Obstacle Avoidance in Underwater Glider Path Planning

Josep Isern-González, Daniel Hernández-Sosa, Enrique Fernández-Perdomo,
Jorge Cabrera-Gámez, Antonio C. Domínguez-Brito and Víctor Prieto-Marañón

***Abstract*—Underwater gliders have revealed as a valuable scientific platform, with a growing number of successful environmental sampling applications. They are specially suited for long range missions due to their unmatched autonomy level, although their low surge speed makes them strongly affected by ocean currents. Path planning constitutes a real concern for this type of vehicle, as it may reduce the time taken to reach a given waypoint or save power. In such a dynamic environment it is not easy to find an optimal solution or any such requires large computational resources. In this paper, we present a path planning scheme with low computational cost for this kind of underwater vehicle that allows static or dynamic obstacle avoidance, frequently demanded in coastal environments, with land areas, strong currents, shipping routes, etc. The method combines an initialization phase, inspired by a variant of the A* search process and ND algorithm, with an optimization process that embraces the physical vehicle motion pattern. Consequently, our method simulates a glider affected by the ocean currents, while it looks for the path that optimized a given objective. The method is easy to configure and adapt to various optimization problems, including missions in different operational scenarios. This planner shows promising results in realistic simulations, including ocean currents that vary considerably in time, and provides a superior performance over other approaches that are compared in this paper.**

***Index Terms*—Path planning, underwater gliders, obstacle avoidance.**

I. Introduction

Robotic Unmanned Underwater Vehicles (UUV) have demonstrated to be a valuable tool for a wide range of applications in oceanography and surveillance, including structure inspection, environmental monitoring and control or security. Since the possibilities of human intervention are quite limited during the robot mission, these vehicles can be conceived as physical agents that must perform their tasks with a high level of autonomy. In fact, they are commonly known as Autonomous Underwater Vehicles (AUV). However, it is hard to accomplish this goal as a consequence of the inherent dynamism and uncertainty of the state of both the vehicle and its environment, estimated with a separate model each.

A glider is a type of UUV that operates by modifying its buoyancy in a cyclic pattern. These changes produce vertical impulsion that is transformed into an effective but low surge speed by means of the combined effect of internal mass displacements and the vehicle wings and tail orientation, resulting in a succession of up/down slope or climb/dive transects (see Fig. 1). In terms of power consumption, the glider saw-tooth profile is very efficient, since the gravity is used as the power source for propulsion, that is the most critical task of UUVs autonomy. Besides processing and communication, the batteries are only used intensively during a small fraction of the cycle time to change the vehicle buoyancy, using an electric pump; and, much less demanding, to modify the vehicle attitude and bearing angle while submerged using low consumption actuators. Ocean gliders have been applied successfully in Maritime Research, and they are expected to become one of the reference technologies as observational tool in the coming years [19].

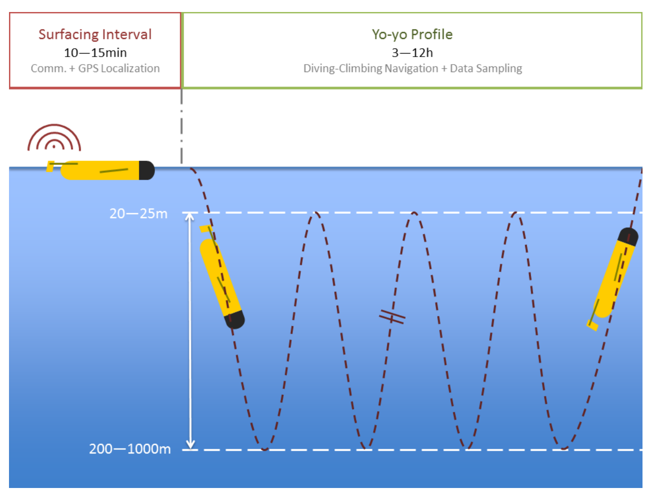

Fig. 1. Glider saw-tooth navigation pattern.

Periodically, the glider surfaces to detect its position by GPS and to communicate data via satellite to the ground station. It waits a few minutes for new orders. While the glider is submersed it does not change its heading. We have taken into account this feature (time discretization) to develop our path planner.

The top view of the surfacing interval and the yo-yo profile

Authors are with University Institute of Sistemas Inteligentes y Aplicaciones Numéricas en Ingeniería (SIANI), Universidad de Las Palmas de Gran Canaria

E-mails:
{ jisern, dhernandez, efernandez } @ iusiani.ulpgc.es
{ jcabrera, adominguez, vprieto } @ iusiani.ulpgc.es

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stint (Fig. 2) shows how on surface the glider trajectory is known using the GPS. But while submerged, after the diving point it is unknown, although it can be estimated up to some uncertainty. At each surfacing point such uncertainty collapses with the first GPS fix.

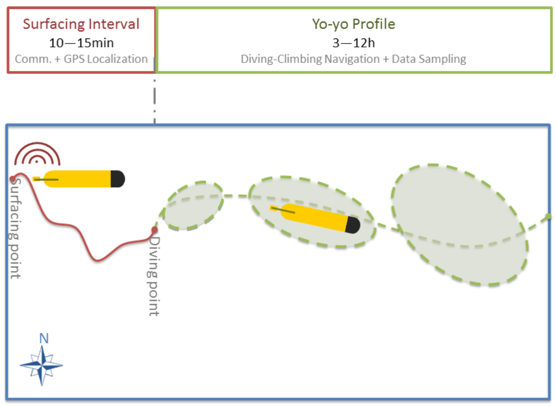

Fig. 2. Top view of a glider navigation pattern.

The main source of uncertainty is the drifting caused by ocean currents. Their low surge speed (aprox. 0.3 - 0.4 m/s) make gliders far more influenced by ocean currents than other UUVs that can overcome them. Gliders may drift significantly from its intended trajectory, making path planning a crucial tool for this type of vehicles, as it might reduce the time spent to reach a given waypoint or save power.

A. Motivation

Our work has been organized around the analysis of path planning requirements in presence of obstacles and the study of its performance in different scenarios. Regarding the former, we have identified several factors that, in our humble opinion, should be assessed at the design phase of a path planner for ocean gliders.

In Robotics, path planning addresses the problem of getting a robot from one point to another. This simple task is very challenging when it is to be solved under the influence of ocean currents. The currents field directly affects the movement of the vehicle so that the cost of displacement is variable and anisotropic at different points in space. Compared to ground mobile robotics, the underwater scenario is much more challenging, since operating conditions can vary notably even on reduced areas and over a relatively short period of time. In the particular case of ocean gliders, all the mentioned difficulties are magnified. Automatic path planning constitutes a key capability because underwater robots are usually commanded in terms of goal navigation waypoints to be hit or target regions to be explored.

For these reasons, most of classical approaches in the path planning field are not directly applicable to this problem. Many path planners apply a certain form of discretization, either on the trajectory or command space, to reduce the computational cost. However, the downside of discretization lies in the presumably degradation of the quality of the results, that might lead to unrealistic trajectories.

The execution time is another factor which is often understated due to the typical long duration of glider missions and immersion periods. Although this is generally true, it is not the case when the path planner must respond within a reduced time interval to face an unforeseen situation.

In this paper we analyze the path planning problem in specially troublesome scenarios, mainly coastal, that include static and dynamic obstacles such as strong currents, land areas or heavy traffic shipping routes. There, the planner pursues the maximization of the distance traveled towards a distant way-point —or, in other words, the minimization of the remaining distance to reach it— over a short and known period of time. This corresponds to a leg/stage range planning with a maximum duration of three or four days and a typical trajectory length around 100 km. For this temporal horizon, ocean current forecasts of high temporal resolution are used. These forecasts can be obtained from some Regional Oceanic Models (ROMs) with hourly outputs. ROMs are forecast systems of currents and other oceanographic variables that are based on numerical models. In such configuration, the path planning problem is clearly performed in a time-varying scenario.

In this work, we present a novel path planning technique for underwater gliders in troublesome coastal environments that introduce an initialization module to avoid obstacles inspired on A*-based search and Nearest Diagram (ND) algorithms [14] that is combined with optimization process. The glider is modeled here as an intelligent agent that senses the speed and direction of forecast of ocean currents via ROMs to generate an optimized trajectory that tries to fulfill a given task. A path planning allows reducing the time, and consequently the energy consumption. Thus, we will have more autonomy. The method is quite flexible, as it can be applied to a number of other optimization problems with few adaptation or configuration. It shows promising results in realistic simulations, under highly time-varying ocean currents. The proposal gives a superior performance when compared with other approaches.

This paper is organized as follows: the next subsection includes a revision of UUVs path planning approaches. The next section presents an explanation of the previous steps of our new approach. Then, in section III, the proposed method is described in detail. Section IV presents the experiments carried out to validate our path planning algorithm. Finally, section V contains the conclusions extracted from this work.

B. Related works

Path planning for UUVs has been a subject of interest for researchers since the introduction of these robotic platforms. Different approaches have been developed applying techniques that include searching algorithms based on artificial intelligence, potential field modeling, multi-objective optimization, etc. Some of the most relevant, in our opinion, are summarized in the following.

There exists a number of works that have addressed this problem with different optimization frameworks. First, graph methods are adequate to solve the problem assuming not time-dependent ocean currents. The A* algorithm [7] is a classical path planning method from Artificial Intelligence. It's a graph method that discretizes the search space using an uniform grid. For example, Carroll et al. [3] apply this strategy on a quad-tree search space. Probably, the first paper that adapted the A* algorithm to AUV's was contributed by Garau et al. [6]. It explains how to apply A* algorithm to marine vehicles, by means of adapting the cost function and incorporating ocean currents on a uniform grid discretization. Then, Petres [16], [17] proposed a combination of Fast Marching and A*, to obtain the accuracy and efficiency of each. It also addresses the discretization problem of the search space that A* has. Soulignac extended this line by presenting a series of papers [21], [22], [23] that manages strong and time-dependent ocean currents. In both cases, the approach bases on Wavefront Expansion, which is Dijkstra's method [4] in essence. Usually, graph methods have as a main drawback the negative effect of the search space discretization.

The high dimensionality of the search space has led to random exploration based approaches. The rapid random trees or RRT [12] [20] are a good example of this, and have been applied to the case of route planning for AUVs [24] and gliders [18]. This approach is particularly fast, but the path found is sub-optimal and requires further refinement. Post smoothing techniques cannot be applied directly with time-dependent conditions. It builds up an exploring tree with nodes that tend to cover the search space, generating trees from both the start and end points. However, it is not applicable in time-varying scenario and there is no guarantee of finding a route, and even less an optimal trajectory.

The problem has also been modeled as a Boundary Value Problem, using Zermelo optimal navigation formula for time-dependent currents, and Dubins curves for not time-dependent [25]. These techniques require fine tuning, and they only find a solution in simple test cases. Interestingly, it is possible to impose speed and acceleration constrains on the vehicle motion, in the case of Dubins curves.

Bio-inspired methods cover techniques like genetic and optimization algorithms that often have a large convergence time. Evolutionary computing has also been successfully applied to this type of problems. A significant example can be found in [1], where genetic algorithms are used for AUV trajectory planning in environments characterized by time-varying currents. The approaches based on minimization of energy functions are also worth commenting. As good examples, we can cite the work of Kruger et al. [11], that includes the time as an extra dimension in the search space, or Witt et al. [27], that incorporate modeling of time-varying obstacles using potential fields. The problem of local minima has been tackled by means of strategies based on particle swarms, simulated annealing, or genetic algorithms. In other proposals, the currents are modeled as continuous time functions, as is the case of the non-linear trajectory generation or NTG method [13] applied over B-Splines of Zhang et al. [29]. Moqin et al. [15] propose an iterative optimization process for glider path planning. However, the focus of that work is centered on the waypoint precision enhancement, and not in optimal path planning. Furthermore, only static ocean currents are considered. Recently, some authors have applied Genetic Algorithms, Particle Swarms, Simulated Annealing, Swarm Optimization [26]. In all these cases, the main drawback is the high computational cost.

Finally, in the last years a line that has received a lot of attention from researchers is the use of multiple vehicles in a coordinated mission. Some relevant examples include [28] and [2], that face the problem of adaptive sampling of oceanic variables by means of gliders fleets.

II. Evolution of the Algorithm

A. Origins

We started our work following the trajectory of a real glider, RU27 *Scarlet Knight* glider. Our first option was the trivial solution, Direct to Goal algorithm. At each surfacing the next bearing is computed as the direction to the goal point Fig. 3. It does not take into account the forecast of ocean currents. Truly, this is not a path planning algorithm, but it resembles the glider behavior. Its main limitation is that the glider drifts significantly in the presence of strong currents and does not find path which can be benefit from favorable currents when these are not in the direction of the target. Basically we have used this algorithm as reference to compare the new developments.

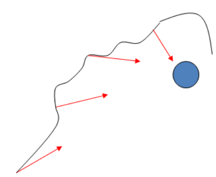

Fig. 3. Direct to Goal algorithm.

In the next step, we adapted A* method to manage ocean currents as in Garau's work [6], using the constrained motion model of Soulignac [21] (Fig. 4). The major drawback of this approach is that it doesn't produce stints of constant time, as gliders do. Also, the optimality is no longer guaranteed, because ocean currents are non-static.

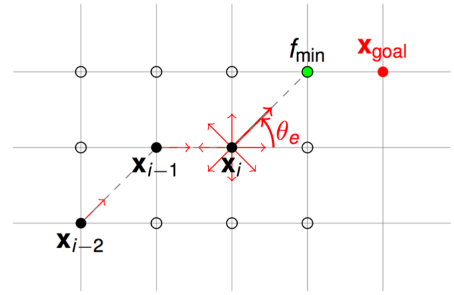

Fig. 4. A* method managing ocean currents.

B. CTS-A* method

To alleviate such limitations, we developed the CTS-A* algorithm [5] (Fig. 5), a variant of A*. At each surfacing point a set of bearings is considered and for each one, the glider trajectory is integrated for a constant-time stint. The surfacing locations are continuous, although they are stored in a search grid. With this approach have two problems, the bearings space is discretized and if we increase the number of bearings, the computational cost increases exponentially.

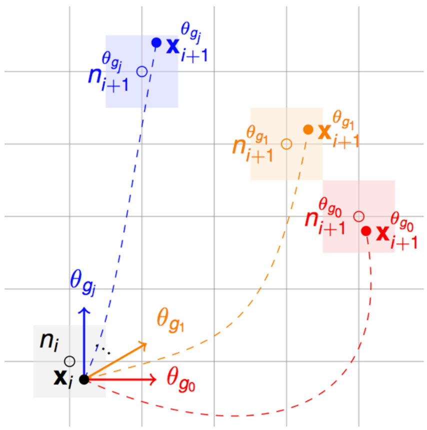

Fig. 5. CTS-A* method.

C. Optimization-based algorithm

Finally we have applied optimization techniques [8], [9] to solve this problem. We have used the distance of the last surfacing to the target waypoint as objective function and the bearings at each submersed stint as variables, which are iteratively optimized to find the path of minimal cost. With this election, the benefit is twofold, avoiding discretization and allowing for a physically realistic simulation. In [10] this method was adapted to coordinate the trajectories of a fleet of gliders.

As commented in the introduction, gliders propel themselves by changing their buoyancy and transforming the resultant vertical motion, of continuous dives and climbs, into a surge movement by means of the combined action of the internal mass displacement and the external control planes. These cycles are repeated typically for 3-12 hours periods, called transects or stints. Once a stint is finished, the vehicle surfaces to communicate the status and data gathered to the control room and receive new orders, commonly the next waypoint or bearing. After 10-15 minutes at the surface, the next immersion period starts. An important fact is that gliders do not communicate while submersed, and the on-board navigation system simply tries to keep the last commanded heading or bearing during the whole stint.

Additionally, the number of variables to optimize is a function of the stint and the total path durations. Therefore when we know the temporal horizon of the trajectory the number of stints is known, consequently the number of bearings that must be commanded and so the number of parameters to be optimized is known. As an example, a 4-day mission using the Slocum Electric Glider would require 12 variables for the standard 8 hours transect. In most cases, the final value returned by the objective function is computed as a distance metric.

The cost function of the optimization process is computed on the basis of a stint simulator that reproduces the glider trajectory combining the commanded bearing with the nominal glider speed and 2D ocean currents. For this purpose, our simulator applies a simple glider kinematic model. Fig. 6 illustrates the strong influence of ocean currents on the resultant glider trajectory, as a consequence of its relative low surge speed. Also, in this figure, it is observed the high variability of currents orientation in only 3 days.

In previous papers we compared optimization-based method with others algorithms. Fig. 7 shows the paths obtained with each method for a particular test case. In all the cases studied, the optimization-based method obtained the best results. In the majority of the test cases the difference was of a few kilometers, but in some cases we found a very large difference, as it happens in the simulation of 4 days that appears in Fig. 8, where the improvement is of approx. 100km with respect to A*.

This approach produces acceptable results for static, moderate-strength ocean currents. However, as indicated previously, in this work we are interested in short-term coastal navigation. There, and due to the complexity of the environment and the coupled nature of the process variables, the optimization can easily get trapped in local minimum or lead to wrong paths, including collisions (Fig. 9).

III. PATH PLANNER

To overcome the limitations of obstacle avoidance, that we have found in the previous versions of our algorithm, we have developed a new path planner, that we call Optimization with Intelligent Initialization. This algorithm integrates a bootstrap module inspired on CTS-A* search and ND algorithms, that generates an appropriate initial set of values to start the optimization phase described thus far.

A. Initialization (obstacle avoidance)

The initialization process makes a division of candidate trajectories in two or more stages. These candidate trajectories use a fixed bearing in all the stints into one stage. The nodes are the division points between stages. In the algorithm the position of these points is flexible (Fig. 10).

First, the initialization process considers a set of angularly equispaced radial vectors emanating from the starting point and simulates the glider trajectory with a fixed bearing for each one, inside the temporal horizon (Fig. 11). Second, a set of points is selected for each trajectory. These points (candidate nodes) are selected at equispaced surfacing points, generally this is corresponded to equispaced time instants (Fig. 12). Third, it considers a set of angularly equispaced radial vectors emanating from every node and simulates a constant bearing for each trajectory for the remaining temporal horizon, that is, recursively, a new set of trajectories is generated for each candidate node, simulating them for the remaining mission time (Fig. 13). Finally, it selects the bearings of the trajectory that reaches the nearest position to the target point as initial guess value for the optimization process (Fig. 14). As an

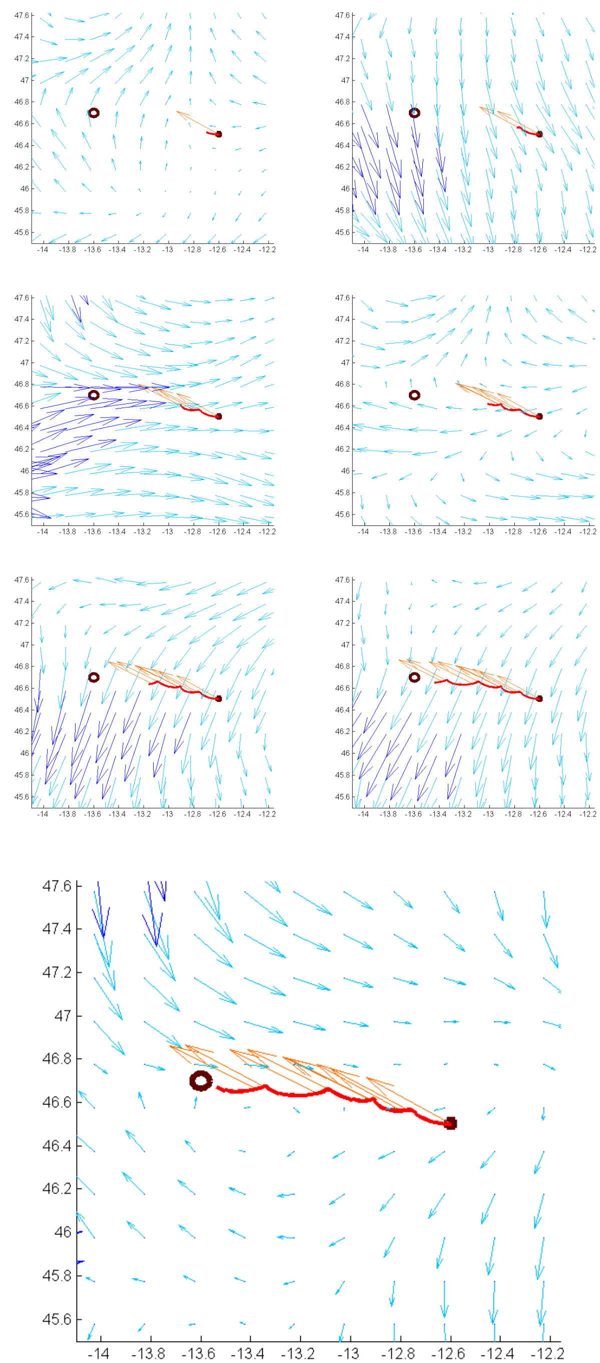

Fig. 6. Snapshots of the optimal trajectory and glider bearings at each surfacing, simulated for a 3-days period with time-varying currents (ocean currents that exceed the glider speed $v_g = 0.4\mathrm{m/s}$ are highlighted) from the start point to the goal point .

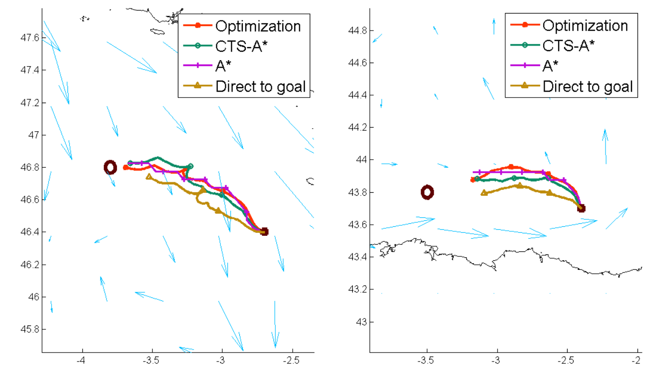

Fig. 7. Example of comparative of trajectories in two different missions of 3 days with glider speed of 0.4 m/s. Light blue arrows show the of ocean currents field. LEFT: Total distance = 95.3 km. Distance to reach the target: Optimization: 8.4 km; CTS-A*: 11.2 km; A*: 9.9 km; Direct to goal: 22.5 km. RIGHT: Total distance = 89.3 km. Optimization: 27.7 km; CTS-A*: 29.9 km; A*: 29.6 km; Direct to goal: 32.8 km.

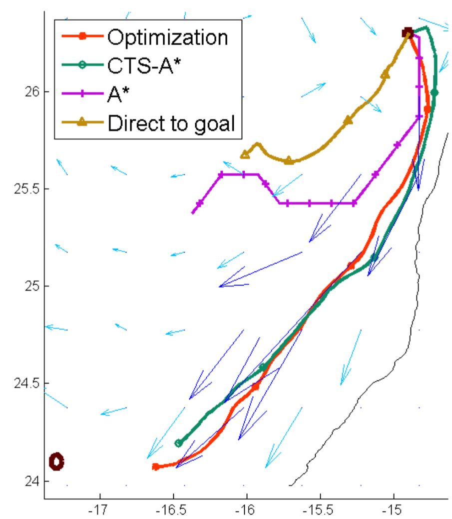

Fig. 8. Example of comparative of trajectories in a mission of 4 days. Light blue arrows show the of ocean currents field and blue arrows the ocean currents that exceed the glider speed (0.4 m/s). Total distance = 344.6 km. Distance to reach the goal point: Optimization: 68.9 km; CTS-A*: 85.1 km; A*: 169.4 km; Direct to goal: 217.6 km.

heuristic, an optimistic estimation of the combined glider-current velocity is computed, allowing to prune non promising trajectories.

In practice, we have observed that it suffices to divide the trajectory in a single turning point (one node). This is a direct consequence of the short path planned, since in a 4-day journey a glider might travel up to approximately 100-150km.

B. Optimization

In this phase, the algorithm takes the initial bearings and applies successive glider stints simulations trying to minimize the distance to the target from the end of trajectory as cost function.

Fig. 15 shows how this new aproach find a trajectory to the waypoint avoiding the coast in the same situation where the previous version hadn't found a good solution (Fig. 9).

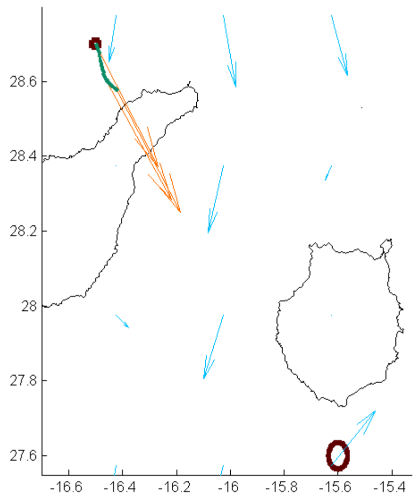

Fig. 9. Response in the presence of obstacles for the optimization method. The path ends after 4 days. Generated trajectories by glider bearings ⟶ at each surfacing, with time-varying currents ⟶ (ocean currents that exceed the glider speed $v_g = 0.4\mathrm{m/s}$ are highlighted ⟶) from the start point ● to the goal point ○. ends after 4 days period

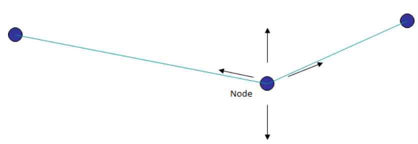

Fig. 10. Flexible location of the division point (node) between stages.

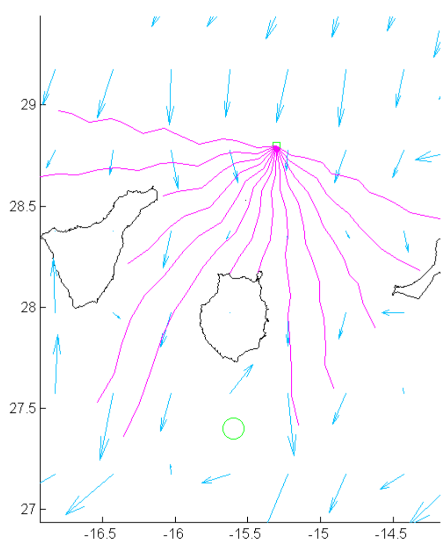

Fig. 11. First level of of the initialization process: Radial vectors emanating from the starting point.

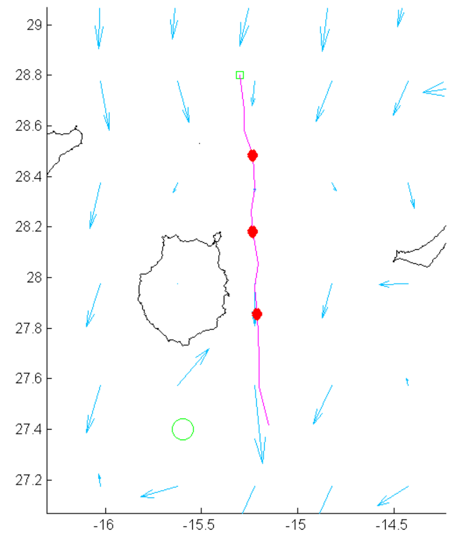

Fig. 12. Second level of of the initialization process: Selection of candidate nodes.

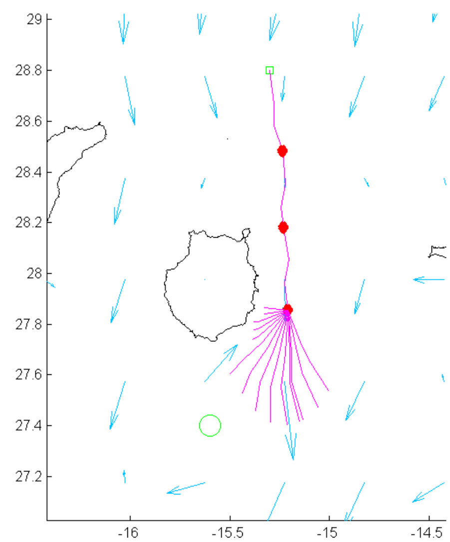

Fig. 13. Third level of of the initialization process: Radial vectors emanating from each candidate node.

IV. EXPERIMENTAL RESULTS

We have carried out several simulations for the path planner presented in this paper using Matlab® to validate the proposal and test its performance. The results have been compared with the ones obtained applying other methods: Direct to Goal, A*, CTS-A* and Optimization-based.

We have simulated different missions in the Canary Islands coast, using real ocean current maps from the ESEOO project model (ESEOCAN domain). This is a ROM model that gives hourly outputs structured in four 24h sets. The simulations described in this paper were configured for a glider speed of 0.2-0.4 m/s and a stint of 8 hours.

The general objective of the simulations have been to obtain the trajectory that leaves the vehicle closer to a goal point navigating for 4 days. For the methods based on the bearing

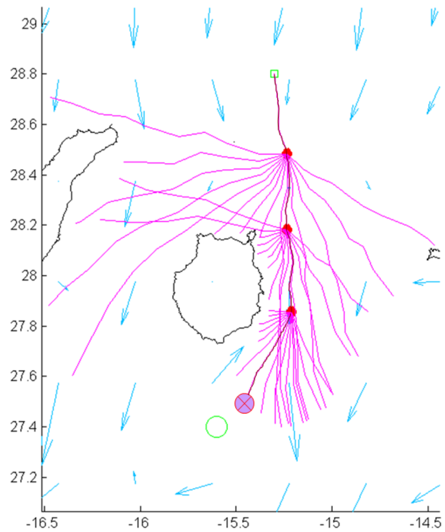

Fig. 14. Fourth level of of the initialization process: Selection of the best trajectory.

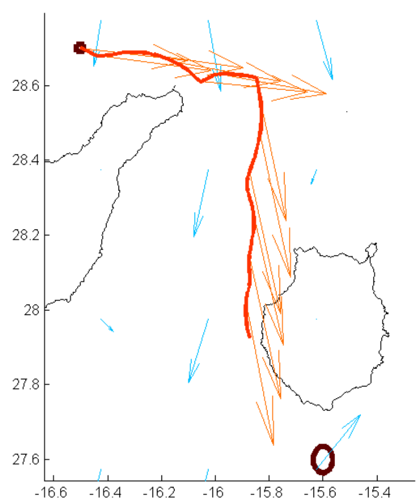

Fig. 15. Response in the presence of obstacles for the Optimization with Intelligent Initialization method. The path ends after 4 days. Generated trajectories by glider bearings at each surfacing, with time-varying currents (ocean currents that exceed the glider speed $v_g = 0.4\text{m/s}$ are highlighted) from the start point to the goal point .

optimization, this requires a total of 12 variables. Fig. 6 illustrates one example of the typical results obtained in these tests.

To validate the algorithm presented in this work, we have compared our results with the ones obtained by other algorithms used in the planning of trajectories for gliders. To compare the performance of each path planning method we have simulated and evaluated 45 cases. We have divided the cases in two situations and analyzed them separately. The first set of cases correspond to coastal trajectories while the second one includes only trajectories in offshore scenarios.

Two measures are computed for the comparison of the

TABLE I
DIFFERENCE OF THE REMAINING DISTANCE TO REACH THE GOAL WITH RESPECT TO THE OPTIMIZATION WITH INTELLIGENT INITIALIZATION METHOD. MEAN AND STANDARD DEVIATION WITHIN BRACKETS, BOTH IN km. SIMULATIONS RUN FOR A GLIDER SPEED $v_g = 0.4\text{m/s}$.

Scen	Optim	CTSA*	A*	Direct
Total	10.3 (21)	5.2 (6)	8.5 (18)	42.4 (46)
Coast	19.6 (26)	5.8 (7)	5.3 (7)	67.4 (39)
Ocean	0 (0)	6.5 (4)	9.1 (6)	13.6 (24)

TABLE II
COMPUTATIONAL TIME. MEAN AND STANDARD DEVIATION WITHIN BRACKETS, BOTH IN SECONDS. GLIDER VELOCITY AT 0.4 M/S AND 0.2 M/S.

Methods	0.4 m/s	0.2 m/s
Init-Optim	26 (10)	24 (12)
Optim	15 (11)	12.5 (10)
CTS-A*	477 (93)	105 (28)
A*	55 (11)	12 (4)
Direct to goal	<1 (0)	<1 (0)

methods: path quality and computational cost. We have established as a quality measure, for the generated trajectories (the lower the better), the remaining distance from the final glider position to the target point.

We should comment here that the A* results require a special consideration, since the method used in the trajectory generation produces unrealistic non-constant surfacing times that are dependent on the grid size. That is to say, the surfacing points in A* do not correspond with the surfacing points of the glider.

The computational cost is also an important factor to be considered, as sometimes it is necessary to obtain a path in a few minutes. For example, when an unforeseen risky situation occurs while the glider is surfacing, a new bearing needs to be computed before the glider initiates a new transect.

Regarding the algorithms' parameters used in the comparison, we have selected the same equivalent discretization level for each method, when applicable. For example, the spatial grid for A* and CTS-A* is fixed to 1/20 degrees. The CTS-A* algorithm has been configured to use a division of 20° in the bearings rose. For our new approach we have used a division of 5° for the initialization phase, inserting a candidate turning point every 3 surfacings, the equivalent to one day of navigation.

Table I shows the mean and standard deviation of the difference of the remaining distance to reach the goal of each method with respect to our new approach. The global result for all cases and the mean in each environment (near the coast, offshore) is shown separately. The average distance traveled by the glider at 0.4 m/s has been 120 km. Table II shows the computing time for each method, measured on a Intel(R) Core(TM) 2 Quad processor computer running at 2.5 GHz. In the tables and graphics, we labeled as Init-Optim the Optimization with Intelligent Initialization method

Compared with the previous optimization-based method (Optim) it is observed that the new approach gets approximately the same results when no obstacles are present, while

TABLE III
DIFFERENCE OF THE REMAINING DISTANCE TO REACH THE GOAL WITH RESPECT TO THE INIT-OPTIM METHOD. MEAN AND STANDARD DEVIATION WITHIN BRACKETS, BOTH IN km. SIMULATIONS RUN FOR A GLIDER SPEED $v_g = 0.2\text{m/s}$.

Scen	Optim	CTSA*	A*	Direct
Total	6.2 (13)	9.9 (10)	13.5 (49)	18.0 (29)
Coast	16.3 (17)	7.0 (7)	10.5 (13)	30.4 (29)
Ocean	0.2 (1)	11.5 (10)	15.3 (19)	10.5 (27)

it shows an important improvement when there is a need to avoid obstacles. Regarding A* and CTS-A* methods we have observed that, in general, we can obtain better quality in the path with less computational cost. On the other hand, we have verified that the computational cost of the new method when the route is free of obstacles is approximately half the value when the obstacles are present.

Fig. 16 shows two of the cases included in the previous analysis, where the trajectory is near the coastal areas. The distance required to reach the waypoint after 4 days is shown. It must be noted that the currents vary on time and only the last snapshot of them is shown in the figure. Fig. 17 shows the same case presented in Fig. 8 where the trajectory is free of obstacles. Here, it is observed that the new approach obtains results very similar to Optimization-based method.

To test the performance of the algorithms on adverse conditions, the simulation of the 45 cases were repeated using a glider at 0.2 m/s (Table III). The average distance traveled by the glider at this velocity has been 60 km. Table II shows the computing time for each method.

The basic version of the optimization method reduces the difference due to the fact that the obstacles are in the same point and the Optimization with Intelligent Initialization method covers less distance. A* and CTS-A* obtain worse results due to the use of discretization in their implementations and in some cases they are not able to avoid obstacles, so it has a high standard deviation. On the other hand, while the two versions of optimization keep their times, A* and its variant reduce notably their cost. In the first group, the process is the same, as they need to optimize the same number of variables, while in the second one the search area has less extension and the number of nodes visited is reduced.

Fig. 18 shows one of the cases include in the previous analysis where the trajectory is near the coastal areas. The distance required to reach the waypoint after 4 days is shown. In this case all methods goes directly to the land except our new approach.

Finally, the influence of some algorithm parameters has been analyzed. If we reduce the division of the bearing rose from $20°$ to $5°$ in Init-Optim, the results are improved in a 4% at a cost of duplicating the computational cost. Similarly, if we use a search grid of double resolution in A*, the results are improved in a 2%, but the computational cost is 5 times higher.

V. CONCLUSIONS

We have described a novel path planning algorithm for gliders based on optimization that offers promising results in realistic simulations. The pattern of displacement of the gliders (the bearing can not be changed while submerged) allows to easily adapt our method to problems where there is a temporal discretization, in which the size of each time window coincides with the duration of the stints. In addition, our method uses a continuous representation of the bearings space using an optimization method and eliminating the problems discussed. Furthermore, it incorporates an initialization phase that allows for obstacle avoidance, at a negligible computational time penalty. This heuristic-guided process generates a coarse initial solution that is then refined using an optimization process. In sum, our method is suitable for dynamic scenarios with

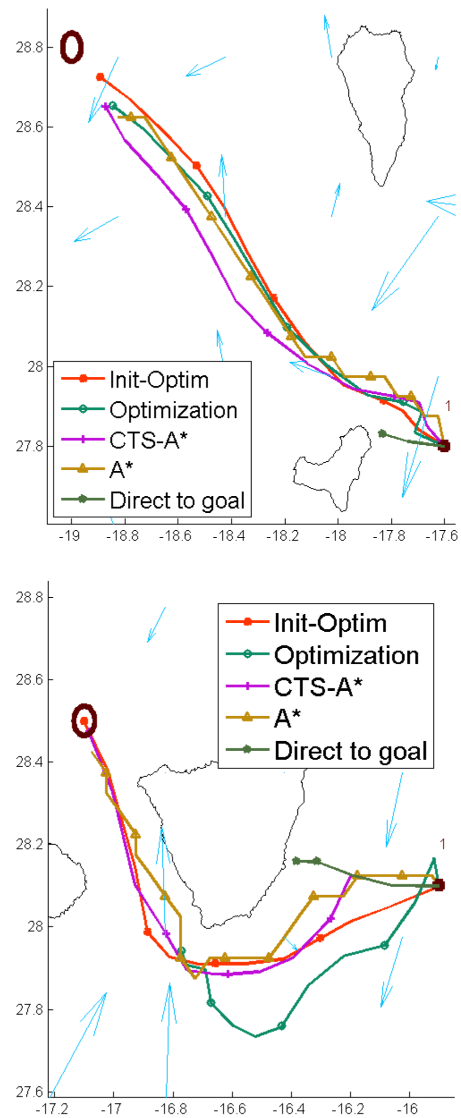

Fig. 16. Two comparatives of trajectories simulated near coastal areas for a 4-days period with time-varying currents (ocean currents that exceed the glider speed $v_g = 0.4\text{m/s}$ are highlighted) from the start point ● to the goal point O. Top graphic: Total Distance = 176.5 km. Distance remaining to reach the goal point: Init-Optim: 13.3 km; Optimization: 22.1 km; CTS-A*: 20.6 km; A*: 25.9 km; Direct to goal: 157.1 km. (stop in land). Bottom graphic: Total Distance = 125.8 km. Distance remaining to reach the goal point: Init-Optim: 0.0 km; Optimization: 69.7 km (stop in land); CTS-A*: 3.2 km; A*: 8.7 km; Direct to goal: 80.0 km. (stop in land).

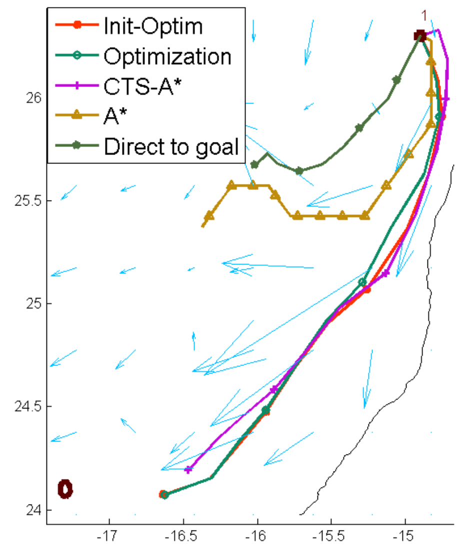

Fig. 17. Comparative of trajectories simulated in offshore area for a 4-days period with time-varying currents (ocean currents that exceed the glider speed $v_g = 0.4\mathrm{m/s}$ are highlighted) from the start point to the goal point. Total Distance = 343.4 km. Distance remaining to reach the goal point: Init-Optim: 67.4 km; Optimization: 68.8 km; CTS-A*: 85.1 km; A*: 169.4 km; Direct to goal: 217.6 km.

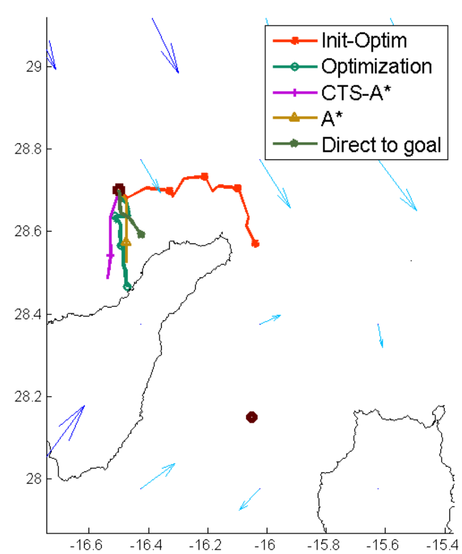

Fig. 18. Comparative of trajectories simulated in offshore area for a 4-days period with time-varying currents (ocean currents that exceed the glider speed $v_g = 0.2\mathrm{m/s}$ are highlighted) from the start point to the goal point. Total Distance = 75.2 km. Distance remaining to reach the goal point: Init-Optim: 46.7 km; Optimization: 54.2 km (stop in land); CTS-A*: 60.7 km (stop in land); A*: 58.9 km (stop in land); Direct to goal: 61.3 km. (stop in land)

obstacles or forbidden areas, making it a practical tool for coastal environments.

The method shows a superior performance when compared with other alternative approaches. In general, classical A* or variants, like the CTS-A* algorithm analyzed here, do not find a path better than optimization methods. Notice that even a slightly improvement of 5-10km in the path cost is advantageous in many glider missions, e.g. it might reduce the economical cost of collection after the mission. Anyhow, it is in the computational cost where the latter clearly outperform the former.

Finally, the solution presented in this paper is valid for this particular problem, but would not have the same benefits if it is applied for path planning with other kind of vehicle, as long as there is no temporal discretization in their pattern of displacement.

A. *Future works*

In future research, we would like to incorporate 3D ocean current data and model the glider motion accordingly. Also we pretend validate these results in the navigation of a real glider.

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