A Suboptimal Strategy for Autonomous Marine Vehicle Navigation in Variable Sea Currents

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Keywords: Suboptimal, Navigation, Uncertainty, Variable, Sea Current, Minimum-time, Marine Vehicle.

Abstract: A navigation strategy achieving suboptimality in the transits of autonomous marine vehicles is presented. The objective of optimal navigation is the minimum-time transit of a marine vehicle moving in a flow field of sea currents. Reactive revisions of an ongoing optimal navigation followed by tracking controls are the key features of the proposed suboptimal strategy. In this research, a globally working numerical procedure for obtaining the solution of an optimal heading guidance law is presented. The developed solution procedure derives optimal heading reference that achieves the minimum-time transit of a marine vehicle in any deterministic sea currents whether stationary or time varying. The proposed suboptimal navigation works as a fail-safe strategy for the optimal navigation when there happen significant hostile actions which possibly cause the failure in ongoing optimal navigation. Simplicity and robustness are notable characteristics of our suboptimal strategy compared to others seeking rigorous optimality. Simulation results of autonomous underwater vehicle routing conducted by suboptimal navigation in various sea currents are presented.

1 INTRODUCTION

The sea environment contains several kinds of flows that significantly interact with the motion of surface or submerged vessels. Among these, sea or ocean currents are the most significant flow disturbances, directly affecting the travelling speed, the power consumption, and thus the endurance and range of a vehicle. Suppose that a marine vehicle is to transit to a given destination in a region of flow disturbance. Then it is quite natural that the transit time of the vehicle should change according to the selection of a specific trajectory. When the power consumption of a vehicle is controlled to be constant throughout the transit, the travelling time is directly proportional to the total energy consumption.

Recently, autonomous marine vehicles (AMVs) are playing important roles in diverse applications, such as oceanographic survey, marine patrol, undersea oil/gas production, and various military applications (Nicholson and Healey, 2008). Relying on an on-board battery system as the main energy source, endurance and moving range of an AMV are limited by its power consumption, as well as its energy capacity. Therefore, the minimum-time transit of an AMV can achieve enhanced vehicle safety and mission effectiveness (Kim and Ura, 2010).

Considerable research has been done on the optimal guidance or path planning for a mobile vehicle through a varied fluid environment. Though aiming at the same objectives, the most notable difference between the guidance and the path planning is the consideration of dynamical constraints. While, in general, dynamical constraints in vehicle motion are incorporated into the formulation of vehicle guidance problems (Crespo and Sun, 2001; Zhao and Bryson, 1990), they are ignored in most path planning problems (Alvarez et. al, 2004; Papadakis and Perakis, 1990). This allows great flexibility in the target path generation, enabling the use of combinatorial optimization techniques in path planning approaches. Dynamic programming (DP) might be one of the most classical and popular techniques for combinatorial optimization. Papadakis and Perakis (1990) treated the problem of minimal time vessel routing in a region of deterministic wave environment on the basis of the dynamic programming approach. In this problem, the navigation region is subdivided into several subregions of different sea states. The optimal navigation path is derived by determining the sequence of subregions to be visited, which minimizes the travelling time to a destination. Aside

Kim, K.
A Suboptimal Strategy for Autonomous Marine Vehicle Navigation in Variable Sea Currents.
DOI: 10.5220/0006906204320439
In *Proceedings of the 15th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2018) - Volume 2*, pages 432-439
ISBN: 978-989-758-321-6

from the difficulty in establishing a practically available numerical procedure adjoining the formulation, the significant solution dependency on the regional subdivision is a critical issue in the approach. Some recent researches reported the application of a generic algorithm (GA) to path planning for an underwater vehicle in a variable ocean. Major advantages of the GA over dynamic programming are reduced computational complexity and time, though it is susceptible to local minima, however. Also, one of its significant drawbacks is a strong constraint in generating the optimal path. In a path planning application on the basis of GA, a user-defined primary coordinate should strictly maintain a monotonic increase in the optimal path (Alvarez et. al, 2004). This is such a strong constraint that makes it impossible to generate the optimal path containing interim backward intervals.

Optimal guidance of a mobile vehicle in an arbitrarily varied fluid environment is a strongly nonlinear optimization problem, which is quite difficult to solve numerically, as well as analytically. One of the recent approach to treating this sort of problems is cell mapping (Crespo and Sun, 2001). Though the cell mapping is known to be especially adequate for strongly nonlinear problems, computational demand for obtaining a stable solution is enormous.

Path finding or guidance algorithms can be classified into two categories according to the instant when its solution is generated. While a pregenerative one derives an unchangeable solution prior to a mission, a reactive algorithm allows revised solution during the mission (Alvarez et. al, 2004; Kamon and Rivlin, 1997). In this research, as a reactive strategy for optimal vehicle navigation in varied sea current environments, we propose a concept of suboptimal navigation. In our problem of optimal navigation, the minimum-time transit of a vehicle is attempted on the basis of the optimal guidance law presented by Bryson and Ho (1975). The solution of this guidance law is a time sequence of the optimal headings. In an actual field application for the minimum-time transit, obtained optimal headings are tracked by a vehicle as the reference in its heading control. Compact as it is, the optimal guidance law is derived without considering any specific dynamic constraint, like many other path planning approaches. In our suboptimal strategy, we compensate for this drawback by incorporating reactive revisions in the optimal navigation followed by tracking controls. Once there happens a failure in tracking the optimal trajectory due to the limitations in vehicle dynamics, revised optimal navigation generates a new optimal trajectory to be followed from then on.

In addition to the dynamic constraints, there are several unfavorable environmental factors that might be fatal in achieving the proposed optimal navigation. Examples of such factors are uncertainties in sea environments, severe sensor noises, or temporally-faulty actuators (Burken et. al, 2001; Kim and Ura, 2009). As a fail-safe strategy, our suboptimal navigation can cope with the failure in ongoing optimal navigation due to any of the abovementioned factors. The result of suboptimal navigation is not rigorously optimal, but achieves a near-optimality realized by the utmost in-situ actions as possible.

Though provides superior adaptiveness, robustness, and more flexibility, a reactive approach in marine vehicle navigation incurs a heavy computational cost in its onboard implementation (Alvarez et. al, 2004; Crespo and Sun, 2001; Kim and Ura, 2009). In this research, we present a practical solution procedure of highly reduced computational cost which derives the numerical solution of the optimal guidance law in implementing our suboptimal as well as optimal navigation. This is a simple procedure applicable to any sea current whether stationary or time-varying, provided that its distribution at a specified instant is deterministic. Robust global convergence is another advantage of our procedure. On the basis of the minimum principle (Bryson and Ho, 1975), it realizes an efficient search space reduction, enabling optimal solution search in a global manner. Due to this algorithmic nature, our numerical procedure has a much lower possibility of taking local minima, compared to other search algorithms, primarily relying on initial guesses.

As mentioned previously, deterministic sea current is the prerequisite for implementing our optimal and suboptimal navigation strategies. In many cases however, it is not easy to obtain a predescribed current distribution in the sea region of interest. One of the simplest ways to build up sea current data is direct measurement. Many governmental, public, or private institutions related to maritime affairs provide tabulated surface current distributions, obtained by field measurements (McCormick, 2007; National Ocean Service, 2002). The availability of these data is more or less restrictive, because there are many sea regions for which the current distribution data are not built up or treated as confidential. As another source of ocean environmental information, numerical estimation models are playing an important role. By assimilating the field measurement into them, some recent numerical models provide both forecasts and nowcasts of ocean fields with sufficiently accurate mesoscale resolution (Robinson, 1999).

2 MINIMUM-TIME NAVIGATION

2.1 Problem Definition

As mentioned previously, the objective of the optimal navigation presented in this study is the minimum-time transit of a marine vehicle in sea currents. In still water, a straight line connecting an initial position and a destination is the shortest and thus the minimum-time path. In regions of sea currents, however, smart navigation possibly achieves the minimum-time transit of a marine vehicle in which it takes the best trajectory differing from the straight-line. In this paper, we present a numerical solution procedure for the minimum-time guidance law by Bryson and Ho (1975). The solution of the guidance law is the optimal heading reference, by tracking which a vehicle achieves the minimum-time transit to the destination, following the optimal trajectory.

In treating the minimum-time guidance law, we use two sets of coordinate systems: the inertial (earth-fixed) coordinate system *o-xy* and the body fixed coordinate system *o'-x'y'*, as shown in Fig. 1.

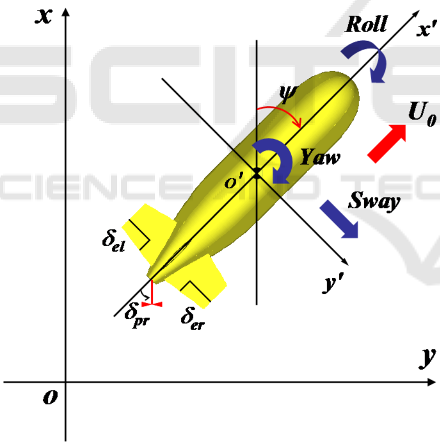

Figure 1: Coordinate systems for optimal guidance problem formulation.

As the marine vehicle used in our navigation problem, we employ an autonomous underwater vehicle (AUV) "r2D4" described in Kim and Ura (2009). In Figure 1, actuator inputs as well as kinematic variables used in the lateral dynamic model of our AUV are represented. While δ_{pr} denotes the main thruster axis deflection, δ_{el} and δ_{er} are the deflections of elevators on left and right sides, respectively. Vehicle heading ψ is defined as the angular displacement of the x'-axis relative to the x-axis. In this work, we approximate that the direction of the vehicle's advance velocity coincides with the x'-axis.

Since the distribution of a sea current is considered to be deterministic in our research, current velocity is described as a function of the position and time. Therefore, on the assumption that the advance velocity of a vehicle and the current velocity are superimposable, the resultant vehicle velocity in a sea current is expressed as

$$\begin{aligned} u &= \dot{x} = U_0 \cos\psi + u_c(x,y,t) \\ v &= \dot{y} = U_0 \sin\psi + v_c(x,y,t) \end{aligned} \tag{1}$$

where u and v are the components of the vehicle velocity relative to the inertial frame, U_0 is the advance speed of the vehicle in still water, and u_c and v_c are the components of current velocity at a given position and time. It is noted that we assume U_0 is constant throughout a mission, which corresponds to the operating condition of letting the rpm of vehicle's main thruster fixed.

Equation (2) shows the minimum-time guidance law of a marine vehicle moving in a sea current (Bryson and Ho, 1975). Detailed procedure deriving (2) are well explained in Kim and Ura (2009). It is noted here that if only deterministic, there is no restriction on the type of the sea current in (2). That is, not only stationary, but also time-varying sea current can be applied to (2) in deriving the solution for optimal navigation. This leads to one of the most powerful aspect of our approach over many other path planning algorithms based on combinatorial optimization.

$$\dot{\psi} = \sin^2\psi \frac{\partial v_c}{\partial x} + \frac{1}{2}\left(\frac{\partial u_c}{\partial x} - \frac{\partial v_c}{\partial y}\right)\sin 2\psi - \cos^2\psi \frac{\partial u_c}{\partial y} \tag{2}$$

2.2 Numerical Solution Procedure

Equation (2) is a nonlinear ordinary differential equation (ODE) for an unspecified vehicle heading $\psi(t)$. If the functions $u_c(x,y,t)$ and $v_c(x,y,t)$ describing current velocity distribution are differentiable as well as deterministic, the solution of (2) seems to be attainable with an initial value of $\psi(t)$, in terms of an appropriate numerical solution algorithm such as Runge-Kutta. However in practice, with an arbitrary initial heading a vehicle travelling by the guidance law (2) does not reach the destination. More precisely, the initial value of vehicle heading is not arbitrary, but is to be assigned correctly, consisting of a part of the solution. This is because (2) is derived from the Euler-Lagrange equation, which is a typical example of the two-point boundary value problem, characterized by split boundary conditions in states and costates (Bryson and Ho, 1975). To obtain the solution of a two-point boundary value problem, an iterative solution procedure is usually required. The most famous and commonly used numerical procedures for such purpose are the shooting and the relaxation methods (Press et. al, 1992). However, direct applications of these methods to our minimum-time navigation problem have significant difficulties. In applying shooting method to a two-point boundary problem in time domain, governing ODEs with proper initial guesses should be integrated until reaching the upper limit of the boundary. However, as noticeable from its name, i.e., the minimum-time navigation, our problem is a so-called free boundary one, having unspecified upper limit in time domain. In treating a free boundary problem by relaxation method, on the other hand, the independent variable should be transformed into a new one defined between 0 and 1. Here, we can anticipate an intrinsic serious difficulty in determining the stepsize in free boundary problems. Properness of temporal grid distribution ensuring convergence is initially unknown and to know it is extremely difficult before the end of a computation. Moreover, strong initial guess dependency of the solution is another serious concern in applying the relaxation method to our problem, inappropriate selection of which possibly leads to a local optimality or divergence (Press et. al, 1992).

As a new approach deriving the numerical solution of the optimal guidance law (2), we presented a search procedure which determines correct initial heading of this two-point boundary value problem. Being named AREN (Arbitrary Reference Navigation), our procedure works globally on the basis of the minimum principle. Figure 2 shows the algorithmic scheme of our solution procedure. In Fig. 2, an asterisked variable denotes the one corresponding to the optimal solution. Refer to Kim and Ura (2009) for the details of AREN. By applying the correct (i.e., optimal) initial heading ψ_0^* derived by AREN to (2) and solving it in time domain, we can obtain the time sequence of the optimal heading reference which achieves the minimum-time transit to the destination. It is noted here that the minimum distance l_{min}^* shown in Fig.2 is to be interpreted as the residual error in the converged solution, since it represents how closely a vehicle has approached the destination. Therefore, when l_{min}^* is unacceptably large, the optimal initial heading should be refined by further searches repeated in the vicinity of ψ_0^*.

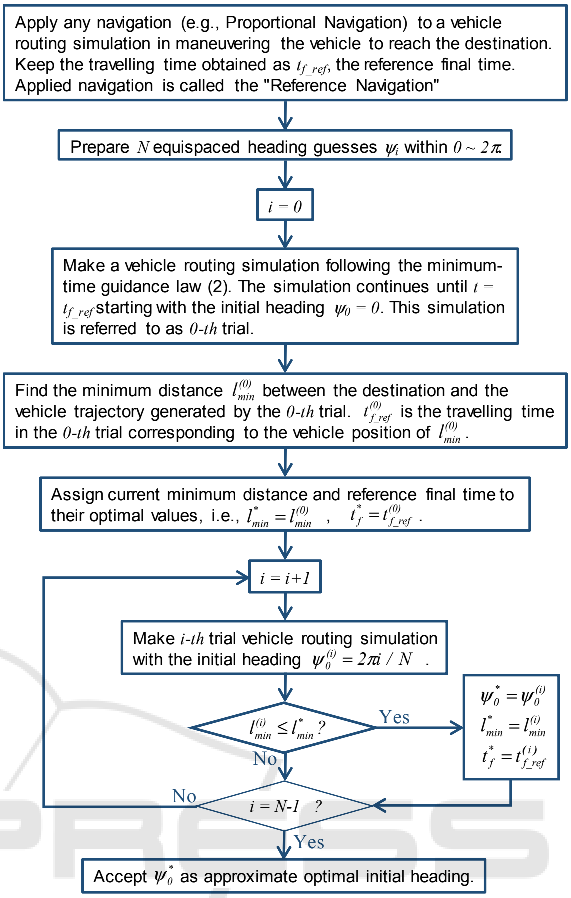

Figure 2: Algorithmic scheme of the numerical solution procedure AREN for deriving the optimal initial heading.

3 SUBOPTIMAL NAVIGATION

3.1 Optimal Navigation Validation

As a validation test of our solution procedure explained thus far, we conducted a simulation of minimum-time vehicle routing in a stationary flow field. Deterministic as it is, the flow field is an artificial one induced by multiple vortical sources. A vortical source is a mathematical singularity made of a point source superimposed by a point vortex. Once its location and strength are determined, flow field induced by a vortical source is immediately calculated (Kim and Ura, 2009). Locations and strengths of the vortical sources used in this example are summarized in Table 1.

In this example, the AUV r2D4 is routed by three different navigation strategies. The first one is so called proportional navigation (PN), which might be the simplest strategy for guiding a vehicle to a target.

In PN, the heading of a vehicle is continuously adjusted to let its line of sight (LOS) direct toward the target. It should be noted here that, by default, PN is used as the reference navigation deriving the reference final time t_{f_ref} (Fig. 2), in our research. The second one used for the performance exemplification of our optimal navigation is straight-line tracking. As noticeable from its name, the straight-line tracking lets a vehicle follow a straight-line trajectory connecting the initial position and the destination. In a straight-line tracking, vehicle heading is determined so as to compensate for the trajectory normal component of the flow velocity at current vehicle position. Detailed descriptions as well as at-sea field results of the straight-line tracking navigation are found in Kim and Ura (2002). In this paper, it is assumed that the main thruster rpm of the AUV r2D4 is controlled to keep its water-reference velocity to be 1.54 m/s throughout any mission. In Fig. 3, vehicle trajectories in the vortical source flow field obtained by three different navigation strategies are shown.

Table 1: Locations and strengths of vortical sources.

No.	Location (m)	Vortical source strength	
		Source strength (m^2/s)	Vortex strength (m^2/s)
1	-50 , 250	-15	-10
2	-100 , 400	-40	-30
3	-100 , 500	-50	-50
4	-250 , 600	40	-35
5	-200 , 150	30	30
6	-300 , 350	-35	-35
7	-400 , 550	30	30
8	120 , 540	-40	60
9	-500 , 0	-50	15

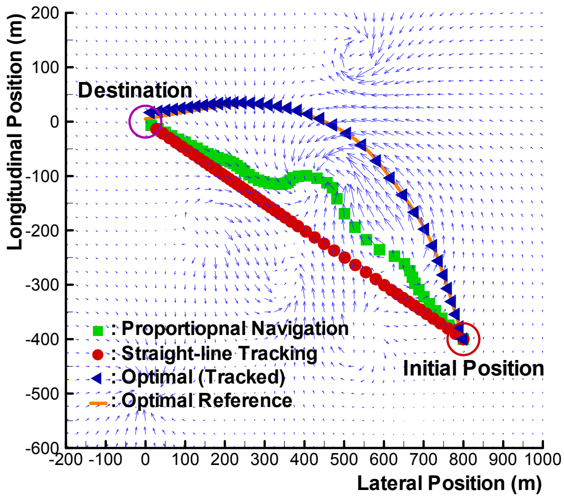

Figure 3: Vehicle trajectories in a vortical source flow.

In each navigation shown above, the vehicle moves towards the destination at the origin, starting from the initial position (-400 m, 800 m). Though it gets to the final state at the destination, the vehicle following PN experiences severe drift due to the interaction with current flow. In the straight-line tracking, the vehicle has difficulty in moving toward the destination, because in a large portion its travel, it is made to advance against the flow. In the optimal navigation however, the vehicle takes a detouring trajectory riding on favorable flows. The optimal navigation enables the vehicle to get flow-induced speed increase in favorable flows. Travelling time reduction by this speed increase prevails over the extra travelling time caused by the detour, resulting in the travelling times of 795.0 s, 762.5 s, and 550.5 s, corresponding to the PN, straight-line tracking, and optimal navigation, respectively.

3.2 Suboptimal Strategy

The optimal navigation implemented by our solution procedure seems to work properly and effectively, as shown in the previous example. Here, it should be noted that one of the essential prerequisites for accomplishing the proposed optimal navigation is that the system being treated is deterministic. Induced by mathematical singularities, vortical source flows are perfectly deterministic without any uncertainty. In real world, however, any measurement data does contain uncertainty. Another significant issue is the dynamic constraint. An optimal trajectory obtained by solving the guidance law (2) is the one derived without considering dynamic constraints of a specific vehicle. This means that some optimal trajectories are not able to be realized unless a vehicle exerts unrealistic velocity or acceleration. As a remedy for such issues, we propose the strategy of suboptimal navigation. The suboptimal navigation is a fail-safe strategy towards the field implementation of the optimal navigation. The basic idea of the suboptimal navigation presented in this paper is rather simple. Let d_l denote the deviation distance between the present vehicle position and the preassigned one on the optimal reference trajectory. When d_l exceeds a prescribed acceptable limit set for preserving an ongoing optimal navigation, the high-level controller for the vehicle navigation is activated and revises the current optimal trajectory. By re-applying the AREN to current vehicle position, velocity, attitude, as well as environmental conditions, optimal trajectory as the reference is newly revised. Figure 4 depicts the schematic of the suboptimal navigation explained thus far.

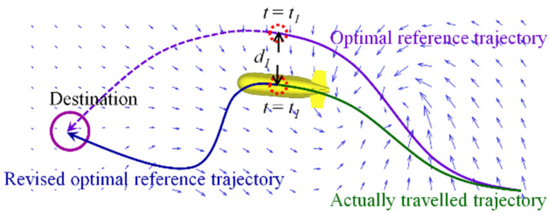

Figure 4: Schematic of the suboptimal navigation.

4 APPLICATIONS

4.1 Suboptimal Navigation in Northwestern Pacific

In what follows, we apply the suboptimal navigation to actual sea environments. The sea region selected for the first example is located in the Northwestern Pacific Ocean near Japan. The daily updated sea current data of this region is available at https://www.data.jma.go.jp/kaiyou/data/db/kaikyo/daily/current_HQ.html?areano=2 presented by the Japan Meteorological Agency. The most notable environmental characteristic in this sea region is the current field dominated by the Kuroshio. The Kuroshio is a strong western boundary current flowing northeastward along the coast of Japan.

At first, the optimal navigation has been applied to the vehicle routing in the abovementioned sea region. In this example, we do not consider any environmental uncertainty in the sea current data. Figure 5 shows the vehicle trajectories obtained by three different navigation strategies: PN, straight-line tracking, and optimal navigation.

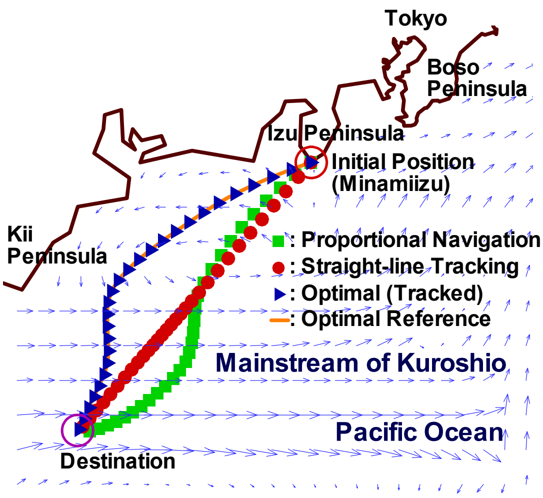

Figure 5: Vehicle trajectories in a Northwestern Pacific Ocean region.

As shown in the figure, like the preceding example in which exact values of current velocity and its gradients are available anywhere in the region, the vehicle tracks the optimal reference trajectory with a negligibly small deviation. This indicates that our strategy of optimal navigation is also valid in the actual sea current data.

In the following example, we apply the optimal navigation to a vehicle routing in the same sea region that was used in the preceding example. The only thing different from the preceding example is we consider uncertainty in our sea current data in order to enhance the reality of our optimal navigation. An environmental uncertainty model is introduced in determining sea current velocities. The uncertainty components in the sea currents are expressed as additive white Gaussian noise (AWGN). Taking the sea current velocities in the Northwestern Pacific Ocean used beforehand as the mean values, on-site current velocities including uncertainty are given by

$$\begin{aligned} u_{cs}(x,y,t) &= u_c(x,y,t) + e_u(\sigma) \\ v_{cs}(x,y,t) &= v_c(x,y,t) + e_v(\sigma) \end{aligned} \tag{3}$$

where u_{cs} and v_{cs} are the components of the on-site current velocity, u_c and v_c are the components of the deterministic current velocity taken from the database, and $e_u(\sigma)$ and $e_v(\sigma)$ are the AWGNs with standard deviation σ. As the parameter for specifying the value of σ in a given navigation region, we introduce the regional mean current speed U_{cm} defined as

$$U_{cm} = \frac{\sum_{i=1}^{N} \sqrt{u_{ci}^2 + v_{ci}^2}}{N} \tag{4}$$

where i denotes the index covering all grid nodes on which the database-based current velocities are defined. In Fig. 6, vehicle trajectories obtained by optimal navigation applied to different levels of velocity uncertainties are shown. When the level of velocity uncertainty is such that $\sigma = 2U_{cm}$, the optimal trajectory derived without considering uncertainty still seems to work acceptably. As a result, though slightly deviating from the destination, the final position of the vehicle remains in the vicinity of the destination. When the level of velocity uncertainty increases up to $\sigma = 4U_{cm}$, however, following the optimal trajectory can no longer make the vehicle approach the destination, as shown. As was demonstrated in this example, the optimal navigation proposed in this research bears the risk of failure which increases in proportion to the degree of environmental uncertainty.

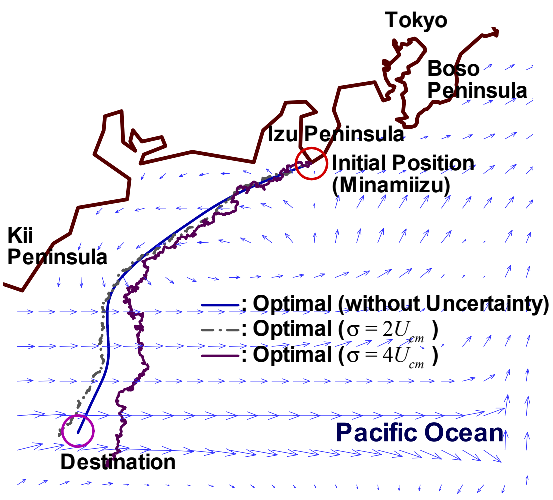

Figure 6: Vehicle trajectories in a Northwestern Pacific Ocean region. In this example, on-site sea current velocities are generated to include uncertainties expressed by AWGNs.

Next, we apply the suboptimal navigation to a vehicle routing in the same sea region. In the suboptimal navigation, however, the vehicle does not merely track the pregenerated optimal reference trajectory throughout, but regenerates and follows new ones whenever necessary, adapting to the current states of environment as well as the vehicle position. Figure 7 shows the result of suboptimal navigation.

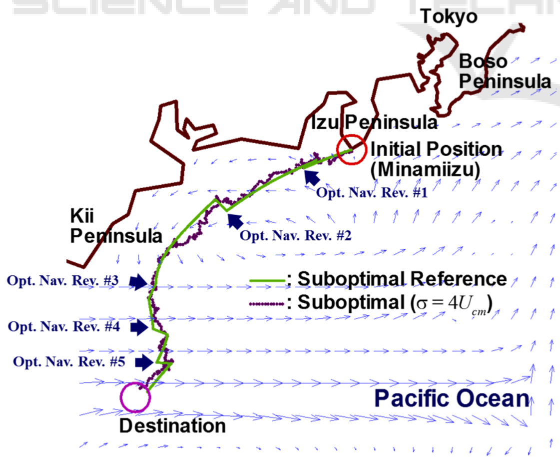

Figure 7: Vehicle trajectories by suboptimal navigation.

In Fig.7, it is noted that during the travel the optimal navigation has been revised five times. Discontinuous intervals appearing in the optimal reference trajectory indicate the occurrences of the optimal navigation revisions. These revisions enable the vehicle to arrive at the destination.

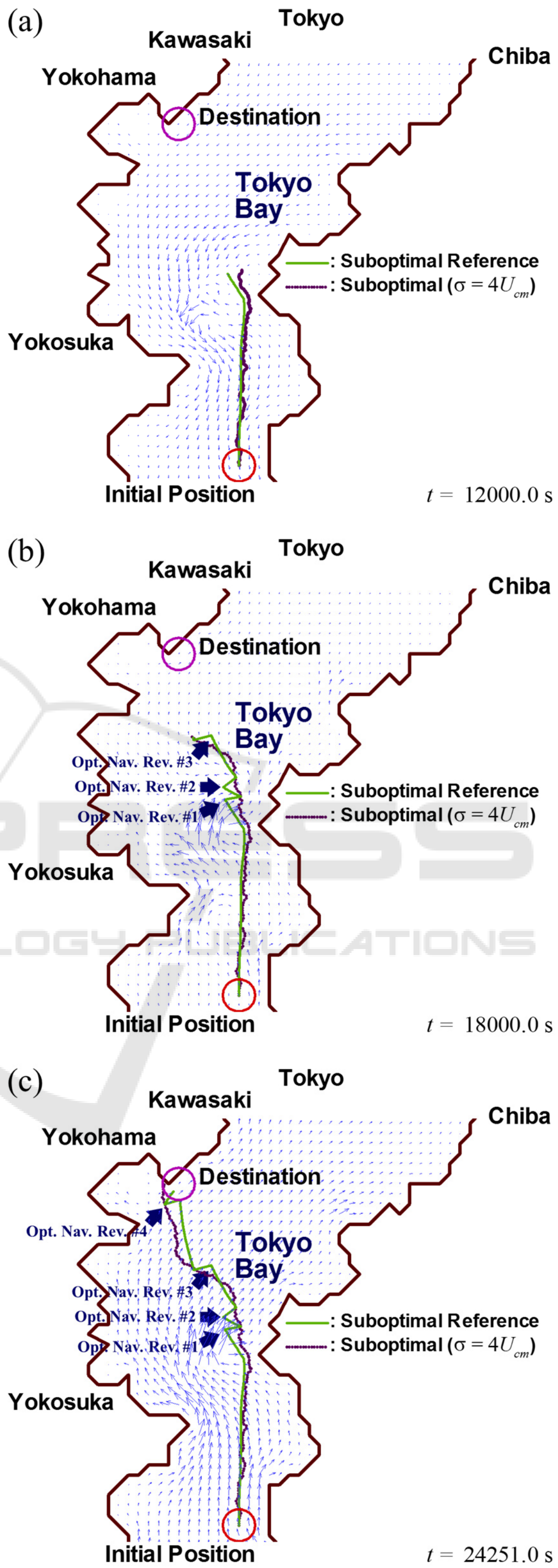

Figure 8: Monitored vehicle trajectories by suboptimal navigation in a tidal flow in Tokyo Bay observed at (a) 12000.0 s (b) 18000.0 s (c) 24251.0 s.

4.2 Suboptimal Navigation in a Time-Varying Sea Current

The last optimal navigation example presented in this paper is an underwater vehicle routing in Tokyo Bay. In this example, we consider the mission of minimum-time homing to the port of Yokohama. Due to its narrow entrance and shallow depth, sea currents in Tokyo Bay are hardly affected by the outer ocean currents such as Kuroshio. Instead, like many other littoral zones, currents in Tokyo Bay are dominated by the tidal flow. In this research, we use the time-varying sea current distribution data in Tokyo Bay, generated by a numerical tidal flow simulation model by Kitazawa et al. (2001). Figures 8(a) ~ (c) are sequential vehicle trajectories derived by applying the suboptimal navigation. By the suboptimal navigation consisting of total four self-revisions, the vehicle has accomplished its homing mission.

5 CONCLUSIONS

In this paper, a systematic procedure for obtaining the numerical solution of the optimal guidance law for a marine vehicle moving in a region of sea current has been presented. Reduced computational cost is one of the outstanding features of our solution procedure. Whilst linearly proportional to the area of a search region in dynamic programming, the computational time in our procedure exhibits square root dependence on it. Moreover, unlike other path finding algorithms such as dynamic programming or generic algorithm, our procedure does not extend search space when applied to a time-varying problem. This means a great advantage that a time-varying problem can be solved merely using the same computational cost as is required for solving a time-invariant one.

As a fail-safe strategy for the field application of the optimal navigation, suboptimal navigation has been proposed. The fact that there actually are several uncertainties which possibly disrupt ongoing optimal navigation emphasizes the practical importance of the suboptimal strategy proposed by us.

ACKNOWLEDGEMENTS

The author would like to thank Prof. D. Kitazawa of IIS, the University of Tokyo for providing simulated tidal flow data of Tokyo Bay.

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