

Article

A Cell-Based Ocean-Current-Aware Travel-Time Cost Formulation for Offline 3D Path Planning of Underwater Vehicles

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Highlights

What are the main findings?

- A cell-transition cost turned measured ocean-current data into a travel-time-aware 3D map for offline path planning, with no change to the search algorithm.
- The same measured current field aided westbound transits (−2.4% and −4.4% travel time) while opposing eastbound transits (+1.3% and +1.8%), and these effects amplified roughly threefold as the vehicle speed decreased from 15 to 6 knots.

What are the implications of the main findings?

- Ocean current information can be operationalized directly into time-efficient routing decisions for underwater vehicles.
- The map-level cost is portable across cell-based planners: A* and Dijkstra's algorithms returned identical optimal routes under the same cost.

Abstract

Underwater vehicles must operate efficiently within the limits of their onboard resources, and travel time is a primary operational objective for extending submerged endurance and range. Ocean currents significantly affect vehicle motion and travel time, either aiding or impeding propulsion depending on their direction and magnitude. This study proposes a cell-based, ocean-current-aware cost formulation for offline three-dimensional (3D) underwater path planning. A 3D grid map integrating ocean current vectors and underwater terrain is constructed, and rather than modifying a specific search algorithm, the proposed approach defines a travel-time-based cost at the cell-transition level by incorporating current effects into the vehicle's effective velocity. Because the cost operates at the cell-transition level, it can be adopted by standard grid-search planners such as Dijkstra's, A*, and D* without modification. Simulation experiments over the Tsushima–Jeju corridor using two measured current fields from the Korea Hydrographic and Oceanographic Agency show that identical fields aided westbound transits (−2.4% and −4.4% travel time versus a current-unaware baseline) while opposing eastbound transits (+1.3% and +1.8%), with the planner exploiting favorable flows and detouring to mitigate adverse flows; these effects amplified roughly threefold as the vehicle speed decreased from 15 to 6 knots. A* and Dijkstra's algorithms returned identical optimal costs under the same formulation, confirming planner independence. The results demonstrate that embedding measured current information at the map level yields realistic, condition-dependent, minimum-travel-time routes for offline mission planning.



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1. Introduction

Autonomous marine vehicles—for both surface and underwater use—increasingly rely on intelligent path planning as a core enabling technology for safe, efficient, and autonomous navigation. Among these platforms, underwater vehicles operate under particularly stringent energy constraints: unlike surface ships, they cannot replenish their onboard power during a mission, which directly limits their submerged endurance, operational range, and mission duration. Because longer transits draw down these limited resources, minimizing travel time is a primary operational objective. This challenge is compounded by the marine environment, in which underwater vehicles must overcome not only mechanical drag but also hydrodynamic forces induced by ocean currents, which can either aid or oppose vehicle motion depending on the direction of travel. Accurately quantifying these current-induced variations in effective speed and travel time is thus a prerequisite for identifying time-efficient routes, a concern that has become increasingly central to research on intelligent marine vehicle navigation.

Extensive research has been conducted on path planning across diverse environments, with algorithms broadly classified as graph-search (deterministic) methods and metaheuristic methods. Among graph-search methods, Dijkstra's algorithm and the A* family are the most widely studied; Dijkstra's algorithm is an uninformed search that expands nodes by accumulated cost, whereas A*, D* and Theta* are informed (heuristic-guided) variants that use a heuristic function to accelerate the search. In the domain of uninformed graph search, Kirsanov et al. [1] proposed an improved Dijkstra's algorithm for path planning in environments with dynamic obstacles, while Singh et al. [2] applied Dijkstra's algorithm to plan a 2D navigation path for an unmanned surface vehicle (USV) under marine conditions including ocean currents and dynamic obstacles; to manage environmental complexity, they restricted the problem to a temporally and spatially bounded domain. Building on the more efficient best-first search paradigm, Li et al. [3] applied the A* algorithm to voyage path generation for an autonomous underwater vehicle (AUV) equipped with obstacle-detection sonar in an unknown environment. Hong-han et al. [4] extended A* to a 3D space–time coordinate framework to incorporate time-varying ocean current information, and Li and Zhang [5] compared Dijkstra's and A* algorithms on a 3D grid map that explicitly models underwater terrain. Within the marine domain, Yang et al. [6] proposed an improved A* algorithm integrated with an artificial potential field for USV path planning in ocean currents, incorporating a current-aware cost function and an adaptive guidance angle to maintain safe clearance from obstacles while reducing computation time. Chen et al. [7] combined A* with a genetic algorithm to account for the influences and constraints of ocean currents on AUV path planning, tailoring the fitness function to current conditions and employing adaptive mutation to improve population diversity and stability. Further recent studies continue to advance current-aware navigation and planning for marine vehicles across diverse platforms and mission settings [8,9]. For unmanned aerial vehicle (UAV) path planning in 2D and 3D spaces with obstacles, Mandloi et al. [10] benchmarked the A*, Theta*, and Lazy Theta* algorithms in terms of computational time and path length. The Theta* series extends A* to support any-angle movements, overcoming the directional discretization inherent in standard grid structures. Exploiting this flexibility, Yin and Ning [11] presented a CNN-augmented Lazy Theta* algorithm for intelligent 3D obstacle avoidance,

and Yuan et al. [12] further improved Lazy Theta* with adaptive heuristic weights for UAV flight path generation in known 3D environments.

Beyond graph-search methods, a broad range of metaheuristic and learning-based approaches have also been applied to path planning in marine and aerial domains, including ant colony optimization [13–16], firefly [17,18], particle swarm [19,20], and genetic algorithms [21,22], as well as bioinspired neural networks [23], recurrent networks [24], and reinforcement-learning-based controllers [25–27]. These methods offer flexibility in complex or uncertain environments by searching for near-optimal solutions, but they generally embed the optimization objective within a solver-specific fitness or policy function, which couples the cost model to a particular algorithm and limits its portability. As such, while these studies establish the broader context of marine path planning, they are only indirectly related to the present contribution, which concerns the cost model itself rather than the search or optimization procedure.

More recently, energy consumption has been recognized as an explicit optimization objective for underwater path planning. Zhang et al. [28] formulated an energy-saving 3D path planning method for AUVs in which the fitness function jointly accounts for path length, energy consumption, and vehicle mobility constraints, and solved it with an improved PSO variant. Liu et al. [29] proposed an energy-optimized path planning algorithm for fully actuated AUVs in complex 3D environments, combining energy-optimized PSO with sequential quadratic programming to minimize energy usage. These studies confirm that, in marine environments, energy-aware route selection differs fundamentally from purely geometric shortest-path planning.

A closer examination of how cost is modeled in grid/cell-based planning reveals a clear gap. Most cell-based studies adopt one of three cost models. The first is a purely geometric distance cost, which yields the shortest path but ignores environmental forcing entirely [3,5]. The second is a travel-time cost under a fixed vehicle speed, which improves temporal realism but still neglects the spatially varying, current-induced changes in effective speed [2]. The third embeds an energy objective within the fitness function of a metaheuristic optimizer [28,29]. Although physically motivated, this approach ties the energy model to a specific solver and is therefore not transferable across planners. The same solver coupling persists in recent graph-search work: an energy-optimized A* embeds a detailed vehicle energy model—accounting for drag, the relative velocity between the vehicle and the flow, and maneuvering—directly into the A* cost function [30], improving energy outcomes but again binding the cost model to a single planner. What is missing is a cost model in which the current-induced effect on effective speed and travel time is represented at the map (cell-transition) level itself, so that any cell-based planner can inherit current-awareness without modification. The present study addresses precisely this gap.

This gap matters because, in an underwater environment subject to spatially varying currents, the geometrically shortest path does not, in general, minimize travel time: a vehicle may spend substantially more time traversing a shorter route against a strong opposing current than navigating a longer but current-aided alternative. Embedding this current-induced effect on effective speed at the map level—rather than within a particular solver—therefore offers both a more accurate cost representation and a planner-independent route to current-aware, time-optimal navigation.

The scope of this study is offline planning: routes are computed prior to the mission over a measured, static current snapshot. This study addresses the identified gap by formulating a current-aware travel-time cost at the cell-transition level of a 3D grid map. The contributions are threefold: (1) a cost formulation that converts measured ocean current vectors into travel-time-based edge costs, independent of the search algorithm; (2) a consistency (monotonicity) guarantee for the accompanying heuristic, preserving the

optimality of A*; and (3) a simulation study over the Tsushima–Jeju corridor comprising four experiment sets—a current-free baseline, bidirectional transits under two measured current fields, a vehicle-speed sensitivity analysis, and a planner-portability comparison between A* and Dijkstra’s algorithms. The remainder of this paper is organized as follows. Section 2 describes the 3D grid map construction and modeling assumptions. Section 3 presents the search framework and the proposed cost formulation. Section 4 reports the experimental design and results, and Section 5 concludes with limitations and future work.

2. 3D Grid Map with Underwater Terrain and Ocean Current Vectors

To faithfully represent the operational environment of underwater vehicles, a 3D grid map was constructed by integrating two categories of environmental data: measured ocean current data (comprising flow direction and speed) and terrain data (comprising land boundaries, reefs, and islands). The target platform is a thrust-propelled underwater vehicle (e.g., a powered AUV or submarine), not a buoyancy-propelled glider: horizontal motion is produced by propulsive thrust, whereas vertical motion relies on buoyancy (depth) control. Three simplifying assumptions were adopted to manage model complexity: (i) the ocean current vector is assumed to be constant within each grid cell, while varying across cells in the horizontal plane and across depth layers, consistent with the gridded structure of the observational data; (ii) vertical ocean currents were not considered, as their velocities are typically on the order of 10^{-4} to 10^{-2} m/s—which is negligibly small compared to horizontal counterparts—and vertical displacement is assumed to be governed entirely by buoyancy control; and (iii) the vehicle’s thrust produces a speed greater than the local ocean current speed, ensuring that the vehicle can always make headway in any commanded direction. This last assumption reflects a universal physical requirement for controlled underwater navigation rather than a vehicle-specific restriction. All terrain and current data were mapped onto a 3D matrix using measured ocean current and terrain data. Figures 1 and 2 show representative examples of terrain and ocean current vector mapping onto a 2D grid map at an arbitrary depth within the 3D structure. Figure 3 illustrates the overall architecture of the resulting 3D grid map.

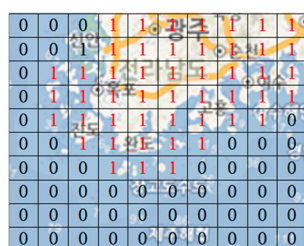


Figure 1. Example of terrain representation.

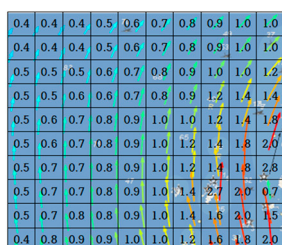


Figure 2. Example of ocean current representation.

It should be noted that the grid map encodes traversability and obstacle clearance at cell resolution; vehicle motion constraints such as turning radius and pitch limits are not embedded at this level. Accordingly, the output of the planner is a discrete, high-level route that guarantees grid connectivity, obstacle avoidance, and current-aware time

efficiency, and is intended to be refined by a downstream trajectory generator that enforces the vehicle's kinodynamic constraints.

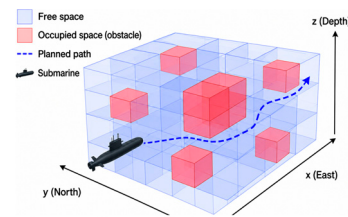


Figure 3. Example of a 3D grid map structure.

3. Travel-Time-Based Path Planning

3.1. Traditional Path-Scoring Method for Cell-Based Search Algorithms

Grid-map-based path planning algorithms—including Dijkstra's, A*, D*, and Theta*—share a common foundation in a neighbor-node path-scoring framework. In these algorithms, the path-scoring method determines how the cost of moving to each neighboring node is evaluated, directly governing the quality of the resulting path. The core contribution of this study lies in reformulating the path-scoring method to incorporate ocean current effects into the cost evaluation, thereby enabling current-aware, time-efficient path planning. Since the proposed path-scoring method operates at the neighbor-node evaluation level, it is not restricted to a specific algorithm. We note that sharing a common edge-cost function across grid-search planners is a standard property rather than a contribution in itself; the contribution of this study is the current-aware travel-time cost formulation, while its compatibility with multiple cell-based planners is presented as a beneficial consequence of operating at the cost level.

Figure 4 illustrates an example of the neighbor-node scoring mechanism. To demonstrate and validate the proposed path-scoring method, the A* algorithm was adopted as the search framework in this study. Given the three-dimensional nature of the underwater mission environment, which contains substantially more nodes than a typical 2D case, A* provides a practical balance between solution quality and computational efficiency by using a heuristic function to guide the search toward the target. Figure 5 compares the node-search behavior of Dijkstra's and A* algorithms in a 2D grid map with obstacles [31], illustrating the computational advantage of heuristic-guided search in large-scale environments. In practical applications, a suitable search algorithm can be selected according to the search characteristics and map types of the given operational scenario, with the proposed cost formulation applied unchanged.

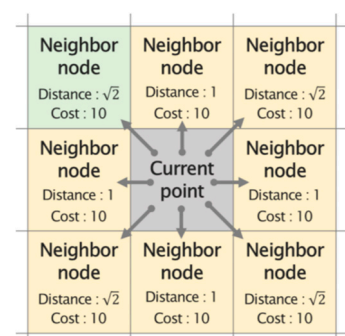


Figure 4. Example of the path-scoring method.

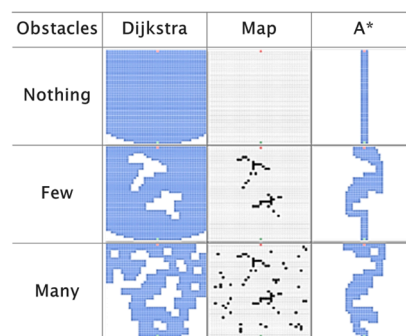


Figure 5. Comparison of node-search behavior.

Among the informed variants, D* and its successors (e.g., D* Lite) deserve particular mention: they are incremental re-planning algorithms designed for environments that change during execution, efficiently repairing the current solution when edge costs are updated rather than re-planning from scratch. In a static, fully known environment, the initial planning phase of D* performs the same computation as A* and returns the identical optimal path. Because the proposed formulation operates purely at the edge-cost level, it supplies exactly the interface that D*-type planners consume when re-planning under updated current fields, making it the natural mechanism for the time-varying extension discussed in Section 5.

3.2. A* Algorithm

In this study, the A* algorithm is employed as the search framework within which the proposed cost formulation is implemented and validated; it is adopted as a representative cell-based planner rather than as a contribution of this work. The A* algorithm is widely used for path planning for objects navigating on land, at sea, and in the air. It is a best-first search algorithm that identifies the path with the lowest estimated total cost from the current node to the target node. The cost at each node n is evaluated using the objective function $f(n) = g(n) + h(n)$, where $g(n)$ is the accumulated cost from the starting node to node n , and $h(n)$ is a heuristic estimate of the minimum remaining cost from node n to the destination. A crucial property of A* is that it guarantees an optimal solution when $h(n)$ is admissible—that is, when $h(n)$ never overestimates the true remaining cost. The procedural steps of the A* algorithm are summarized in Table 1.

Table 1. Search steps of the A* algorithm.

Step	Description
Step 1	► Define the starting node (S) and target node (T).
Step 2	► Initialize an empty CLOSED list; add the starting node to the OPEN list and compute its objective function $f(n)$.
Step 3	► Move the starting node from the OPEN list to the CLOSED list; place all neighboring nodes of the starting node into the OPEN list.
Step 4	► Calculate $f(n) = g(n) + h(n)$ for all unvisited nodes in the OPEN list; update $f(n)$ for previously evaluated nodes if a lower-cost path is found, where, $g(n)$ is the accumulated cost from the starting node to node n , and $h(n)$ is a heuristic estimate of the minimum remaining cost from node n to the target.
Step 5	► Select the node with the lowest $f(n)$ from the OPEN list; move it to the CLOSED list.
Step 6	► If the selected node is the target node, the algorithm terminates and the optimal path is recovered by backtracking. Otherwise, place all unvisited neighboring nodes into the OPEN list and return to Step 4.

3.3. Proposed Path-Scoring Method for Travel-Time-Based Path Planning

The proposed path-scoring method extends the A* framework to explicitly incorporate the effects of ocean currents on the effective navigation speed, rendering it generalizable to any neighbor-node search algorithm. The fundamental insight is that ocean currents can either aid or oppose vehicle propulsion, significantly affecting travel time depending on the direction of travel.

The effective navigation speed of the vehicle depends on the local ocean current vector, which varies with both time and spatial position. The 3D grid map stores the ocean current velocity vector at each node, allowing for the effective speed to be computed at every step of the path search. The path search evaluates all 26 neighboring nodes surrounding the current node: six face neighbors along the coordinate axes, twelve edge-diagonal neighbors at 45° within each coordinate plane, and eight body-diagonal neighbors at $\arctan(1/\sqrt{2}) \approx 35.26^\circ$ from the horizontal plane. Note that these angles correspond to a uniform grid; in the present study, the actual movement angles in the vertical direction differ from the values above, as the grid spacing along the z-axis is set independently of the horizontal spacing. Since vertical (z-direction) displacement is governed by buoyancy control rather than propulsive thrust, ocean current effects on heading angle correction are confined to the horizontal plane. Accordingly, for the 18 neighboring nodes involving vertical movement (i.e., ascending or descending directions), the horizontal velocity vectors and the corresponding heading angle corrections remain identical to those of the eight nodes at the same depth level. The current-induced heading deviation for all 26-neighborhood nodes is therefore fully determined by the horizontal current components, and the three representative cases (0° , 90° , and 45°) derived in the following cover the complete range of horizontal directional corrections. The vehicle is assumed to operate at constant thrust, and its heading angle is continuously adjusted to compensate for local current conditions in order to achieve the desired movement direction. The governing equations for the modified heading angle θ are derived as follows. The general relationship between the actual movement angle δ and the modified heading θ is expressed as

$$\tan \delta = \frac{\Delta V_y}{\Delta V_x} \quad (1)$$

$$\frac{\Delta V_y}{\Delta V_x} = \frac{V \sin \theta + v_y}{V \cos \theta + v_x} \quad (2)$$

where δ is the actual movement angle, θ is the modified heading angle of the underwater vehicle, V is the vehicle's thrust speed, and v denotes the ocean current speed. Since the target movement direction δ takes one of three representative values (0° , 45° , or 90°), the modified heading θ is derived separately for each case. Figure 6 illustrates the corresponding geometric interpretation.

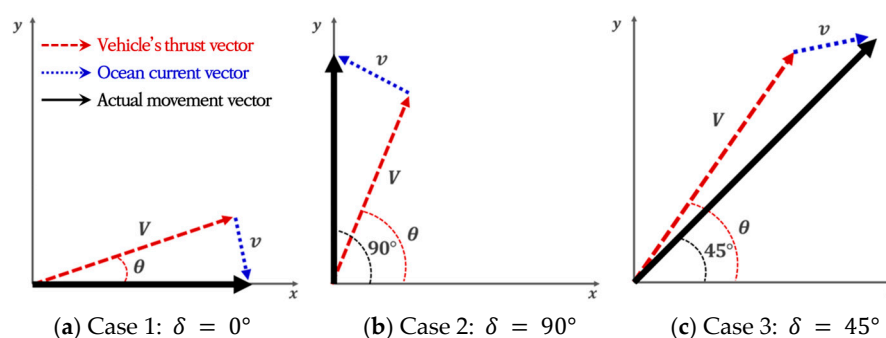


Figure 6. Modified heading angle under ocean currents for each movement case.

For clarity, the symbols are defined as follows: V denotes the vehicle's constant still-water (thrust) speed; $v = (v_x, v_y)$ is the local ocean current vector with speed $|v|$; δ indicates the actual movement direction, defined as the direction of the vehicle's resultant ground-referenced motion from the current node to the selected neighboring node; and θ denotes the commanded thrust heading required to realize δ under the local current. The three representative cases ($\delta = 0^\circ, 45^\circ, 90^\circ$) derived below cover the complete range of horizontal directional corrections through the corresponding sign-adjusted forms; equivalently, for a desired unit direction the heading satisfies $\theta = \delta + \arcsin\left(\frac{-v_\perp}{V}\right)$, where $v_\perp$ is the current component perpendicular to the movement direction, and the effective speed along the movement direction is $s_{\text{eff}} = V\cos(\theta - \delta) + v_\parallel$, with $v_\parallel$ being the along-track current component. For the 18 transitions involving a vertical component, the heading correction is determined by the horizontal projection of the movement direction, to which the same expressions apply.

Case 1—Movement along the x -axis ($\delta = 0^\circ$): the y component of the resultant velocity must be zero:

$$V\sin\theta + v_y = 0 \quad (3)$$

$$\theta = \arcsin\left(-\frac{v_y}{V}\right) \quad (4)$$

Case 2—Movement along the y -axis ($\delta = 90^\circ$): the x component of the resultant velocity must be zero:

$$V\cos\theta + v_x = 0 \quad (5)$$

$$\theta = \arccos\left(-\frac{v_x}{V}\right) \quad (6)$$

Case 3—Diagonal movement ($\delta = 45^\circ$): the x - and y -components of the resultant velocity must be equal, as expressed in Equation (7). By applying the trigonometric identity $\sin\theta - \cos\theta = \sqrt{2}\sin(\theta - \pi/4)$, θ is obtained as Equation (8).

$$V\sin\theta + v_y = V\cos\theta + v_x \quad (7)$$

$$\theta = \frac{\pi}{4} + \arcsin\left(\frac{v_x - v_y}{V\sqrt{2}}\right) \quad (8)$$

From the modified heading angle θ and the local ocean current vector, the effective navigation speed for each grid movement can be derived. Because the vehicle maintains a constant commanded thrust and hence a constant water-referenced speed, any change in the ocean current alters its effective (ground-referenced) speed and, consequently, the travel time between nodes. Accumulating these current-dependent transition times along a path yields the total travel time, which is adopted as the planning objective of this study. This travel-time cost is the foundation of the proposed cost function reformulation.

Based on the above analysis, the path-scoring components $g(n)$ and $h(n)$ of the A^* algorithm are reformulated as follows to reflect current-affected travel time rather than simple geometric distance. Equation (9) computes the incremental travel time between consecutive nodes: the inter-node distance is divided by the magnitude of the resultant velocity vector, which combines the vehicle's thrust vector and the local ocean current vector. The accumulated value of $g(n)$ thus represents the total travel time from the starting node to the current node, accounting for the influence of ocean currents on the effective speed at each step. Because each edge cost is a travel time, it is inherently non-negative; moreover, under Assumption (iii) ($V > |v|$; Section 2), the effective speed in the denominator of Equation (9) is strictly positive, so every edge cost is strictly positive. The cost function therefore contains no negative or zero-cost edges, which preserves the validity

and optimality guarantees of Dijkstra's and A* search and ensures that the vehicle always makes positive headway in the commanded direction.

Remark (motivation). Under an idealized constant-thrust cruise—with constant water-referenced speed and negligible maneuvering transients—propulsion energy scales with travel time, which motivates travel time as a practical planning objective for endurance-limited vehicles. A rigorous energy evaluation, accounting for thrust dynamics, maneuvering, and load, is beyond the scope of this study; accordingly, all results in this paper are formulated, evaluated, and discussed in terms of travel time.

$$\text{Modified } g(n) = \max \left(\frac{\text{Horizontal distance to next node}}{\sqrt{(V \cos \theta + v_x)^2 + (V \sin \theta + v_y)^2}}, \frac{\Delta z}{w} \right) \quad (9)$$

where Δz is the vertical displacement of the transition and w is the buoyancy-driven vertical speed. The horizontal and vertical motions proceed concurrently, so the transition time is governed by the slower component. For purely vertical transitions, the cost reduces to $\Delta z/w > 0$, ensuring strictly positive edge costs; for mixed transitions with Δz on the order of meters and horizontal distances on the order of kilometers, the horizontal term dominates and the cost is governed by the horizontal effective speed, consistent with the vertical-negligibility argument above.

Here, both the speed in the denominator and the inter-node distance are evaluated in the horizontal plane. Vertical displacement, governed by buoyancy control rather than propulsive thrust (Section 2, assumption (ii)), is decoupled from the current-affected horizontal motion. Because the vertical grid spacing (on the order of meters; Section 4.1) is small relative to the horizontal spacing (on the order of kilometers) and buoyancy control effects a depth change rapidly, the time required for vertical movement is negligible compared to that for horizontal movement. Accordingly, the travel-time cost in Equation (9) is governed by the horizontal effective speed, and the vertical component of any transition contributes negligibly to the edge cost.

Equation (10) provides the heuristic estimate of the minimum remaining travel time from the current node (x_m, y_m, z_m) to the target node (x_n, y_n, z_n) . This term directs the search toward the destination. Since A* guarantees an optimal solution only when the heuristic is admissible—that is, when $h(n)$ never overestimates the true minimum remaining travel time—the speed used in the denominator must be an upper bound on the vehicle's maximum achievable effective speed. Because the effective speed varies with the local ocean current, ranging from $V - |v|$ under a fully opposing current to $V + |v|$ under a fully aiding current, the denominator is set to the maximum attainable effective speed, defined as the vehicle's still-water speed plus the maximum ocean current speed over the operational area ($V + |v|_{\max}$; see Section 4.1 for the still-water speed of 15 *knots* used in this study's simulations). This choice ensures that $h(n)$ never exceeds the true remaining travel time, thereby preserving admissibility and the optimality of the resulting path. Together, Equations (9) and (10) replace the corresponding terms in Step 4 of Table 1, yielding a current-aware A* algorithm. Figure 7 illustrates an example of how ocean current and vehicle motion information are integrated into the path-scoring process.

Beyond admissibility, the heuristic is consistent (monotone). Let $h(n) = \frac{D(n, \text{goal})}{s_{\max}}$, with $s_{\max} = V + |v|_{\max}$ being the maximum attainable effective speed over all motion modes. For any transition (n, n') , the edge cost satisfies $t(n, n') \geq \frac{d(n, n')}{s_{\max}}$, and the Euclidean triangle inequality gives $D(n, \text{goal}) \leq d(n, n') + D(n', \text{goal})$; dividing by $s_{\max}$ yields $h(n) \leq t(n, n') + h(n')$. Consistency implies admissibility and guarantees that A* never re-expands a closed node, preserving the optimality of the returned route.

$$\text{Modified } h(n) = \frac{\sqrt{(x_n - x_m)^2 + (y_n - y_m)^2 + (z_n - z_m)^2}}{V + |v|_{\max}} \quad (10)$$

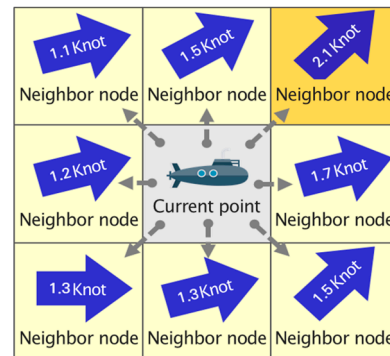


Figure 7. Incorporating ocean currents and vehicle motion into the proposed path-scoring process.

4. Simulation Experiment

It should be noted that the standard A* algorithm is employed without any structural modification in this study. The core contribution lies in the formulation of the edge cost function, which incorporates ocean current effects into the travel time estimation between neighboring nodes, as detailed in Section 3.3. The experiments below evaluate the formulation from four complementary angles: (Experiment I) equivalence with a purely geometric baseline when currents vanish; (Experiment II) directional response under two measured current fields; (Experiment III) sensitivity of routes and travel times to vehicle speed; and (Experiment IV) portability of the identical cost across planners (A* versus Dijkstra’s algorithm).

4.1. Experimental Design

The Korea Hydrographic and Oceanographic Agency (KHOA) supplies ocean current data in polar coordinate form, specifying flow speed and direction at a spatial resolution of 15 km. To directly utilize this data without interpolation, the horizontal grid spacing was set to 15 km. The grid was configured as 15 km along the x- and y-axes and 5 m along the z-axis. These grid dimensions are chosen for illustrative purposes—to verify the behavior of the proposed cost formulation rather than to reproduce the actual bathymetry or operating depths of a specific vehicle—and would, in practice, be set according to the operational area and vehicle characteristics. In practice, grid resolution involves a trade-off between path accuracy and computational cost, and should be determined based on specific operational requirements and available data sources. In particular, the storage requirement of a grid-based representation scales as $O(n_x \cdot n_y \cdot n_z)$ with resolution, so finer grids increase memory demand as well as computation. For large-scale or high-resolution deployments, this can be mitigated through hierarchical or sparse representations—such as the octree-based map of Yuan et al. [12], which significantly reduces the number of stored and searched nodes—and on-demand tiling that loads only the active region of the map.

Based on the KHOA data, the mission area was modeled as a 3D grid map following the procedure described in Section 2. Figures 8 and 9 present the ocean current conditions and terrain layout in the mission area. Regions occupied by land or islands are impassable and were therefore excluded from the path search. To evaluate the algorithm’s behavior in the presence of underwater terrain features such as reefs, additional sub-surface obstacles were incorporated into the grid map as shown in Figure 10. The vehicle was assumed to operate under a constant thrust, defined as the thrust required to achieve a speed of 15 knots. For the heuristic function in Equation (10), the denominator is set per current

field to the maximum attainable effective speed $V + |v|_{\max}$, where the still-water speed V is 15 knots and $|v|_{\max}$ is the maximum current speed observed over the operational area in the respective field—17 knots for Field A and 19 knots for Field B—ensuring the admissibility and consistency of the heuristic, as discussed in Section 3.3.



Figure 8. Ocean current map: 27 April 2022, at 11:30 (Field A).



Figure 9. Ocean current map: 27 April 2022, at 19:30 (Field B).

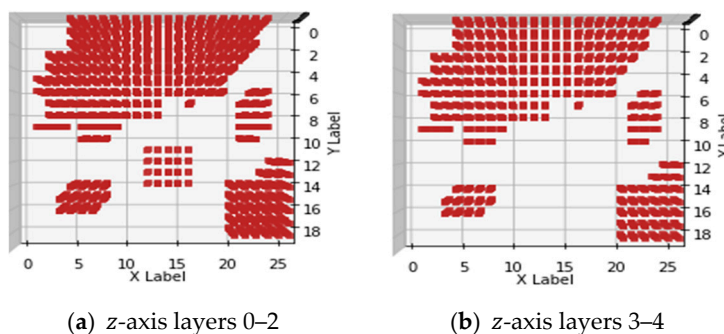


Figure 10. Experimental environment with additional underwater terrain.

Two measured current fields from 27 April 2022, are used: Field A, observed at 11:30 (Figure 8; maximum current speed 2.0 knots), and Field B, observed at 19:30 (Figure 9; maximum current speed 4.0 knots). To characterize each field relative to the mission, the mean along-path current component $v_{\parallel}$ —the projection of the current vector onto the local path tangent, length-weighted along the current-free nominal route—was computed: +0.17 knots (Field A) and +0.82 knots (Field B) in the westbound (Tsushima→Jeju) direction, with equal magnitudes and opposite signs eastbound. Both fields therefore aid westbound transits and oppose eastbound transits, with Field B being roughly five times stronger in the along-path effect.

The vehicle operates under constant thrust with a still-water speed of $V = 15$ knots in Experiments I, II, and IV; Experiment III varies V from 15 down to 6 knots while maintaining Assumption (iii) ($V > |v|_{\max}$). Four evaluation metrics are reported: total travel time (h), relative change versus the current-free baseline at the same speed (%), route length (km), and the number of node expansions of the search. All experiments perform offline planning over static, measured current snapshots; time-varying re-planning is beyond the present scope (Section 5).

4.2. Experiment I: Current-Free Baseline and Equivalence with Standard A*

With ocean currents set to zero, the effective speed reduces to V in all directions and the proposed cost degenerates to distance/ V . The planned route from Tsushima to Jeju required 14.79 h over 410.8 km. This result is identical—node for node—to that of the standard A* algorithm with a conventional geometric distance cost, which was verified computationally: both searches expanded identical node sets and returned identical routes. Experiment I therefore serves both as the reference for Experiments II and III and as a correctness check that the formulation introduces no artifacts in the absence of currents.

4.3. Experiment II: Bidirectional Transits Under Two Measured Current Fields

Experiment II plans optimal routes in both directions (westbound: Tsushima→Jeju; eastbound: Jeju→Tsushima) under Fields A and B at $V = 15$ knots. Figure 11 presents the resulting routes in top view and 3D view, and Table 2 summarizes the metrics. Both fields shortened westbound travel (Field A: 14.43 h, −2.4%; Field B: 14.14 h, −4.4%) and lengthened eastbound travel (Field A: 14.97 h, +1.3%; Field B: 15.06 h, +1.8%), in agreement with the along-path characterization of Section 4.1. Two complementary adaptation behaviors are observed. Westbound under Field A, the planner selected a longer route (415.9 km versus the 410.8 km geometric optimum) to exploit stronger favorable flow, trading distance for current assistance. Eastbound under Field B, the planner detoured (415.9 km) to circumvent the core of the opposing flow, trading distance to limit adverse exposure. The same measured field thus acts as a tailwind or a headwind depending solely on the transit direction, and the formulation responds asymmetrically and consistently in both cases; a current-unaware cost cannot reproduce either behavior.

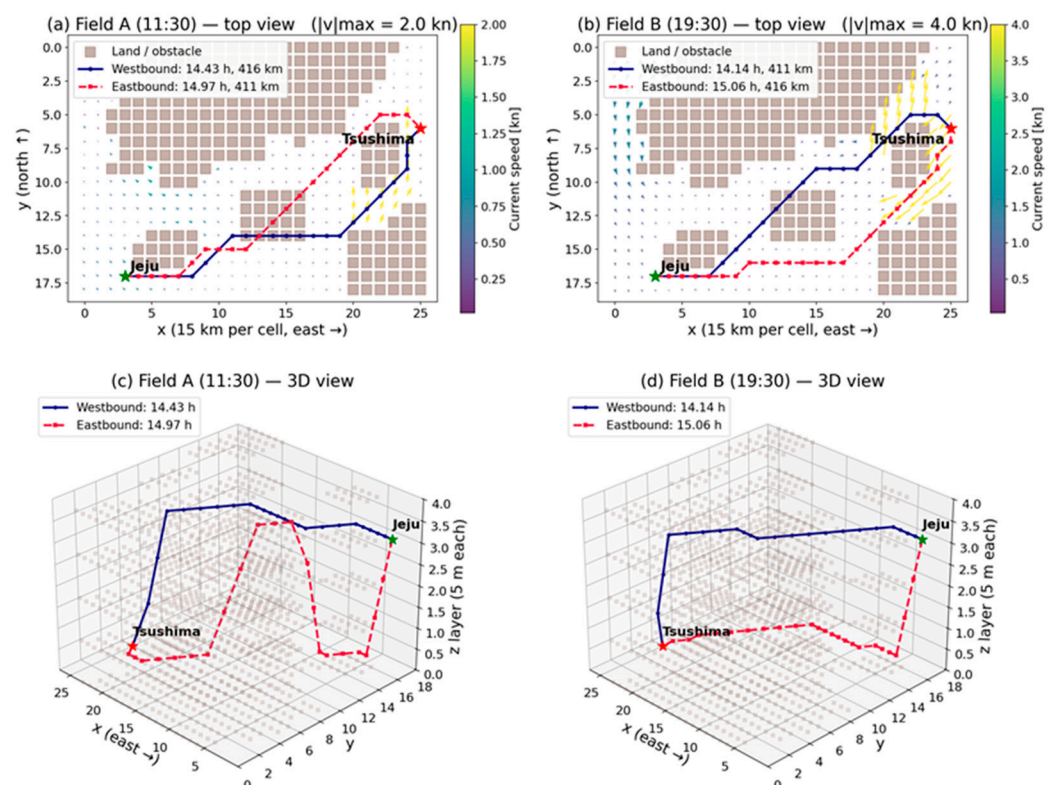


Figure 11. Directional optimal routes under the two measured current fields: (a,b) top views of Fields A and B with current vectors; (c,d) corresponding 3D views.

Table 2. Bidirectional planning results under the measured current fields ($V = 15$ knots).

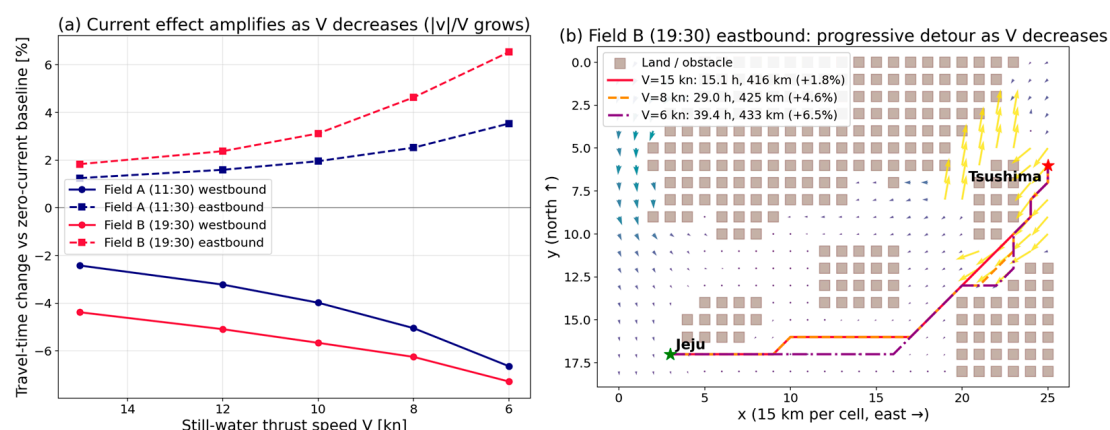
Case	Direction	Time (h)	Δ vs. Baseline	Length (km)	$v_{ }$ (knots)
Baseline	—	14.79	—	410.8	0
Field A (11:30)	Westbound	14.43	−2.4%	415.9	+0.17
Field A (11:30)	Eastbound	14.97	+1.3%	410.8	−0.17
Field B (19:30)	Westbound	14.14	−4.4%	410.8	+0.82
Field B (19:30)	Eastbound	15.06	+1.8%	415.9	−0.82

4.4. Experiment III: Sensitivity to Vehicle Speed

Because the influence of a current of magnitude $|v|$ on the effective speed scales with the ratio $|v|/V$, the current effects should intensify as the vehicle slows. Experiment III repeats the bidirectional planning for $V \in \{15, 12, 10, 8, 6\}$ knots. Table 3 and Figure 12a confirm a roughly threefold amplification over this range: westbound savings grow from −2.4% to −6.7% (Field A) and from −4.4% to −7.3% (Field B), while eastbound penalties grow from +1.2% to +3.5% (Field A) and from +1.8% to +6.5% (Field B). Moreover, the optimal route itself reorganizes as V decreases: under the strong opposing conditions of Field B eastbound, the route lengthens progressively from 415.9 km ($V = 15$) to 424.7 km ($V = 8$) and 433.5 km ($V = 6$)—the planner pays up to 22.7 km of additional distance to bypass the opposing core, as visualized in Figure 12b. Under the weaker Field A, routes remain unchanged across all speeds. These results indicate that current-aware planning is most consequential for slow, long-endurance vehicles operating in strong current regimes, and that the benefit is structural (route reorganization) rather than merely arithmetical (speed correction).

Table 3. Travel-time change vs. the current-free baseline for varying still-water speed V .

V	Field A West	Field A East	Field B West	Field B East (Length, km)
15 knots	−2.4%	+1.2%	−4.4%	+1.8% (415.9)
12 knots	−3.2%	+1.6%	−5.1%	+2.4% (415.9)
10 knots	−4.0%	+2.0%	−5.7%	+3.1% (415.9)
8 knots	−5.1%	+2.5%	−6.3%	+4.6% (424.7)
6 knots	−6.7%	+3.5%	−7.3%	+6.5% (433.5)

**Figure 12.** Speed sensitivity: (a) travel-time change versus V ; (b) progressive eastbound detours under Field B for $V = 15, 8$, and 6 knots.

4.5. Experiment IV: Portability Across Planners (A* Versus Dijkstra's Algorithm)

Because the proposed cost is defined at the cell-transition level, any planner that consumes edge costs inherits current awareness without modification. To verify this experimentally, Dijkstra's algorithm was run with the identical cost in all six configurations of Experiments I and II. In every case, Dijkstra's algorithm returned the same optimal travel time as A*, differing only in search effort: A* expanded 592–1037 nodes versus 1030–1272 for Dijkstra's algorithm (Table 4), a 20–45% reduction attributable to the heuristic guidance, with all runs completing well under 0.1 s. For D*, whose initial static-environment planning phase coincides with A*, portability follows from the shared edge-cost interface; its incremental re-planning capability becomes relevant in the time-varying setting discussed in Section 5.

Table 4. Search effort under the identical cost formulation ($V = 15$ knots).

Case	Direction	Optimal Time	A* Expansions	Dijkstra Expansions	Identical Optimum
Baseline	Westbound	14.79 h	592	1040	Yes
Baseline	Eastbound	14.79 h	739	1272	Yes
Field A (11:30)	Westbound	14.43 h	817	1030	Yes
Field A (11:30)	Eastbound	14.97 h	942	1267	Yes
Field B (19:30)	Westbound	14.14 h	852	1040	Yes
Field B (19:30)	Eastbound	15.06 h	1037	1247	Yes

4.6. Discussion

The experiments collectively support three operational insights. First, when the along-route current is favorable, modest deviations into stronger favorable flow reduce travel time; when it is adverse, detours around high-speed opposing cores limit losses—both behaviors emerged endogenously from the cost formulation without direction-specific tuning. Second, the magnitude of the benefit scales with the current-to-thrust ratio $|v|/V$ and with route length; the percentage effects reported here (up to -7.3% favorable and $+6.5\%$ adverse at $V = 6$ knots) correspond to a short corridor (≈ 411 km) under moderate currents, and proportionally larger absolute time savings are expected for long-endurance, low-speed missions in strong current regimes. Third, the study demonstrates the mechanism—that a map-level current-aware cost systematically and physically plausibly reshapes routes and travel times using measured fields—rather than asserting a universal performance gain over alternative planners; the observed effects are condition-dependent by design.

5. Conclusions

This study proposed a cell-based, ocean-current-aware cost formulation for offline, travel-time-optimal path planning of underwater vehicles operating under measured, spatially varying current conditions. A 3D grid map was constructed from measured ocean current and terrain data provided by the Korea Hydrographic and Oceanographic Agency, and a cell-transition cost was developed to directly incorporate the vehicle's effective heading and speed under the influence of local ocean current vectors. By defining a travel-time-based cost at the cell-transition level under a constant-thrust assumption, the formulation yields discrete, high-level routes that are geometrically feasible (avoiding all terrain obstacles) and time-efficient. Because the formulation operates at the cell-transition level rather than being tied to a specific search strategy, it is independent of the path planning algorithm, a property verified experimentally in this study: A* and Dijkstra's algorithms returned identical optimal routes under the identical cost, and the same edge-cost interface extends to D* for incremental re-planning.

Simulation experiments over the Tsushima–Jeju corridor using two measured current fields (11:30 and 19:30 on 27 April 2022) demonstrated that the planned 3D route and travel time respond systematically to current conditions. Relative to the current-free baseline (14.79 h), identical fields aided westbound transits (−2.4% and −4.4%) while opposing eastbound transits (+1.3% and +1.8%); the planner exploited favorable flow through longer routes and mitigated adverse flow through detours; and the effects were amplified roughly threefold as the vehicle speed decreased from 15 to 6 knots, with the route itself reorganizing (up to 22.7 km of additional detour) under strong opposing conditions. These behaviors—none of which a current-unaware, purely geometric cost can reproduce—establish that embedding measured current information at the map level provides a realistic, condition-dependent basis for time-efficient navigation. The practical implication is that the proposed method shortens transit times under prevailing currents without any hardware modification, with the largest relative gains for slow, long-endurance missions in strong current regimes.

This study is confined to offline path planning over static, measured current snapshots. The applicable scope comprises thrust-propelled underwater vehicles (powered AUVs/UUVs and submarines) in constant-thrust cruise with still-water speed exceeding the local current speed ($V > |v|_{\max}$), independent of hull size; buoyancy-propelled gliders are outside the scope. When current information is unavailable a priori, the formulation can ingest operational forecast products or onboard measurements (e.g., from an acoustic Doppler current profiler) and smoothly fall back to the geometric baseline in the complete absence of current data.

Three main directions are identified for future work. First, the routes produced here are discrete, high-level routes; coupling the formulation with a downstream trajectory generator that enforces kinodynamic constraints (turning radius, pitch, and ascent limits), followed by physical experimental validation on an actual underwater platform, is the immediate next step. Second, multi-waypoint mission planning will be investigated, in which the vehicle must visit a set of target points in an optimal sequence—a problem structurally analogous to the vehicle routing problem (VRP). Third, reinforcement learning will be explored to address the computational scalability challenge that arises as the 3D mission environment expands. Since real ocean currents vary temporally, a single static snapshot may not adequately represent conditions over extended missions. Beyond the offline scope of this study, a potential re-planning strategy is to establish intermediate waypoints at time intervals corresponding to significant changes in the ocean current field, and to sequentially re-plan the path between consecutive waypoints using updated current data, for which the incremental re-planning capability of D*-type planners, consuming the same edge-cost interface, is the natural mechanism. Scaling the approach to larger or higher-resolution environments will also require addressing the storage complexity inherent to grid-based representations; memory-efficient structures such as hierarchical/sparse grids and on-demand map tiling are promising directions in this regard. Finally, a quantitative energy evaluation based on a vehicle powertrain and drag model—linking the travel-time results reported here to actual energy consumption—will complement the present travel-time-based framework.

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