An approach to route underwater mobile robots under continuous squad rotation

M.Yu. Kenzin, I.V. Bychkov and N.N. Maksimkin
Matrosov Institute for System Dynamics and Control Theory SB RAS, Irkutsk, Russia
gorthauers@gmail.com

Abstract - Multiple cooperative vehicle systems hold great promise for use in large-scale oceanographic operations due to ability of high-resolution surveying in both time and space. Multi-objective missions of long-duration require underwater robots to recharge their batteries periodically by docking to the specialized underwater bases (resurfacing in case of solar batteries). Furthermore, it should be taken into account, that the real world underwater vehicle systems are partially self-contained and could be subjected to any malfunctions and unforeseen events. Thus, it is a problem of considerable practical interest to effectively route the group of vehicles under continuous rotation. We propose a dynamic rendezvous point-selection scheme based on pre-estimated vehicle rotation cycle and an evolutionary path planner to route the group of robots ensuring well-timed accomplishment of all tasks and simultaneous arrival of vehicles at their selected rendezvous destination.

I. Introduction

Autonomous Underwater Vehicles (AUVs) have proven their efficiency in implementing such underwater works as seabed mapping, inspection and survey, sampling and monitoring, searching and deactivating mines, etc. These underwater mobile robots are capable of carrying out large-scale underwater missions of long duration at lower costs comparing manned vessels. Currently, the state of the art in mission planning is dominated by single AUV operations using preplanned trajectories [1]. Obviously, a single AUV is not able to meet all specified tasks in a single mission with limited time and energy. In this regard, multiple cooperative vehicle systems hold great promise for use in large-scale oceanographic operations due to ability of high-resolution surveying in both time and space.

Autonomous cooperative operation of AUVs in a vast and dynamic underwater environment is a complicated process: a number of different underwater works should be collaboratively and efficiently accomplished under specific requirements and environmental changes. Thus, the effective coordination of AUVs network is crucial for the likelihood of the mission success. As a result, the middle level of the group control system that is responsible for the allocating tasks between robots and both route- and path- planning is coming to the fore. Development of such self-controlled systems tightly depends on the design of robust mission-motion planning and task allocation scheme [2].

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In general, the problem of task allocation and path planning is vehicle routing problem (VRP) under specific spatio-temporal constraints imposed by the uncertain dynamic nature of water environment and by inaccuracy of the measuring devices. In many real cases, like patrolling and guarding, taking samples and measurements, etc., certain underwater tasks require not the single but the series of periodic attendances by AUVs. In this context, multi-objective underwater operations could be classified as either exploration or monitoring missions. Exploration missions relate to a wide range of different tasks, each of which demands single accomplishment. Monitoring missions, inversely, include underwater tasks that require continuous and regular inspections by AUVs at scheduled intervals. In both cases, different tasks may involve additional conditions and requirements (temporal, equipment, quantitative, etc.). Between two suggested mission types, the latter is of greater scientific interest since it combines both complex temporal and spatial constraints.

In addition to all constraints, it should be taken into account, that the real world underwater vehicle systems are partially self-contained and could be subjected to any malfunctions, environmental changes and unforeseen events. Necessity for AUVs battery recharging during the long-term missions make routing problem even more challenging: firstly, it causes periodic changes in the group compositions resulting in necessity of regular strategy adjustments; secondly, it causes necessity of regular rendezvous of all currently working vehicles at a specified location for the purpose of data exchange and vehicle recharging, maintenance, or collection [3]. Despite the fact, that frequent rendezvous allow AUVs keeping up with all essential changes, they also significantly distract vehicles from well-timed accomplishment of mission tasks. Inter-vehicle communication is also a critical aspect of effective cooperation and must not be trivialized [4].

In this paper, we propose two-level approach to solve the AUVs group routing problem under the high dynamic conditions for the multi-objective monitoring missions of long duration. The first level employ simple genetic algorithm to dynamically select AUVs rendezvous points according to expected vehicle rotation cycle. With consideration of group composition changes after each rendezvous point, second level utilizes evolutionary route planner to find trajectories for currently working squad ensuring maximal efficiency of the group work and simultaneous arrival of all vehicles at the selected rendezvous destination.

II. Problem Formulation

In general, multi-objective monitoring missions require group of AUVs to visit and inspect (perform some underwater works) the set of tasks at scheduled intervals [4]. The routing problem here is to find a feasible group route ensuring, as far as possible, the well-timed inspection of the majority of tasks under continuous change of currently working squad due to the AUVs battery limitations and recharging needs. The problem is formally defined as follows.

Assume there is a set of tasks $N = \{1,...,n\}$ distributed over a specific operation area. These tasks are defined not only by their location in space, but also with the demanded periodicity of inspections $p_i, i \in N$ and the single-inspection accomplishment time $s_i, i \in N$, which are known in advance by AUVs. The periodicity value p_i means that the duration of the time interval between two successive inspections of i -th task must not exceed p_i. In other words, it is an upper bound on time allowed between leaving task and coming back to it. We denote by T the whole mission length and suppose that it is a big value.

The group of robots performing the mission consists of m functionally equivalent vehicles, which however may differ by their cruising speed v^k and battery capacity $b^k, k = 1,...,m$. Here we rate AUV's batteries not in energy units but as average run-time on cruising speed.

Battery limitations force vehicles to recharge at intervals by docking to the specialized underwater bases or resurfacing (in case of solar batteries). Concrete locations of the charging bases, if any, are not essential, since we only need the estimated traveling time for each vehicle to resurface/get to the nearest free recharging dock from the operation area. We assume that the number of bases/docking spaces is not limited so that there is always a free dock for a vehicle in need. We denote the average charging speed for all batteries by constant parameter $0 < c < 1$. In that case, charging time of fully empty battery with capacity of b hours will be $c \cdot b$ hours.

Assuming that different tasks are distributed over a specific water area, they can be mapped by a network in which each task is presented by a waypoint. In this way, the complication of vehicle routing in a graph-like terrain can be addressed straightforwardly [2]. Additionally, we define the waypoint V_0 for the specified rendezvous location. Let $V = N \cup V_0$ denote the set of all waypoints. Let the $\varepsilon = \{(i, j) : i, j \in V, i \neq j\}$ define the set of edges. Each edge represents the shortest traveling path between each pair of tasks. It is assumed that all paths for the initial set of tasks are pre-computed and paths for all new tasks, if any, are calculated by AUVs on-board via specialized path planner. The path length is assigned as edge weight as it can be easily translated into traveling time cost for all AUVs relying on their cruising speed. Thus, the undirected fully connected weighted network $G = (V, \varepsilon)$ represents the "roadmap" for the current mission of the group.

Before proceeding with our model development, we should note that the process of mission implementation is self-contained, i.e. all calculations are performed exclusively on AUVs board computer systems. It is obvious, that all parallelizable calculations should be distributed among accessible vehicles to achieve maximal cumulative processing power and allow fully decentralized group control. In order to achieve proper decentralization, all vehicles should possess identical data about current conditions and environment. To fulfill this requirement, robots in the squad should coordinate in a such way to periodically establish common information space when possible. Group coordination here is provided by transferring data between robots through hydro-acoustic channel. Hence, complete synchronization of actual data within the group could be achieved only if each vehicle of the group would be able to transfer data directly to each other vehicle co-instantaneously. As underwater communication is slow and limited in range, we assume that the common information space and following full data synchronization could be completed only during so-called rendezvous, when current squad simultaneously arrives at a specified location. In what follows the group routes are called *communicatively stable*, if they guarantee the ability to synchronize data regularly.

Communication stability requirement primarily arises due to the dynamic nature of real underwater missions: firstly, the inspections results alone may require modifying the current task set; secondly, the uncertainty of external environment and possibility of delays and malfunctions may lead to unexpected changes in the status of the working group. All these changes may occur in real time, making it necessary to adjust the current route (re-plan) in order to maximize the group efficiency in new conditions. Among the events that require route re-planning are:

- Adding new tasks or withdrawing the old ones;
- Changing task's required periodicity;
- Unexpected AUV loss or malfunction;
- Collecting previously lost AUVs or new ones;
- AUVs leaving the group for recharging;
- Collecting recently recharged AUVs.

It is worth noting individually, that the two latter cases should not be initially included to the list above as these events can be accurately pre-estimated according to the vehicle rotation cycle. However, since occurrence time of these events may shift due to the dynamic nature of the mission, we consider them also as the key points for mission-planning procedure alongside with other more unpredictable cases.

The effectiveness of the group as a whole is defined by maintaining the regularity of well-timed inspections of all tasks. Situations of AUVs arriving too late and delaying the inspection are undesirable and should be excluded, if possible. Thus, our objective is to develop a synchronous control architecture able to construct communicatively stable group routes providing minimum delays during continuous and regular task's inspections up to the moment of the mission's end under continuous squad rotation and high dynamic conditions.

III. TWO-LEVEL CONTROL SYSTEM

Effective mission planning for real underwater operations of AUVs group is a complicated and challenging problem, especially when it is required to respond to environmental changes and unexpected disturbances. Since, even in ideal (static and fully known) environment, high dimensional routing alone is a problem of high computational complexity, given dynamic conditions make it meaningless to build optimal solution straight for the whole mission. In this regard, we propose the following two-level control system that allows performing complex monitoring of long duration. Two levels of the proposed approach utilize dynamic mission planning strategy and task assignment (routing), correspondingly.

As long as finding new global optimal solutions with each change of conditions is impractical, prompt and accurate local planning with consideration of nearest expected changes is more essential. Therefore, the suggested upper-level mission planner is designed to the purpose of simple on-line mission decomposition that provides both communication stability and computational load reduction, while lower-level route planner is required to handle graph search constraints and carry out the task assignment.

It is obvious that, ideally, decomposition points should be associated with essential condition changes. In this case, the routing problem for each operating period (period between two consecutive decomposition points) could be regarded as static. Nevertheless, as we can predict reliably only those events among previously mentioned that relate to AUVs recharging needs, we propose following mission decomposition scheme based on the expected vehicle rotation cycle (Fig. 1).

According to this scheme, each decomposition point involves rendezvous of the currently working squad at a specified location for a purpose of sending AUVs to and receiving from the charging bases, continued by full data synchronization within the group and mission conditions adjustment if any changes has occurred. Following that, as the newly formed squad continues task's inspections until the next point of rendezvous, each vehicle in the squad computes to find the best group route for the next operating period. While doing so, the expected upcoming squad rearrangement should be taken into account: which AUVs would leave the group for recharging during next rendezvous and which would re-join. Such pre-planning would allow for a saving time and shortening the rendezvous length alongside with decentralization and distribution of calculation among vehicles. In this regard, full data alignment at the end of operating period should include exchange of the AUV's best-found solutions.

To this end, upper-level mission planner strategy is to manage mission time by scheduling AUVs group rotation cycle. As vehicles are not obliged neither to leave the squad only being completely discharged nor to always recharge up to entirely full battery (although it is preferable), we can adjust charging periods for each vehicle in order to obtain reasonable group rotation cycle. Firstly, we want to exclude as far as possible simultaneous mass charging of several vehicles since it reduces performance capability of the remaining squad. If it is found impossible, we want at least to achieve equal distribution of number of simultaneously charging vehicles (cumulative speed of simultaneously charging vehicles, to be specific) during the course of the mission. Secondly, since each rendezvous distracts vehicles from task's inspection, as it requires squad spending a significant portion of time to make it to the rendezvous location, perform all required actions and travel back, we want to minimize the rendezvous' frequency. In order to do this, we want to conjoin closely-spaced events together where possible by shifting them to the common timepoints. For example, in Fig. 1 two short-timed operating periods #4 and #6 (#5 successor) could be avoided by sending AUVs "C" and "D" to the charging bases a period earlier. Still, even with all requests considered the main requirement here is maintaining AUVs group in good working order by organizing well-timed recharging for all vehicles in need.

Upper-level mission planner should be simple, reliable and fast, as quick and effective re-planning is required each time an unexpected event occurs. Unlike to mission planning strategies, the lower-level route planner is not designed to react on environmental dynamic changes. However, as the operating field is split to smaller spaces, routing system should be capable of high-performance local group motion planning under spatiotemporal constraints. The main goal of routing here is not only to achieve punctual task's inspection for group of vehicles with different speeds, but also to ensure simultaneous group arrival at the rendezvous location by the end of operating period. It should be also considered, that task allocation problem on a single operating period should not be treated separately from the global objective, as mission timer does not pause when squad interrupts inspection in the interest of rendezvous and task's inspection would be continued immediately at the next operating period.

As both mission planning and local task allocation are essential for well-timed monitoring over operating periods, providing cooperation and synchronization between both level planners would allow ultimate control system to deal with complex requirements and restrictions, which are aimed to a more accurate simulation of real-world problems [2].

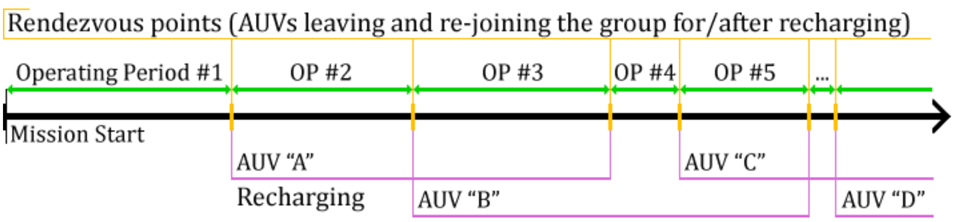

Figure 1. Mission decomposition on the basis of vehicle squad rotation

IV. MISSION PLANNER

Summarizing the above, mission planner's goal is to construct a reasonable group rotation schedule coming from AUVs recharging needs to provide maximal performance capabilities of the working squad alongside with its high condition-change responsiveness.

As mission length T is supposed to be a considerable big value, we see no rational for building schedule for the entire mission at once, since it would require periodic re-planning due to unexpected events. Hence, we define T_M as planning period that should be long enough to include at least several recharging cycles of each AUV. For the large-size planning problems, the search space discretization proves itself to be rational and efficient way to speed up both encoding of and finding the solutions. For that reason, we will consider planning period as a sequence of equal time intervals $T_M = \langle T_1, ..., T_e \rangle$, $e = T_M / T_0$, where T_0 is the duration of each interval.

In this case, single AUV schedule can be represented by e-dimensional binary vector, where x-th attribute is 0 if the vehicle is within the working squad during corresponding time interval T_x and 1 otherwise (vehicle is traveling to the base, charging, or traveling back). A single vehicle schedule is considered as feasible if none working period (continuous sequence of 0-attributes) lasts longer than vehicle's battery level at the beginning of that period. The group schedule at this point can be represented as *e*-by-*m* binary matrix $H = \{h_{ij}\}$ (Fig. 2). The objective function for the group schedule H is as follows:

$$f(H) = \sum_{i=1}^{e} \left(\left(\sum_{j=1}^{m} h_{ij} \right) \left(\sum_{j=1}^{m} h_{ij} \cdot v^{j} \right) \right) \quad (1)$$

Loss function (1) evaluates the performance capability of currently charging AUVs on each interval T_i of the planning period. With the use of (1), we are trying to exclude simultaneous charging of both big number of vehicles and fastest vehicles in the group. The planning problem here is to minimize loss function $f(H) \rightarrow \min$.

A series of computational experiments has shown that even under severe constraints a large number of different solutions are able to deliver the same minimum value of the objective function (1). Because of that, we define an additional criterion which purpose is estimating the number of expected rendezvous (time intervals, where at least one vehicle is changing its status):

$$f_T(H) = \sum_{i=2}^{e} \left(1 - \prod_{j=1}^{m} (1 - |h_{ij} - h_{i-1j}|) \right) \quad (2)$$

Tiebreaker-function (2) is used to determine a preferable solution among equally efficient according to (1).

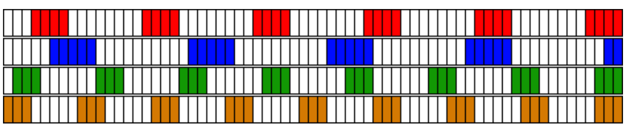

Figure 2. Rotation schedule for the group of four vehicles with different battery capacites. Colored sell represents charging periods.

V. TASK ALLOCATION AND PATH PLANNING

Operating field decomposition made by the mission planner leads to problem space reduction and reducing the computational burden, which is another reason for fast operation of the proposed approach. Limited duration of operating periods allows us to define the routing problem as follows.

The input to the group routing problem includes AUV's and task's characteristics proposed above in the "Problem Formulation" section, task's initial status inherited from the previous period, and duration of the current operating period T_p. Then, we define the route of single vehicle $r = \langle V_0, V_1(r), V_2(r), ..., V_h(r), V_0 \rangle$ as a list of task numbers in the consecutive order of their planned visits, where h is the route length. As can be seen, vehicles start each period from the rendezvous point and travels back there at the end of the period. It also should be noted that any task could be included more than once into the route of a single vehicle. The group route $R = \{r_1, ..., r_k\}$ is a set of all single AUVs routes. Thus, the routing problem is to generate the group route providing:

- Minimum delays during regular inspection of all mission tasks within the current operating period;
- Simultaneous arrival of all vehicles at the rendezvous location;
- Favorable mission conditions to be inherited by the routing problem for the next operating period.

The proposed routing problem on a single operating period has many similarities with the cyclic routing problem for the unmanned aerial vehicles (CR-UAV) [5]. The main difference is that we are trying not to find the minimal number of vehicles in order to guarantee the total absence of delays, but instead to find the optimal group route for the given heterogeneous squad. For another thing, although cyclic routes are indeed easier to handle [5], they still represent a very restricted class of solutions; hence we are not considering cyclic-type routes only and keep ours options open to generate any type of routes.

To evaluate and compare the effectiveness of different group routes under given requirements, we propose using scenario-based scheme that relies on the list of *desirable* and *undesirable* modes of group behavior that should be pre-organized beforehand by the human operators. Each scenario includes a priority-order value, set of triggering events, scoring type (penalty or reward) and scoring conditions. All scenarios are checked during virtual simulation of the group work with the output being a sum of penalty and reward points weighted according to given priorities. For the proposed routing problem, we suggest using the following list of three scenarios:

#1. Each time an AUV arrives to inspect a task / Penalty / If inspection is already delayed;
#2. Group collection at the rendezvous point / Penalty / For the time gap between arrivals of first and last AUVs;
#3. Group collection at the rendezvous point / Penalty / For each task with currently delayed or almost delayed inspection.

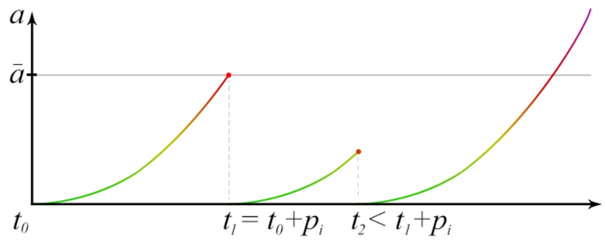

Figure 3. Graphical representation of the "hotness" function

To normalize penalty points we use the scoring technique presented in our earlier works [6,7]. This technique is based on the additionally defined "hotness" function $a_i(t)$ corresponding to each task $i \in N$ of the mission and following two rules: the inspection of the i-th task by any AUV resets its hotness to a zero value; the hotness exponentially grows from zero value up to the constant threshold value $\bar{a}$ (common for all tasks) in a period of p_i (Fig. 3). Now we define the penalty-charging function for the first scenario proposed above:

$$\varphi(i,\mathrm{t}) = \begin{cases} a_i(\mathrm{t}) - \bar{a}, a_i(\mathrm{t}) > \bar{a} \\ 0, \quad a_i(\mathrm{t}) \le \bar{a} \end{cases}. \tag{3}$$

In the similar manner, we define the penalty function for the third scenario:

$$\phi(i, t_0 + T_P) = a_i(t_0 + T_P), \tag{4}$$

where t_0 stands for the start moment of current operating period. In effect, using penalty function (4) not only encourages group to inspect regularly each task of the mission, but it also allows us to provide favorable mission conditions for the next operating period, and, what's even more important, it indirectly normalizes route's durations of all vehicles in the group. Thus, we do not really need a specified penalty function for the second scenario, as it is already included in (4).

It is also should be noted that the function (3) is constructed in such way, that "hotness" of tasks with lesser periodicity grows faster. In that way, inspections delays, if any, would happen preferably with tasks of the biggest periodicity, which are likely to be less prioritized.

Turning to the planning procedure, it should be reminded, that the group route for the current operating period is always calculated at the previous operating period with consideration of the expected group changes during the nearest rendezvous. If any unexpected event occurs up to the rendezvous point, all previously calculated routes usually become less of an issue, but still they could be utilized as being in some sort of knowledge base for more intelligent plan re-adjustment.

Besides, we can negate impact of some unpredictable events in advance by constructing additional back-up plans if the computational capacity allows. For example, an additional group route could be constructed for the group of one less vehicle (in the event of a single AUV's malfunction or delaying from the charging base). It would be reasonable to consider the fastest vehicle in that role as it could replace any other missing vehicle with hardly any trouble at all.

VI. Control System Implementation

In this study, two different modifications of genetic algorithms (GA) are developed and applied in the context of group mission planning.

For the upper-level mission planner we propose using a simple genetic algorithm with some modifications since GA offer near-optimal solutions in faster time with better scalability in number of tasks at average than other heuristic- and meta-heuristic approaches. GA are appropriate for large-sized high-dimensional problems, but may converge to local optima in a finite time.

We use the matrix $H = \{h_{ij}\}, i = 1,2,...,e, j = 1,2,...,\mathrm{m}$ representation in the form of a one-dimensional binary array as the chromosome, function (1) as the objective function with (2) as the tiebreaker during tournament selection. The feasibility of all chromosomes is checked additionally with specialized algorithmic procedure considering AUV's cruising speed, battery capacity, traveling time to reach the charging base and, finally, charging speed. For the genetic operators, we suggest using "1+1"-point crossover of our own design [7] instead of or in addition to standard one- or two-point versions.

Lower-level routing problem is much more complicated and computationally intensive problem as it is known to be NP-hard. Thus, there are no algorithms solving it in polynomial time, which leads us to the class of approximation algorithms allowing to obtain rational sub-optimal solutions in low computational time.

Evolutionary methods have proven to be efficient on the standard vehicle routing problems and on a number of other variants like periodic routing and routing with time windows [8], that shares very similar and restrictions and constrains with our regular routing problem. Their main advantage of evolutionary algorithms (EA) is ability to find solutions for poorly structured problems and problems with complex constraints, as EA require a relatively small amount of information about the nature of the problem. Essential drawback of evolutionary methods is in very strong speed and efficiency dependence on the construction and improvement heuristics being used.

Another layer of complexity is implied by a "bad" neighborhood structure of the described multi-objective routing problem, making it difficult to allocate and to find qualitative and feasible solutions, as they may not be in the neighborhood of other feasible high-quality solutions in the search space.

We propose a hybrid evolutionary approach featuring specialized genetic operators, advanced local search heuristics and solution improvement techniques to address both the expectable large-size of the problem and complex spatio-temporal constraints. Both algorithm's structure and original heuristics are in-depth studied in our previous works [6,7] devoted solely to the low-level routing problems, so we omit the details here.

Both mission- and route- planning algorithms were integrated with offline hierarchical pathfinding (HPA*) [9] and implemented in our simulation framework "AUV Multiobjective Mission Planner" to run a series of simulation studies.

VII. Conclusion

This paper presents a two-level approach to the AUVs dynamic routing problem that incorporates rendezvous point-selection scheme providing advantageous mission decomposition and local task allocation scheme to maximally utilize currently available vehicles during the course of the mission.

Simulation tests have been performed to route the heterogeneous group of vehicles with inconstant lineup under the complex constraints coming from the regular nature of mission tasks. The high efficiency of the suggested approach is shown through these tests. Upper-level mission planner is proved to be fast, accurate and reliable for the purpose of dynamic scheduling. It allows fast construction of reasonable group schedules and their prompt re-building, if needed. Lower-level routing system, in return, offers efficient near-optimal task allocation procedure even under strict constraints and large-sized search field. The proposed cooperation scheme between both planners allows group to maintain its efficiency in ever changing environment and under continuous squad rotation.

The next stage in this work is to introduce the heterogeneity in functional capabilities of vehicles with each AUV being able to inspect only those tasks that require the available type of equipment. In this case, upper-level mission planner should construct schedules specifically taking care of full equipment availability at each operating period. Another extension of this work is to develop an advanced three-dimensional online path planning system to deal with collision avoidance, ocean currents, dynamic and uncertain obstacles.

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