Real time detecting of harmful dinoflagellate *Cochlodinium polykrikoides* using unmanned surface vehicle in dynamic environments

Sung Mok Seo¹, Wan Kyun Chung¹ and Eun Seob Cho*²

¹Division of Mechanical and Industrial Engineering, Pohang University of Science and Technology, Pohang 790-330, Republic of Korea
²Fishery and Ocean Information Division, National Fisheries Research and Development Institute, Busan 619-705, Republic of Korea
*Corresponding Author E-mail: escho@korea.kr

Abstract

Since the first occurrence in 1982, red tides have been observed annually in Korean coastal waters in the form of harmful dinoflagellate *Cochlodinium polykrikoides* blooms. The distinction in the proposed method for red tide monitoring is the focus on the narrow stripe red tide at an early stage to allow for advanced actions. The distance graph between Head of Narrow Red tide (HNR) and location of the robot have suggested in reference to unknown searching area. With mapping and path planning, then, it can quickly keep tracking out even if the magnitude and direction of current flow was changed. The one-hundred times simulations of different situations were attempted to comparison by box plot both algorithms of speed by reaching the right side of simulation window. Consequently, the red tide tracking algorithm is based on the red tide probability map and the tracking & recovering path planner. Inputs to the algorithm include the measured flow velocities and the detection or non-detection state at each robot location. Furthermore, a USV (Unmanned Surface Vehicle) model is added to evaluate the effectiveness of the algorithm. This approach for red tide monitoring may lead to a breakthrough in the field of environmental surveillance.

Key words

*Cochlodinium polykrikoides*, Harmful algal blooms, Initiation stage, Modeling, Red tide, USV (Unmanned Surface Vehicle)

Introduction

Target is the narrow stripe red tide that flows along the ebb and flood of tide, and will be one part of Harmful Algal Blooms (HABs). Meeting the narrow stripe red tide in surveillance, and tracking the red tide in dynamic environments, a robot could send useful information in real time through a communication device. For example, the robot’s position, detection time, speed and the drift of red tide, concentration, temperature, salinity, etc. Those messages transmitted from an Unmanned Surface Vehicle (USV) could help to keep watch for the red tide for a monitoring team or fisherman whose fishery is near the location. There is no doubt about it that a real time and daily surveillance using robot is more efficient than monitoring by human.

A number of researchers have investigated similar problems of monitoring/ tracking with autonomous vehicles. Most of these approaches to track boundaries fall into two main categories (Joshi et al., 2009): one is the gradient measurement (Marthaler et al., 2003; Zhang et al., 2007; Srinivasan et al., 2008) and another is the gradient-free approach (Barat et al., 2003; Kemp et al., 2004; Andersson 2007). Gradient-free method needs less information than the other to track boundaries on the ground that gradient-free approaches depend only on sensor measurements (Joshi et al., 2009). In this regard, Marthaler et al. (2003) and Joshi et al. (2009) propose a cumulative sum (CUSUM) filter for processing sensor noise. CUSUM filter addresses the current position of vehicle whether inside of a boundary or not based on a counting specific value. There are a number of papers developing algorithm based on gradients of the environmental field. One of them was developed in (Zhang et al., 2007) and uses gradient information in the field of salinity. This study was to develop an algorithm that will operate an unmanned surveillance system for disaster prevention.
Materials and Methods

Red tide modeling for robot: Farrell et al. (2002) suggests a low computational cost flow simulation model based on physical principles. Red tide flow is grounded on fluid mechanics and the components of blooms called red tide filaments. They help to depict the short time-scale signature of HABs concentration rather than long-term exposure, the Gaussian Red tide Model, which is relevant to the range of the boundary to track continuously. With short time-scale exposure, temporally and spatially varying environment can be modeled for robot and describe time varying sinuous form of red tide that is determined by the integrated effect of the current field. The simulator utilizes the blooms that are composed of filaments at sea. The model includes a current field which varies with location and time in both magnitude and direction defined over the region of interest, Yeosu area in Korea. The arrow array based on time-mean motion equation and continuity equation indicates both magnitude and direction of current (Farrell et al., 2002). The area between grids needs interpolation of flow and red tide diffusion is modeled as random process relative to the centerline.

Two main platforms that can be applied for HABs tracking are UAV (Unmanned Autonomous Vehicle) and USV (Unmanned Surface Vehicle). Strategically deployed USV can communicate easily to address useful information associated with such natural phenomena especially HABs (Manley, 2008). Further, principally distributing fifty centimeter away from the surface of the water, red tide can be detected by USV that does not need to control buoyancy and hardware limitations including sealing and size (Hover, 2010). As in this research, most of the surveillance systems using USV are recently focused on guidance and navigation such as path planning (Hover, 2010), collision avoidance (Dunbabin et al., 2010), we have been producing a 3 degree of freedom (surge, sway, and yaw) USV hardware for real environment tests (Fig. 1). As the prestige of applying algorithm, the robot is modeled to verify the tracking red tide using equation of motion (Fossen, 2002; Oh et al., 2010) and suggests the values of equation that is utilized in similar USV. The effect of the vehicle on the flow is not considered (Farrell et al., 2002) and the measurements of current velocity sensors are not a relative value at this simulation phase.

Considering aspects in robot, red tide has a different role from red tide model (Farrell et al., 2002) previously explained based on physical principles. In application like tracing red tide and to locate the HABs head that leads lengthily, we definitely need to develop a model to learn in reference to HABs. Unfortunately, it is difficult or impossible to the instantaneous structure of the red tide in dynamic environments. We have employed probabilistic descriptions of the spatial and temporal evolution of it. Sensed data will be able to address where the red tide was headed for and location. The two main estimations of pollutant advection and dispersion processes at sea are such, one approach is the Eulerian method generally used such as the finite element method (FEM) and the finite difference method (FEM), another approach is based on the Random-walk theory called the Lagrangian particle tracking method. In this paper, we assume that the HABs could be divided into Particle or Filament which have a small constant volume and they can move separately by advection and dispersion processes. The solution for tracking HABs using a Filament based method can be mainly employed to predict short-time scales, can decrease the computational cost and the numerical instability, and easily depict the change of Particle amounts. In such initiation stages, the Filament location using the Lagrangian particle tracking method is modeled as (Pang, 2009).

\[ X(t) = U(X(t), t) + N(t) \]  \hspace{1cm} (2.1)

where \( X = (x, y) \) is the red tide filament location, \( U = (u_x, u_y) \) is the mean flow velocity, and \( N = (n_x, n_y) \) is a random process which is assumed to be Gaussian normal distribution with zero mean and \( \sigma_x^2, \sigma_y^2 \) variance.

For estimating the location of HABs based on Eqn 2.1, we begin by understanding of the simple Filament model for the distribution of blooms in current flow. We assume that bloom Filament released from a place called source, and two Filaments were produced from the source. Note that in reality, the concept of source may not exist but helps for tracking a head of HABs in vehicle. Assuming one met a robot and another Filament simultaneously positioned at the head of HABs, as we describe as shown in Fig. 2.

For estimating each filament location, the robot needs grid (or Cell) to measure the distance. C Cell denotes the position of source, assuming each Filament in Cell \( C_i \) and \( C_j \). Continuous flow of HABs is also handled when we examine a probability map. Fig. 3 briefly sketches the probabilistic description of red tide flow. The green arrow denotes the trajectory of a robot at time from \( t_0 \) to \( t_1 \) and \( X(t) \) the vehicle location at each time. We assume the time \( t_0 \) defined by a first filament came from a source and the mission start time of robot. \( t_0 \) means when robot met a Filament and the position of vehicle denotes \( C \). Cell. Continuous flow of HABs is also handled when we examine a probability map. The blue arrow depicts the direction of current and Probabilistic based \( X(t) \) defined as

\[ X(t) = X(t_0) + \int_{t_0}^{t} U(X(t)) dt + \int_{t_0}^{t} N(t) dt \hspace{1cm} (2.2) \]

where \( X(t) \) is filament detected vehicle location at time \( t \). Define distance, \( S \cdot U(X(t)) dt \), which is integration of mean flow velocity with time \( t \) to \( t_0 \). Note that the robot cannot know the whole grid of sea velocity whereas it can measure current velocity along...
its trajectory $X(t)$. Given this gathering set with time $t$ to $t_0$, we assume that the current velocity along HNR trajectory was same as the in-situ measurement. To understand why we calculate the distance by using current from $t$ to $t_0$, the first step is to estimate the location of source (Cell $C_i$). For source localization, we can deploy the Filament vehicle met at time $t_i$. Since Filament came from source at time $t$, the location of source will be estimated by current velocity from $t$ to $t_i$. In this manner, our sub goal that is to locate the HNR when robots detect Filament is easily explained by integration of mean flow velocity with time $t$ to $t_i$. The Random component $\hat{x}(t)|d_t$, which physically could be not only a dispersion term aspect in a Filament but also the width of narrow type red tide when the Filaments released continuously.

**Red tide probability map**: The assumptions made herein concerning vehicle, red tide Filaments, and search area are that: 1) the robot can measure basic information to operate autonomously such as GPS, IMU or Compass sensor, and detect red tide (including chlorophyll $a$) and flow velocity using such sensors; 2) HABs are a neutrally buoyant and passive scalar being advected by a dynamic flow; 3) red tide is a composite of Filaments that each have a small volume each (Farrell et al., 2002); 4) for computational feasibility, the search area that is of interest is divided by cell; the cell size is defined as $L_x L_y$, define $C = [C_1, ..., C_n]$ which is a vector of cells that covers the area of interest. The basic idea of estimating a HNR is that the vehicle deploying flow record data along trajectory line and measured events including the detection or non-detection state at each robot location. Since surveillance unknown search area with those information is not sufficient to track a HNR in dynamic flow, the probability red tide map concept is needed to complete our aim.

**Path planning**: Let the circle in Fig. 3 stands for a robot, the rectangle surrounding the robot stands for the Active window that moves with the vehicle and always centered about the robot’s position. In our simulation, we deployed an 11 by 11 active window that includes momentarily belonging to the active region called Active cell having probability $\alpha_i(t)$ that will be changeable by multiple sequential events. Each active cell generates a virtual attractive force on the robot. Defining the magnitude of this force as proportional to Likelihood Value (LV) ($LV$ is proportional to $\alpha_i(t)$) and inversely proportional to the distance between the cell and the center of the vehicle. Then, command inputs to the path planning is obtained by the sum of the forces on active cells considering the magnitude of the force used as reference for speed, and the direction of $i$ used as robot heading commands.

$$F = \frac{LV}{d} \left( \frac{X - X_i}{d_i} \right), \quad F = \sum_i F_i$$  \hspace{1cm} (2.3)

**Results and Discussion**

In Fig. 4a,b,c,d even if the direction of current was set by southeast, the robot can trace the HNR using storage data along the trajectory and produce map for path planning through detection and non-detection sequential events. Continuously detected HABs allow the vehicle to speed up by tracking path planning. Let the search of interest area set to 100m x 100m, and the length of each rectangle cell defined by 1m. The coordinate of simulation window is completely reversed by up and down. Let the mission start position of vehicle set by (30,45), the releasing Filament source set by (20,0), and put releasing rate in 10 Filament sec\(^{-1}\). Set the average rate of current by 1 m sec\(^{-1}\) (0.78 ~ 1.15 m sec\(^{-1}\)) and the direction of current by $10^\circ$ ~ $42^\circ$ (east direction set to $0^\circ$). We address the performance of tracking in (a) of Fig. 5. The distance graph between HNR and location of the robot have suggested in reference to unknown searching area (Evan et al., 2003). The location of HNR was calculated by ground truth value in simulation. During the first 25 seconds the robot approached the HNR, and then detection events allowed tracing HNR. As time went by, the vehicle almost caught up with HNR by continuous detection events even if turning motion was at (30, 90) as shown in (b) of Fig. 5. The defined red line in the search area of interest by trajectory line of a robot, and the yellow square by the points of detection event, which prove that the trajectory of robots performed by tracking algorithm was correct in dynamic environments (Yu et al., 2007).

The following two simulation results have been attempted for path recovering; turning motion Fig. 6a,b and spiral motion Fig. 7a,b,c,d. At least 5 seconds are needed to turn in a circle when the robot has located near HNR. To catch up with this simulation window that has limited on 100m x 100m, the mission start point was set close to the HABs as shown in Fig. 6. The second step stands firstly for catching HNR up, and the forth step stands for catching it up again. If the turning motions have been kept up continuously, it indicates that the robot may reach to the HNR in the search area of interest (Kim et al., 2002). In Fig. 6, the angle difference between a robot heading and ground truth value of HNR direction at each time step was depicted by the blue line, and red circles indicate a zero difference between them. The direction of HNR was estimated to average the value of filaments that between the first one released from a source and released at time $t$, Continuous red circles refer to the tracing of HNR, and the two big angle gaps are produced by turning motion as shown in (b) of Fig. 6.

Spiral motion was added when the vehicle keep non-detection of HABs even if operating turning motion for recovering path planning. As shown in Fig. 7, when the flow of the unknown searching area was strong enough to hardly track, it needs the whole steps of path recovering including under 5 seconds, turning motion, and spiral motion. With mapping and path planning, then, it can quickly keep tracking out even if the magnitude and direction of current flow was changed (Kim et al., 2006). Let spiral motion be depicted along the trajectory in (d) of Fig. 7 where the motion was emphasized in the area.
The general method that proves the algorithm performance is in comparison with well-known algorithm (Yu et al., 2006). Since the lack of knowledge for method to track HABs, we have considered boundary tracking algorithm. Boundary tracking, however, has a low performance in dynamic environments excluding the current information. Thus, considering plume odor source localization which we refer to develop our algorithm, we have found a method to trace a target by biological algorithm. The followed algorithm to maintain the heading of vehicle to up flow direction as Moth-behavior was deployed for testing performance (Marani et al., 2006). This biological method is simple but powerful to find a target in dynamic flow region (Li et al., 2006). In this application, we have utilized to the down flow direction instead of up flow wind, and applied identical recovering path planning to verify only the ability of Red tide probability mapping. We have attempted the Moth-behavior inspired tracing Algorithm that could be the best way to track since actual narrow typed red tide moves with current (Marani et al., 2003). As shown in Fig. 8a that denotes the Moth-behavior method, a lawn mower path planning have been applied for reality, we can know easily there is an unnecessary motion even if the current flows only in an easterly direction.

The performance of the mapping algorithm we deployed was relatively outstanding as shown in Fig. 8b,c. This result came from that Biological algorithm only use on the data in-situ measurements such as the concentration of HABs, and current velocity whereas mapping algorithm exploits the historical information including the expected releasing time and storage of previous current data set. Thus, mapping algorithm can expect the direction of HABs that have located at time $t_0$ in cell $C_{0}$, and it elevates tracking performance more robustly in dynamic environments. The one-hundred times simulations of different situations were attempted to comparison by box plot both
Fig. 4: Tracking path planning: (a) First detection of filaments in dynamic current, (b) After non-detection event by maneuvering of vehicle, the redetection occurred, (c) Continuous detection events make the robot speedy, (d) During turning motion, robot detects the Filaments again by path planner.

Fig. 5: Further analysis with ground truth values: (a) Distance between red tide head and Vehicle decreased through planning algorithm, (b) Yellow rectangle defined by location of detection event proves the performance of mapping and planner.
Fig. 6: Tracking of HNR: (a) Two times of turning motion here means that the robot caught up with HNR, (b) With ground truth values, heading error between vehicle heading and Red tide direction

Fig. 7: Recovering Path planning by spiral motion: (a) First detection of filaments, (b) after 5 seconds, one turning motion occurred, (c) Added spiral motion to track the Red tide, then it shows continuous detection events, (d) Vehicle Trajectory with Spiral motion; cyan color line
Fig. 9: Assuming 3 Different Cases: (a) Starting red tide and robot at one time (0t), (b) Robot start at time before red tide did, (c) Red tide started before the robot did at time.

In conclusion, *Cochlodinium* red tide in the first stage usually has a narrow stripe formation which is easy to rapidly move by water current and very difficult to predict. Although recent advanced satellite method combined with geometric estimation has developed and is used, it is difficult to detect the first stage of *Cochlodinium* red tide. When a robot meets the first occurrence of *Cochlodinium* red tide, it is possible to track them and provide useful environmental information (i.e. position, time, velocity, direction, temperature, salinity, etc) by real-time to monitoring team or fishermen. In the near future, we need to study the supporting of the algorithm on obstacle avoidance and following water current.

Acknowledgments

This work was supported in part by National Research Foundation(NRF) of Korea grant funded by the Ministry of...

References


