Go with the Flow: Optimal AUV Path Planning in Coastal Environments

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Abstract

This paper describes a novel optimum path planning strategy for long duration AUV operations in environments with time-varying ocean currents. These currents can exceed the maximum achievable speed of the AUV, as well as temporally expose obstacles. In contrast to most other path planning strategies, paths have to be defined in time as well as space. The solution described here exploits ocean currents to achieve mission goals with minimal energy expenditure, or a tradeoff between mission time and required energy. The proposed algorithm uses a parallel swarm search as a means to reduce the susceptibility to large local minima on the complex cost surface. The performance of the optimisation algorithms is evaluated in simulation and experimentally with the Starbug AUV using a validated ocean model of Brisbane’s Moreton Bay.

1 Introduction

Extending the range and endurance of Autonomous Underwater Vehicles (AUVs) in ocean environments is particularly challenging when missions are required in coastal or reef areas which exhibit strong, time varying currents. Further challenges arise when regions of the environment become exposed or non-traversable during low-tide. All these factors have a great impact on the feasibility and energy requirements of generating safe underwater trajectories between goal points. Therefore, the straight unblocked connection between two locations is often not the favourable path as opposed to surface based path planning.

In recent years, a number of authors have been investigating the problem of large-scale AUV path planning in ocean environments. The works relating to pregenerative AUV path planning in anisotropic environments that have been published so far mostly have considerable limitations concerning the computation of energy optimal paths in space and time.

One of the first pregenerative large-scale AUV path planners was proposed by [Carroll et al., 1992]. It utilizes a quadtree to partition a large oceanic environment for an implementation of the graph-based A* path planning algorithm. Their path planner is still closely related to surface based planners, as the planning accounts mostly for the geometric two-dimensional shape of the environment.

[Alvarez et al., 2004] use genetic algorithms on grids to compute energy optimal paths with the limitation of monotonicity in one coordinate of the path. Also the AUV thrust is assumed to be constant. Accordingly, paths cannot take full advantage of currents to generate zero energy paths for example due to the lack of decision freedom.

An A* based approach to incorporating currents into the path planning was proposed by [Garau et al., 2005]. The currents are assumed to be constant and two-dimensional. The paths are constrained to a grid where moves are either axis-aligned or 45° angled, degrading the maximum possible utilisation of currents. Also here the vehicle thrust is assumed constant.

A continuous approach to AUV path planning in the face of currents was presented by [Petres et al., 2007] with the anisotropic Fast Marching algorithm. The main drawback of their approach is that only linear energy cost functions can be used. Also the original publication did not account for strong currents which could lead to infeasible paths. The energy savings due to accounting for currents were only as large as 10% [Petres et al., 2007]. The approach has been improved to work more reliably in the face of strong currents by [Soulignac et al., 2008]. However, the algorithm still cannot leverage ocean currents sufficiently due to the lack of variable vehicle thrust in the planning phase and the associated nonlinear cost functions.

An interesting continuous approach to energy optimal path planning was proposed by [Kruger et al., 2007]. They introduce the time as an additional search dimension, allowing the vehicle thrust to be chosen in an optimisation problem for minimal energy expenditure. The method does not theoretically involve any limitations provided it is always possible to find the global minimum of the multidimensional cost function. [Kruger et al., 2007] does not comment much on the involved optimisation and techniques to find the globally op-
timal path in complex environments.

This paper builds upon the work by [Kruger et al., 2007] and proposes optimisation swarms to aid in finding paths that are close to the global minimum. The examples considered in [Kruger et al., 2007] involved a rather simple artificial model of an estuary with static currents and obstacles. This work investigates more demanding planning cases in time-varying environments with dynamic obstacles using real ocean data.

1.1 Paper Outline

The remainder of this paper is structured as follows; Section 2 describes the basis behind path planning in dynamic environments with Section 3 presenting the cost function proposed for optimising energy efficient AUV paths. Section 4 describes the optimisation problem with modifications to the global search routine. Section 5 describes the ocean forecast model used in this investigation with Section 6 presenting simulated and experimental results showing the ability of the proposed optimisation routines to generate energy efficient paths for AUV navigation.

2 Path Planning in Dynamic Environments

A path planning algorithm is to be developed that is capable of utilizing sampled data of an ocean simulation. The ocean simulations data samples provide information about water height and two-dimensional ocean current both of which are strongly time-variant. The path performance shall be evaluated by the following criteria:

- Energy expenditure for the path
- Path Duration
- Obstacle penetrations
- Shallow water regions
- Excess of maximum vehicle speed by path requirement

The problem in this work is a three-dimensional one (two dimensions in space plus the time dimension). The search space is a large bay area with the environment characterized by its highly anisotropic, time-varying nature. Instead of the common search problems between a start and a goal point, in this case the goal is a straight line extending in the time dimension, as visualized in Figure 1. Paths are naturally constrained to be monotonic in time, thus to point downwards in the visualization. Furthermore, an apparently traversable path can be unfeasible at certain times when strong currents flow in the opposite direction. Thus obviously the cost of a direct path between two points in this environment depends not only on the location, but also on the vehicle speed and the time of travel.

2.1 Path Planning in Partitioned Search Space

Path planning has traditionally been approached by graph based planning whereby the search space is partitioned in a discrete representation of the environment comprised of edges and nodes. A number of graph based methods appear in literature such as Breadth First Search, Dijkstra’s algorithm [Dijkstra, 1959], and the A* algorithm [Hart et al., 1968]. D* or Dynamic A* [Stentz, 1994], developed to enable efficient navigation in dynamic or previously unknown environments, with properties like optimality and completeness has found application in AUV related mission planning [Carroll et al., 1992; Garau et al., 2005].

Due to the problem of finding appropriate heuristics, the A* approaches do not address the problem of finding energy-efficient paths that use the vehicle thrust as a degree of freedom, nor are they capable of handling time-variant currents which requires time as an additional search dimension. Furthermore, as currents do not usually flow in the direction of the links between nodes, graph-based planning for AUVs are less suitable as the vehicle is constrained to follow these graph edges.

Discrete graph representations can also lose significance when the resulting path is transferred back to the continuous domain. This is particularly true in the proposed class of problem where the grid node spacing used in the hydrodynamic models can be many kilometres apart. Continuous path planning approaches are required to include a search space not limited to grid or node locations. A continuous path planning approach is employed in this work, however, for conciseness, the remainder of this paper focuses on cost function evaluation in continuous space, and not on the method of interpolation data sets for continuous path planning.

2.2 Global Path Planning with Potential Fields

Global or pregenerative path planning methods create the path before the robot starts to travel. Artificial potential fields can be used to do global path planning as suggested by [Warren, 1990]. The underlying idea is to introduce a cost function
that evaluates a path candidate as a whole and then optimize the path parameters until a minimum of the cost function is found.

In the following sections, \( \Gamma \) will be used as notation for the path parameters and \( \Gamma_i \) will be used to refer to segment \( i \) of that path. A path is comprised of \( n \) nodes including the start and goal node and thus has \( n - 1 \) path segments:

\[
\Gamma = (\vec{N}_1, \vec{N}_2, \ldots, \vec{N}_i, \ldots, \vec{N}_n)^T = (X_1, Y_1, \ldots, X_i, Y_i, \ldots, X_n, Y_n)^T. \tag{1}
\]

Each node \( \vec{N}_i \) is made up of two coordinates in this case, although readily extendable to higher dimensions. The coordinates are also not restricted to lie on a grid.

Cost Function

The basic cost function to yield a short path suggested by [Warren, 1990] is comprised of a spring-term and an obstacle penalty term. The potential energy \( U_{\text{length}} \) stored in a single spring segment can be formulated as follows:

\[
U_{\text{length}} = (\ell_i - \ell_{\text{init}})^2 \tag{2}
\]

where \( \ell_{\text{init}} \) is the initial segment length and \( \ell_i \) the current length of segment \( i \). The obstacle penalty term suggested by [Warren, 1990] is obtained by calculation of the sum of the maximum obstacle potentials \( U(\vec{p}) \) of every path segment \( \Gamma_i \):

\[
\tau_{\text{obst}} = \max(U(\vec{p})) \; \forall \vec{p} \in \Gamma_i. \tag{3}
\]

As the proposed solution can consist of varying numbers of path segments throughout the optimisation which can change the absolute value of the cost function, a modified cost function is proposed such that

\[
\tau_{\text{total}} = w_o \tau_{\text{obst}} + \sum_{i=1}^{n-1} U_{\text{length}}. \tag{4}
\]

where \( w_o \) is a path weighting factor, and \( \tau_{\text{obst}} \) is the integral of the the obstacle potentials over the entire path length \( s \) such that

\[
\tau_{\text{obst}} = \int_{I} U(\vec{p}) \, ds. \tag{5}
\]

However, directly evaluating this integral in practice is generally infeasible and a good approximation is obtained by

\[
\tau_{\text{obst}} = \sum_{i=1}^{n_{\text{samples}}} U_i \Delta s_i. \tag{6}
\]

The problem then is defining the obstacle potential in continuous space.

2.3 Dynamic Obstacles using Potential Fields

In this paper we considered environments which can contain many obstacles with time varying footprints such as islands, reefs and sand banks. A popular way to describe obstacles in the continuous domain is to introduce artificial potential fields to repel path candidates. Since the performance of a path is usually evaluated by some cost function, a path that penetrates an obstacle is assigned a high cost due to the high potential of the obstacle.

In order to guide path candidates away from the obstacle, such as an island or tidal flats, slopes are introduced on both sides of the obstacle border. In Figure 2 a linear function defines the inner slope and an asymptotic function the outer one as described in [Warren, 1990]:

![Figure 2: Representation of the artificial potential field of an obstacle. Shown is an island that has been simplified by a coarse polygon.](image)

\[
U(\vec{p}) = \begin{cases} 
0.5 \cdot U_{\text{offset}} \left( \frac{1}{1 + x(\vec{p})} \right), & x(\vec{p}) > 0 \\
U_{\text{max}} \left( 1 - \frac{R_{\text{off}}(\vec{p})}{R_{\text{max}}} \right) + U_{\text{offset}}, & x(\vec{p}) \leq 0 
\end{cases}
\tag{7}
\]

The vector \( \vec{p} \) represents the position in question. The scalar \( x(\vec{p}) \) is the distance to the obstacle border and \( x(\vec{p}) > 0 \) represents the outside of the obstacle. The function can be tuned with the constants \( U_{\text{offset}}, R_{\text{max}} \) and \( U_{\text{max}} \) where \( U_{\text{offset}} \) represents the step height of the potential field at the border of the obstacle, \( U_{\text{max}} \) determines the elevation of the obstacle centroid above its border and \( R_{\text{max}} \) is the farthest distance of the obstacles centroid to its border. \( R_{\text{off}}(\vec{p}) \) is the distance of the point in question to the obstacles centroid. By means of the three introduced constants the artificial potential field can be shaped appropriately.

These expressions for the potential field of an obstacle are merely a sensible choice. Other expressions like the following are also possible:
The absolute speed between two nodes is constant. The relative velocity \( \dot{\mathbf{v}}_{\text{rel}} \), that the vehicle thrusters have to deliver can be determined by subtracting the current speed from the absolute speed, see (12). The time \( T_{\text{seg}} \) is special as it is not a differential time to get from one node to another. It is assigned the start time of the path.

### 3.2 Cost Function

An efficient cost function can be designed to incorporate many different factors as suggested by [Kruger et al., 2007]. For example, a cost can be introduced for moving the start and end points of the path so that the planner can suggest advantageous locations. The cost function that was used in this work is comprised of terms for energy, obstacles and shallow water regions, time and excess speed such that:

\[
\tau_{\text{total}} = \tau_{\text{energy}} + w_o (\tau_{\text{obst}} + \tau_{\text{shallow}}) + w_t \tau_{\text{time}} + w_s \tau_{\text{speed}}
\]

where the weighting constants \( w_o, w_t \) and \( w_s \) can be used to scale the individual cost terms.

### Energy Term

The energy term comprised of the accumulated force required to overcome the inertia and drag forces \( F_{\text{accel}} \) and \( F_{\text{drag}} \), the relative velocity \( V_{\text{rel}} \) and time such that:

\[
V_{\text{rel}}(t) = \left| \bar{V}_{\text{abs}}(t) - \bar{V}_{\text{current}}(t) \right|
\]

\[
\tau_{\text{energy}} = \frac{\int (F_{\text{drag}}(t) + F_{\text{accel}}(t)) V_{\text{rel}}(t) \, dt}{\tau_{\text{time}}}
\]

As we are merely interested in an appropriate energy measure we can leave out the actual fluid dynamics parameters and introduce forces that are proportional to the physically correct ones such that:

\[
F_{\text{drag}}(t) = c_d V_{\text{rel}}^2(t),
\]

\[
F_{\text{accel}}(t) = c_i V_{\text{rel}}(t),
\]

where \( c_d \) and \( c_i \) are constants that can either be chosen to be physically correct if this is desired or freely chosen to tune the cost function. For the scale of the planning problem the effect of inertia forces resulting by different path segment speeds is considered negligible, hence \( c_i = 0 \), with the drag forces dominating.

Equation (13) is discretised in this study to

\[
\tau_{\text{energy},i} = \sum_{j=1}^{n_{\text{sub},i}} (F_{\text{drag},j} + F_{\text{accel},j}) V_{\text{rel},j} \Delta t_j
\]

\[
= \sum_{j=1}^{n_{\text{sub},i}} (c_d V_{\text{rel}}^2(t) + c_i \bar{V}_{\text{rel}}(t)) V_{\text{rel},j} \Delta t_j
\]

\[
\tau_{\text{energy}} = \sum_{i=1}^{n_{\text{seg}}} \tau_{\text{energy},i}
\]

where each segment \( \Gamma_i \) in the path \( \Gamma \) has been discretized into an appropriate number of sub-steps \( n_{\text{sub},i} \), depending on the variance of the environment at the respective segment location.
Obstacle and Shallow Water Term
For the obstacle penalty term (6) is used with samples at the same locations as for the energy term for efficiency. Additionally, shallow water regions below a minimum water level $h_{\text{min}}$ are also incorporated as a forbidden zone similarly to (6) with (8):

\[
U_{\text{shallow},j} = \begin{cases} 0, & h(\vec{p}_j) \geq 1.3 h_{\text{min}} \\ U_{\text{offset}} & 1.3 h_{\text{min}} > h(\vec{p}_j) > h_{\text{min}} \\ U_{\text{offset}} + U_{\text{grad}} & h(\vec{p}_j) \leq h_{\text{min}} \end{cases}
\]

(18)

where $h(\vec{p}_j)$ is the water height at sampling point $\vec{p}_j$. This is possible because natural seafloor topography is quite similar to an artificial potential field as in Figure 2 except for the step increase at the border. This is a computationally inexpensive way to incorporate time-variant obstacles into the cost-function without any need for precomputation.

Time and Excess Speed Term
The time term can be used to shift the weight from energy efficient paths to fast ones, penalizing unnecessary long path durations in terms of time, velocity and distance. The cost associated with time is defined as

\[
\tau_{\text{time}} = \sum_{j=1}^{n_{\text{sub}}} \triangle t_j
\]

(21)

which accounts for factors such as vehicle hotel load.

High relative vehicle speeds $V_{\text{rel}}$ are also naturally avoided due to greater engine power requirements and thus high energy expenditure. However, there may be scenarios whereby it is beneficial in energy terms to use high speeds for short path segments to avoid adverse currents that are present at certain times for example. This can result in invalid paths where the vehicle may have to move at impossible speeds. This needs to be accounted for specifically with an excess speed term. A similar scheme like the other potential functions is used here:

\[
U_{\text{speed},j} = \begin{cases} U_{\text{offset}} + U_{\text{grad}}(V_{\text{rel},j} - V_{\text{max}}), & V_{\text{rel},j} \geq V_{\text{max}} \\ 0, & \text{else} \end{cases}
\]

(22)

\[
\tau_{\text{speed},j} = \sum_{j=1}^{n_{\text{sub}}} U_{\text{speed},j} \triangle s_j
\]

(23)

where the constant $V_{\text{max}}$ resembles the maximum possible vehicle speed and $U_{\text{offset}}$ and $U_{\text{grad}}$ are function shaping constants.

4 Path Optimisation
Solving for energy efficient paths in the proposed spatially and temporally varying complex environments requires a robust optimisation technique/s capable of avoiding local minima solutions. Many local and global optimisation routines exist to solve this problem each with their pros and cons.

4.1 Local Optimisation
Local optimisation techniques are generally categorized into gradient-based and direct methods. In this problem, an analytical or even robust numerical gradient is not readily available making Gradient-based techniques infeasible.

Direct techniques on the other hand do not rely on the gradient and typically have a higher tolerance for noise, since only the absolute value of the cost function is used instead of small differences. A Local Random Search algorithm was developed as a simple alternative to the gradient descent technique which is robust to noise and can overcome small local minima.

The algorithm applies a random Gaussian-distributed offset to every parameter and keeps the change if it is an improvement. If the first try is not an improvement, the negated offset is tried. The step size, which is the standard deviation of the random offsets if the respective weight equals one, is initially coarse to not get stuck in local minima easily and improve the convergence speed. It is gradually reduced to allow for finer optimisation, similar to an annealing schedule except that at all times only steps in descent direction are permitted. A good initial step size is the mean half segment length, since the offset is concentrated to a region where improvements are the most likely. Weights are used when parameters have significantly different value ranges as a means of scaling the random offset. If scaling for individual parameters is not required all weights can be set to one. Although the technique is able to overcome small local minima due to the randomness and the annealing schedule, it clearly is a local optimisation with all the usual weaknesses and strengths.

4.2 Global Optimisation
Global optimisation has the goal of finding the global minimum of an arbitrary objective (or cost) function. Popular approaches, that are suitable for continuous multimodal problems, are particle swarm optimisation [Kennedy and Eberhart, 1995], simulated annealing [Kirkpatrick et al., 1983] and genetic algorithms [Goldberg, 1989]. In this investigation, it was determined that genetic algorithms provided inconsistent solutions compared to the other global optimisation algorithms.
4.3 Swarm Optimisation

Of the previously presented techniques, only local random search and simulated annealing were deemed suitable optimisation methods and the problem of finding globally optimal paths remains. Since both techniques depend to some extent on the initial path, it has to be selected wisely to be able to find the globally optimal path. Unfortunately without preprocessing of the environment this is not possible. Our solution to this is to optimize a set of different paths simultaneously in the hope that one is sufficiently close to the global optimum.

This work has addressed multiple initial path optimisation by parameterizing splines to span the area between the start and goal location. Figure 3 shows a set of cubic $C^2$-splines from which the initial paths are generated. The geometry of the swarm of initial paths can be controlled by the angular range $\alpha$, the swarm width factor $\lambda$, the node number $n_N$ and the number of paths $n_P$ in the swarm. For each path, two symmetric splines are parameterized with the middle point $\vec{p}_{m,i}$ and the offset angle $\alpha_i$:

$$\alpha_i = (i - 1) \frac{\alpha}{n_P - 1} \frac{\alpha}{2} ,$$

$$\vec{p}_{m,i} = \vec{p}_m + \alpha_i \lambda \|\vec{p}_{\text{start}} - \vec{p}_{\text{goal}}\| \vec{d}_{\text{perp}} .$$

The tangent at $\vec{p}_{m,i}$ points in the same direction as $\vec{d}$. The scaling by the distance between the start and goal location is done to preserve the spline shape for varying setups. Now that the splines are fully determined, with the spline equations from [Weisstein, 2008] the path swarm can be parameterized by equidistant sampling of the spline variable.

As the node number is chosen to be low to keep the problem as simple as possible, the resulting path usually needs further refinement to exploit the full optimisation potential. Such refinement is achieved in this investigation by increasing the number of path segments and further optimising the chosen path using either simulated annealing or local random search.

5 Ocean Model

The survey area for this work is Moreton Bay in Queensland, Australia (see Figure 4(a)). Due to the topography with the two large islands, Moreton and Stradbroke Islands, and many smaller islands the currents are mostly driven by the tidal circle. Thus the currents completely reverse direction within about 6 hours. Accordingly, a path taking 24 hours involves four current inversions along with time-variant obstacles due to tidal water level changes.

The ocean forecast used in this work is provided by a hydrodynamic simulation which is driven by tidal boundary constraints and wind forecasts. The simulations original purpose was focused on water quality management [Bell and Amghar, 2002]. As such, the ocean simulation only solves currents in two spatial dimensions using an average of the currents in vertical direction. This model limitation simplifies the search space for path planning, however, the solutions provided in this paper are readily extendable to include the vertical current distribution if available.

5.1 Sampled Ocean Data

The path planner described here does not include the actual ocean simulation. Instead it works with pregenerated forecast.
data sets that are imported as files. As can be seen in Figure 4(b), the data is sampled on a non-uniform grid. The data is sampled every 15 minutes at every sample point.

5.2 Environment Complexity

The proposed AUV operating environment is highly dynamic. Figure 5 illustrates a typical change of the environment within a 6 hour period. Path planners that do not incorporate these time-varying currents and obstacles cannot succeed under these circumstances. Further complexity arises from the maximum current speed in this region of 1.5 m/s which is approximately 50% greater than the maximum possible AUV speed.

The temporally and spatially variable environment can result in many possible infeasible path configurations that do not even penetrate any obstacles. The passage between the two islands also features a large sandbank (black region in Figure 5) that can be completely exposed to covered with about 2m of water during a complete tidal cycle. Additionally, the area of possible operation is large, spanning about 73km East/West and 112km North/South. The non-uniform mesh is comprised of about 8000 nodes in total and the time of one data set can span several months sampled every 15 minutes. Thus this is a very interesting and challenging environment for a path planner to perform.

Figure 5: Environment snapshots of model data with a time difference of 6 hours of the passage between Moreton and Stradbroke Island. The black regions identify exposed seafloor (sand banks). The blue arrows are proportional to the current at that location.

6 Ocean Data Results

A numerical and experimental evaluation of the proposed optimal path planning algorithm were conducted using the ocean model of Moreton Bay presented above to assess its performance.

6.1 Simulation: Dynamic Obstacle Case

As an exemplar, the proposed algorithms of Sections 2, 3 and 4 were applied to a case scenario whereby the AUV must travel across the channel between Moreton and Stradbroke Islands. The start and goal location are 3.1 kilometres apart with the location having the strongest currents of the whole bay area due to the bottleneck topology between the islands and there is a sand bar between them that is exposed on low tide.

Figure 6(a) shows the problem setup with the initial swarm parameterisation, with Figure 6(b) showing the results of the first to fourth rank solutions averaged over a set of 79 runs for two optimisation routines: Simulated Annealing and Local Random Search. All optimisations were conducted with a low weight on the required path time, thus optimizing for low energy consumption. The minimum allowed traversable water level was chosen to be 1.4 meters to allow only safe passages.

Figure 6: (a) The problem setup with the swarm parameterisation \( \alpha = 4 \text{rad}, \lambda = 1, n_N = 7 \) and \( n_P = 7 \). (b): The mean path performance (along with standard deviation) of the first to fourth ranked solutions over a set of \( N = 79 \) runs.

The results of Figure 6(b) reveal that apart from the first ranked solution there is a high diversity in solutions, hinting towards the complexity of this problem. Figure 7 shows three examples of common low-cost solutions. It has to be noted though, that the first ranked solution is usually similar in shape to 7(a), which corresponds to the left most bar graph in Figure 6(b). While the first ranked solution is usually similar among both optimisation algorithms the following ranks can differ significantly. Simulated annealing has a much higher variance in the performance for the lower ranks than local random search.

A common feature of the optimised paths was that they
wait in one or another form before the shallow region becomes passable. The near optimal solution is able to leverage the present currents to the fullest, and although taking a large detour compared to the other solutions, its cost outperforms them by a factor of more than two.

6.2 Experimental Results

The performance of the algorithms to generate efficient paths was applied to the CSIRO developed Starbug AUV [Dunbabin et al., 2005; Dunbabin and Allen, 2007]. The mission was to travel from the south to the north of Peel Island, approximately 2.24km in a straight line, in an energy efficient manner. The generated path was uploaded to the Starbug AUV, shown in Figure 8, which was then released at the appropriate time before autonomously performing the mission. The mission was specified as a series of waypoints, times and velocities.

Figure 8: The Starbug Mk3 AUV used to evaluate path planning strategy.

Figure 9 shows an overview image of Peel Island and the location (track) of the resulting mission. The AUV was commanded to conduct the mission at the surface so that a complete GPS record could be obtained to evaluate mission tracking performance.

Figure 10 shows a close up of the demanded and actual trajectories during the mission. The total mission time was 125 minutes and distance travelled was 2.92km, giving an average speed of 0.39m/s. The measured battery capacity used was 4.8 Amp hours. This suggests the proposed optimal path provided a 32% energy saving over a straight line mission of equivalent total length and average speed in still water (estimated to be 7.1 Amp hours).

Figure 9: Overview of the location of the Peel Island field mission with actual path. Reference image from Google Earth.

Figure 10: Closeup of the reference path (green) and the actual path (red) that was taken by Starbug AUV during the Peel Island field mission.

Overall, the mission shown was successful demonstrating the energy benefit of the proposed algorithms. However, as seen in Figure 10 there is a tracking error between the demanded and actual paths. This is due to an initial error in deployment location of the AUV between the planned path and experiment with the vehicle unable to completely re-acquire the desired trajectory, although the error was only 100m.

7 Conclusions

This paper provides an overview of a novel optimally energy efficient path planning algorithm for ocean environments which exhibit strong, time varying currents with temporarily varying dynamic obstacles such as sand banks and islands.
The solution considers a cost function evaluated in continuous space which includes time, obstacles, traversability, propulsion energy and speed. To avoid local minima, the solution uses a swarm search approach to increase search space, with either simulated annealing or local random search with dynamic node allocation for refinement. The performance of the algorithm has been demonstrated using an ocean forecast model of Moreton Bay in Brisbane in both simulation and experiment with energy savings greater than 32% over simple still water paths of equal length. The algorithm is currently being extended to include variable water velocity with depth, with experimental evaluation of missions exceeding 24 hours.

Acknowledgments

This work was funded by the Commonwealth Scientific and Industrial Research Organisation (CSIRO) through its National Research Program in Wealth from Oceans. The authors would like to express their sincere thanks to Prof. Tony Howes from the University of Queensland and the Queensland Healthy Waterways Initiative for their kind support and supplying of the oceanography modelling data used in this study. Also, thanks goes to Alistair Grinham from the University of Queensland for his assistance during vehicle field trials.

References


