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Arctic sea route path planning based on an uncertain ice prediction model

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ABSTRACT

As the global temperature has been increasing, the ice-covered area in the Arctic region has been decreasing. One of the opportunities to take advantage of the situation is the Arctic shipping between Asia and Europe. For economical and safe route selection, an ice navigation system is required for ships operating in the region, since the ice condition is changing hour after hour, and the ships sail long distances for weeks. Therefore, route selection by hand is challenging. The ice model in an ice navigation system simulates dynamic sea ice behavior, and its result is delivered to an optimization model for the path planning domain. During the map generation process for the path planning, both the ice model and the input data for the ice model have uncertainties, which cause prediction uncertainties in the sea ice behavior. For safety, the uncertainties should be considered carefully. Otherwise, accidents in the extremely severe conditions can happen because of unexpected events caused by the uncertainties of the prediction. Notwithstanding the safety issues, uncertainties in the ice navigation system have not been considered in previous research. In this work, the path planning problem in ice-covered waters is presented as a dynamic stochastic path planning problem by generating a map through the ensemble simulation of an ice model. And an uncertainty-based path planning model is proposed to find an optimal route under time-varying stochastic conditions. A heuristic path planning algorithm is employed, and different path planning models (stochastic vs. deterministic) are compared through simulations in two different scenarios for validation of the model.

1. Introduction

Today the drastic melting of ice in the Arctic region is one of the most important problems in science and engineering. Many researchers have studied and tried to solve the environmental issue by developing technologies for reducing, preventing, and capturing CO_2. On the other hand, shipping, and oil and gas companies consider this unfavorable environmental trend as a money-making opportunity. The decreased ice-covered area enables people to have deeper access to the Arctic, which would result in the possibility of developing Arctic resources and economical shipping through the Arctic between Asia and Europe as well as between Asia and North America.

Compared to the traditional ship path planning problem (Benjamin et al., 2006; Churkin and Zhukov, 1998; Szlapczynski, 2006; Witt and Dunbabin, 2008), there have only been a few studies on the Arctic sea ice path planning problem since it has not had a long time to come to the forefront. Kotovirta et al. (2009) did practical research on the Baltic Sea area. In their research, they introduced and integrated three models (a ship transit model, ice model, and optimization model, See Fig. 1) to organize an ice navigation system. Their ship transit model is an advanced and accurate model.

Nam et al. (2013) developed an ice navigation system. This system was a combined system with a numerical ice model, transit model, and route optimization model. Their simulation covered the whole Arctic area, and the cost function of the system included diverse parameters such as port charge cost, icebreaker fee, capital cost, etc. The integrated system employed a modified ship transit model from the transit model by Mulherin et al. (1996) in the Cold Regions Research and Engineering Laboratory (CRREL) for convenient application.

However, an important issue has not been considered in previous research. The ships sailing through the Arctic area are exposed to the risk of ice collision, freezing temperatures, and icebound situations at every moment. When it comes to the risky environment, the uncertainties should be taken into account in an ice navigation system for safety. Otherwise, serious accidents in the extremely severe conditions can happen because of the unexpected events caused by the uncertainties of the prediction. There are two possible sources of uncertainty. The first source is the models' validation errors in the ice navigation system. Currently developed ice navigation systems have been combined systems with an ice model, a ship transit model, and an optimization model. The ice model predicts future events of the ice behavior in

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time series. Every prediction brings uncertainty. The ice model which covers the whole Arctic still has challenges in precise prediction. Similarly, the ship transit model also brings uncertainty. In the system, the model functions as a ship transit time and cost evaluator. Usually, the model is derived from numerous experiments in specific conditions. Thus, it could have a limitation for application to general conditions. The optimization model searches for an optimal path under the given conditions from the other models. Therefore, the optimization model highly depends on the accuracy of the other models.

The second source is the measurement errors in ice information. The input data for the ice model consists of two types of data. The first type of data, initial ice and ocean data, is used only at the initial stage for the model calculation, and it contains information on initial ice and ocean conditions. The second type of data, forcing data, is used at every time step for the ice model simulation, and it is not changed by the ice model calculation. The forcing data acts as atmospheric condition and ocean boundary condition in an ice numerical prediction model. Atmospheric condition affects sea ice state to change, for example wind velocity is related with wind force and it causes wind stress which affects the sea ice's movement. The ocean boundary condition determines the flux of ocean velocity, salinity, and temperature, which are important factors and affect ice–ocean interaction process during the simulation. Therefore, both initial and forcing data have an effect on the result of the sea ice model simulation.

The input data could also have uncertainty. The uncertainty of input data can arise since the measurement tools have limitations, and sometimes, partially measured information is used to explain the entire area by interpolation. For example, ice thickness information is estimated through CryoSat-2 radar altimeter freeboard data, and the estimation approach can have an uncertainty of up to 46% depending on the year of ice in Alexandrov et al. (2010). When it comes to the effect of the input data's variation in regard to the sea ice thermodynamics and dynamics in Renganathan (2010), the input data's uncertainties should be considered in the ice navigation system, since the effect caused by variation could give rise to severe difficulties to sailors, including becoming stuck in ice.

Owing to the uncertainties from the two sources, the domain for the path planning in the optimization model also has uncertain characteristics. Information on each grid has a variation, so that probabilistic information becomes significant. Thus, a dynamic stochastic approach is required for the optimization model (our domain is a time-varying domain, so a dynamic term is added). For dynamic stochastic path planning, there have been many studies in diverse areas. One of the areas is the transportation network area. The researchers in the transportation network area also have had the same difficulties regarding uncertain information. Such information makes the problem harder to find the shortest expected time path, which is their main interest. To solve the Dynamic Stochastic Shortest Path Planning (DSSPP), Polychronopoulos and Tsitsiklis (1996) and Miller-Hooks and Mahmassani (2000) suggested replanning-based approaches, where all link information is updated when stochastic information is realized, and Ji (2005) applied genetic-algorithm-based simulation to the DSSPP. Fu and Rilett (1998) emphasized the importance of the variance of the arrival time at each node, since the arrival time affects the link cost in DSSPP. He developed a mathematical model with consideration for the arrival time's variation.

There have been diverse approaches for DSSPP. For the significance of the uncertainty to the ice navigation system, an uncertainty-based model is introduced, which uses the idea from previous DSSPP approaches, and a heuristic path planning approach is employed for the uncertain domain. In the next chapter, the detailed approach is described.

2. Approaches

2.1. System architecture

This chapter describes the overall view of our system. The system is a modified version of the system suggested by Kotovirta et al. (2009) and is configured with three modules, which consist of seven components (Fig. 2).

2.2. Ice prediction module

The ice prediction module brings ice and ocean data (which are described in Table 1) into the system, and based on the initial measured data, it predicts Arctic sea ice behaviors in a stochastic manner through the ensemble simulation. In mathematical physics, the ensemble indicates all possible input states, and the ensemble simulation is the repeated experiments or the simulations with the ensemble data. This concept has been employed to consider practical environments and conditions. In many cases, input data for an analytical model or a numerical simulation is considered deterministic for convenience. However, in most cases, input is actually not deterministic, and it can have a certain level of variation caused by diverse known/unknown factors. For example, the ice concentration data is retrieved from satellite-borne passive microwave radiometer sensors, and it has a certain level of error and variation. Since the uncertainty of input data is considerable, and it has an effect on the simulation result in the ice navigation system, we employ the concept of the ensemble simulation. For the ensemble simulation, we assume that the given initial data has measurement errors with variation that follows a uniform distribution on the interval $[\text{mean} - 10\%,\ \text{mean} + 10\%]$. This is just an assumption for our simulation, and it can be changed depending on the input data's characteristics. In our simulation, the atmospheric data indicates given initial condition data, both the initial ice and ocean conditions, and the forcing atmosphere and boundary ocean flux conditions. As an ice model, we employ an ice/ocean-coupled numerical model, Ice-POM (De Silva et al., 2013; Fujisaki et al., 2010) to generate the ice statistical distribution map for the simulation. The reason why we selected the Ice-POM is that, by assuming floe collision rheology of Sagawa (2007), the model considers the behavior of sea ice in the Marginal Ice Zone (MIZ), which is important in a ship passage prediction. It also calculates ocean dynamics and sea ice thermodynamics. For the ocean dynamics, it uses the Princeton Ocean Model (POM) under the assumption of primitive equation. For the ice thermodynamics model, it uses the zero-layer model of Semtner (1976) with the heat balance assumptions of Parkinson and Washington (1979). The data treatment component has a role in the calculation of the required statistics from the ensemble simulation, and the obtained statistics are delivered to the next module, the optimization module.

2.3. Optimization module

The optimization module finds an optimal path under given conditions and requirements from the User Interface (UI) module and Ice prediction module. The domain size is 233×274, and the duration is 61 days (Sep. 1, 2011–Oct. 30, 2011). The statistics delivered from the ice prediction module is organized into a time-varying and stochastic domain (See Figs. 3–5), and each grid in the domain contains four types of statistics: 1) mean ice concentration, 2) mean ice thickness, 3) variance of ice concentration, and 4) variance of ice thickness. The standard deviation (STD) can be easily obtained from the variance. To understand the characteristics of the statistics in the domain, it is analyzed, and the result is summarized in Table 2. In our domain, the mean ice thickness is up to 6.378 m, and the STD of each ice concentration and thickness is up to 9% and up to 2.73 m, respectively. Here, a noticeable characteristic of the domain is a 6.378 meter mean ice thickness. It seems to be an outlier, an extremely high value compared with the average value, and we consider that this is due to very local ice accumulation. The simulation error has been found at narrow channels in the ice model we use. However, the outlier is only a minor part of the domain, so that it would not have a great influence on the results of the route optimization. The time-varying and stochastic path planning problem has been studied in other areas, and it has a rather long history.