fitted with a variety of sensors would provide a best possible solution in terms of energy and time efficiency. For mission with long distance and mission length, a team with more gliders is preferred, whereas for a mission with long distance and smaller mission length a team with more PDVs is preferred.

VII. Conclusion

We have presented a framework that allows to form an optimal team based on task allocation for networked Autonomous Underwater Vehicles (AUVs) capable of accomplishing critical missions. The team formed as a result of this task allocation framework is the subset of all deployed AUVs that is best suited to accomplish the mission while adhering to the mission constraints. Through simulations, we showed the reliability and the optimality of the results obtained using the proposed framework. The framework was analyzed using four different criteria, i) the effect of geocast region size on the solution of the optimization problem with special consideration to underwater acoustic communication overhead, ii) the effect of underwater currents on the choice of geocast region, iii) the effect of underwater current on the localized nature of the problem which in turn also affects the choice of geocast region, and iv) the comparison of energy efficiency of team of only gliders with a team of only PDVs. The important conclusion is that the optimized solution derived is not only giving the best possible solution, but also a feasible solution, which can be obtained through distributed or localized heuristics. We showed that a trade off exists between the time required for underwater communication, solving the optimization problem, and the feasibility of the solution. For missions with short mission length a smaller geocast region with less number of AUVs is a necessity. We finally show that task allocation for networked AUVs in critical missions is based on the choice of geocast region, its size, the number of AUVs present in the region, and the time allotted to complete the mission.

Appendix

The time constraint (15) can be derived as follows. Let T_1^Ω [hr] be the time required by the first glider to perform the total work Λ [MJ] to complete the mission; the glider rate of work is κ_1^Ω [MJ/hr]. Similarly, let T_2^Ω, T_3^Ω, $\cdots$, T_N^Ω be the time required by the remaining $N-1$ gliders and let κ_2^Ω, κ_3^Ω, $\cdots$, κ_N^Ω be their respective rate of work. Hence, we have,

$$T_1^\Omega \cdot \kappa_1^\Omega = \Lambda, \cdots T_N^\Omega \cdot \kappa_N^\Omega = \Lambda, \quad \Lambda = \Lambda_1 + \Lambda_2 + \cdots + \Lambda_n.$$

Let T^{Total} be the total time required to complete the mission. Hence,

$$\kappa_1^\Omega \cdot T^{Total} = \Lambda_1 \cdots \kappa_N^\Omega \cdot T^{Total} = \Lambda_N,$$
$$T^{Total} \le \delta,$$
$$\Lambda = \frac{\Lambda}{T_1^\Omega} \cdot (T^{Total} - T_1^M) + \cdots + \frac{\Lambda}{T_n^\Omega} \cdot (T^{Total} - T_n^M),$$

where T_1^M is the time to reach the target object, $T^{Total} - T_1^M$ is the time the first glider will work alone on the mission until the second glider arrives. Rearranging the terms we obtain,

$$T^{Total} = \frac{1 + \sum_{i=1}^{N} \frac{T_i^M}{T_i^\Omega}}{\sum_{i=1}^{N} \frac{1}{T_i^\Omega}} \le \delta.$$

References

[1] A. Howard, M. J. Mataric and G. S. Sukhatme. Localization for Mobile Robot Teams Using Maximum Likelihood Estimation. In *IEEE/RSJ International Conference on Robotics and Intelligent Systems (IROS)*, pages 439–459, Laussane, Switzerland, Oct. 2002.

[2] I. F. Akyildiz, D. Pompili, and T. Melodia. Underwater Acoustic Sensor Networks: Research Challenges. *Ad Hoc Networks (Elsevier)*, 3(3):257–279, May 2005.

[3] D. J. Stilwell and B. E. Bishop. Platoons of underwater vehicles. In *Control Systems Magazine, IEEE*, volume 20, pages 45–52, Dec. 2000.

[4] D. O. Popa, A. C. Sanderson, R. J. Komerska, S. S. Mupparapu, D. R. Blidberg, and S. G. Chappel. Adaptive Sampling Algorithms For Multiple Autonomous Underwater Vehicles. In *Autonomous Underwater Vehicles, IEEE/OES*, pages 108–118. Rensselaer Polytech. Inst., Troy, NY, USA, June 2004.

[5] Department of Navy Science and Technology. *AUVSI/ONR Engineering Primer Document for the Autonomous Underwater Vehicle (AUV) Team Competition.*

[6] W. B. Dieter, D. Fox, M. Moors, R. Simmons, and S. Thrun. Collaborative Multi-Robot Exploration. In *IEEE International Conference on Robotics and Automation, ICRA '00*, volume 1, pages 476–481, Apr 2000.

[7] E. Fiorelli, N. E. Leonard, P. Bhatta, D. Paley, R. Bachmayer, and D. M. Fratantoni. Multi-AUV control and adaptive sampling in Monterey Bay. In *Autonomous Underwater Vehicles, IEEE/OES*, pages 134–147, 2004.

[8] C. C. Eriksen, T. J. Osse, R. D. Light, T. Wen, T. W. Lehman, P. L. Sabin, J. W. Ballard, and A. M. Chiodi. Seaglider: A Long-Range Autonomus Underwater Vehicle for Oceanographic Research. *IEEE J. Ocean Engineering*, 26(4):424–436, Oct. 2001.

[9] D. W. Gage. Command Control For Many-Robot Systems. In *the Nineteenth Annual AUVS Technical Symposium*, pages 22–24, Hunstville Alabama, USA, 1992.

[10] J. G. Graver. *Underwater Gliders: Dynamics, Control and Design*. For the degree of doctor of philosophy, Princeton University, May 2005.

[11] J. G. Graver, R. Bachmayer, N. E. Leonard and D. M. Fratantoni. Underwater Glider Model Parameter Identification. In *Proc. Int. Symp. on Unmanned Untethered Submersible Technology (UUST)*, 2003.

[12] K. Seada, A. Helmy. Efficient and robust geocasting protocols for sensor networks. *Elseiver Computer Communications Journal Special Issue on Dependable Wireless Sensor Networks*, 29(2), Jan. 2006.

[13] D. Katsaros and Y. Manolopoulos. The Geodesic Broadcast Scheme for Wireless Ad Hoc Networks. In *Proc. IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM)*, Buffalo, NY, Aug. 2006.

[14] I. S. Kulkarni and D. Pompili. Coordination of Autonomous Underwater Vehicles for Acoustic Image Acquisition. In *Proc. ACM International Workshop on UnderWater Networks (WUWNet)*, San Francisco, CA, Sept. 2008.

[15] T. Melodia, D. Pompili, V. C. Gungor, and I. F. Akyildiz. A Distributed Coordination Framework for Wireless Sensor and Actor Networks. In *Proc. ACM International Symposium on Mobile Ad Hoc Networking and Computing (MobiHoc)*, Urbana-Champaign, IL, May 2005.

[16] A. A. Nimbalkar and D. Pompili. Reliability in Underwater Inter-Vehicle Communications. In *Proc. ACM International Workshop on UnderWater Networks (WUWNet)*, San Francisco, CA, Sept. 2008.

[17] D. Pompili, T. Melodia, and I. F. Akyildiz. Three-dimensional and Two-dimensional Deployment Analysis for Underwater Acoustic Sensor Networks. *Ad Hoc Networks (Elsevier)*, 7(4):778–790, June 2009.

[18] R. Bachmayer and J. A. Rice and R. Crebert and C. Fletchert. Navigation and Control of Multiple Gliders in an Underwater Acoustic Network. In *Autonomous Underwater Vehicles, IEEE/OES*, pages 54–58, June 2004.

[19] R. Bachmayer and N. E. Leonard, J. Graver, E. Fiorelli and P. Bhatta and D. Paley. Underwater Gliders: Recent Development and Future Applications. In *IEEE International Symposium on Underwater Technology (UT)*, pages 195– 200, Taipei, Taiwan, Apr. 2004.

[20] S. A. Jenkins, D. E. Humphreys, J. Sherman, J. Osse, C. Jones, N. Leonard, J. Graver, R. Bachmayer, T. Clem, P. Carroll, P. Davis, J. Berry, P. Worley, J. Wasyl. Underwater Glider System Study. Technical Report 53, Scripps Institution of Oceanography, May 2003.

[21] R. G. Simmons, D. Apfelbaum, W. Burgard, D. Fox, M. Moors, S. Thrun, and H. Younes. Coordination for multi-robot exploration and mapping. In *AAAI/IAAI*, pages 852–858, 2000.

[22] T. Melodia and D. Pompili and V. C. Gungor and I. F. Akyildiz. Communication and Coordination in Wireless Sensor and Actor Networks. *IEEE Trans. Mobile Comput.*, 6(10):1116–1129, Oct. 2007.

[23] R. J. Urick. *Principles of Underwater Sound*. McGraw-Hill, 1983.

[24] R. Vincent, D. Fox, J. Ko, K. Konolige, B. Limketkai, B. Morisset, C. Ortiz, D. Schulz, and B. Stewart. Distributed multirobot exploration, mapping, and task allocation. *Annals of Mathematics and Artificial Intelligence*, 52(2-4):229–255, 2008.

[25] M. B. Wolfram, W. Burgard, and S. Thrun. Exploiting Constraints During Prioritized Path Planning for Teams of Mobile Robots. In *Proc. Int. Conf. on Intelligent Robots and Systems (IROS)*, pages 393–398, 2001.

Indraneel S. Kulkarni received the Bachelor of Engineering (B.E.) Degree in 2006 with Distinction from the University of Mumbai (Bombay). Currently, he is pursuing the M.S. degree in Electrical and Computer Engineering at Rutgers, The State University of New Jersey. From August 2007, he has been working on task allocation for autonomous underwater vehicles under Dr. Dario Pompili as a part of his MS thesis. His main research interest are in control and coordination of autonomous underwater vehicles.

Dario Pompili joined the faculty of the Department of Electrical and Computer Engineering at Rutgers, The State University of New Jersey, as Assistant Professor in Fall 2007. He received his Ph.D. in Electrical and Computer Engineering from the Georgia Institute of Technology in June 2007 after working at the Broadband Wireless Networking Laboratory (BWN-Lab) under the direction of Prof. I. F. Akyildiz. In 2005, he was awarded Georgia Institute of Technology BWN-Lab Researcher of the Year for “outstanding contributions and professional achievements.” He had previously received his ‘Laurea’ (integrated B.S. and M.S.) and Doctorate degrees in Telecommunications Engineering and System Engineering from the University of Rome “La Sapienza,” Italy, in 2001 and 2004, respectively. His research interests include ad hoc and sensor networks, underwater acoustic communications, wireless sensor and actor networks, and network optimization and control. He is author and co-author of many influential papers in these fields. He is in the editorial board of Ad Hoc Networks (Elsevier) Journal and in the technical program committee of several leading conferences on networking. He is also member of the IEEE Communications Society and the ACM.