Adaptive Cleaning of Oil Spills by Autonomous Vehicles under Partial Information

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***Abstract*—Oil spill pollution is a critical issue because of its severe influence on our economy and ecological environment. A large amount of efforts have been made for detection, monitoring and localization of oil spills; however, the cleaning of oil spills remains a challenging problem. Due to dynamic currents on the ocean surface and the limitations of the localization systems, it is not feasible to obtain the exact information of the oil spill location. Therefore, the oil spill region is approximated by an area which may not match the shape of the oil spill. Thus, an effective complete oil spill cleaning algorithm is needed that allows the autonomous vehicle to adapt its trajectories to the oil spill shape.**

This paper presents a concept of multi-resolution navigation for oil spill clean-up using an autonomous vehicle. The exact a prior knowledge of the oil region is assumed to be unknown or only partially known. This algorithm can dynamically discover and adaptively clean the oil spill in the workspace. A concept of multi-resolution navigation is developed which integrates local navigation and global navigation to avoid being stuck into a local minima that is generally encountered by potential field based methods. The algorithm provides complete coverage and cleaning of the oil spill via minimum overlapping trajectories, and its efficiency is validated on the high-fidelity Player/Stage simulator of mobile robots.

***Index Terms*—Oil spill cleaning, Complete coverage, Adaptive navigation**

I. Introduction

Oil spill pollution is one of the most serious environmental damages caused by intensive industrial and transportation activities. Examples include the tragedies during the Gulf of Mexico oil spill and the Bohai Bay oil spill. Oil spill not only leads to a huge waste of natural resources and economy damage but can also cause serious contamination of the seawater that can lead to the death of marine life, e.g., undersea creatures and birds, and can even affect the humans. Moreover, if the polluted region is not completely cleaned, then the long term effects will present a consistent threat to the ecological balance of marine life and resources.

Satellites, aircrafts, ships and underwater sensor networks have been deployed for environmental surveillance and for oil spill detection and localization. Commonly used systems for remote oil sensing include optical sensors, laser fluorosensors, microwave sensor and acoustic sensors [1]. However, due to the lack of accuracy of prior information, the exact knowledge of oil spill region may be inaccurate and uncertain. Furthermore, dynamically changing ocean currents can cause the polluted zone to vary in shape. Therefore, it is necessary to develop an adaptive algorithm that incorporates the above uncertainties in cleaning of oil spills using autonomous underwater vehicles. An adaptive autonomous cleaning system can help decrease the amount of time for recovery and can protect more marine life from oil spill pollution.

Oil spill problem has drawn interests from researchers for decades and recent literatures have contributed to the problem of oil detection, monitoring and localization [2][3][4][5]. However, only a limited number of papers have focused on the critical problem of cleaning oil spills using autonomous vehicles. A decision support system to assist oil spill management and clean-up was reported in [6]. Cooperative control of two vehicles on the surface was designed for oil clean-up [7]; however, the proposed method was not designed to be adaptive to the oil shape. The skimming operation on the surface only accounts for the smallest impact [8]. An onboard high power air conveyer oil skimming system was proposed and experimentally validated in [9], but the proposed skimming system was required to be manually carried by vehicles and the vehicle autonomy was not considered. Typical ship-borne oil detection systems include technologies such as those used in the technical literature [10][11][12][13][14].

This paper presents an algorithm of adaptive oil spill cleaning using autonomous vehicles. The exact *a prior* information of the spill region is either unknown or partially known. This algorithm enables dynamic discovery and cleaning of the oil via adapting to the oil spill shape. A concept of multi-resolution navigation is presented which integrates local and global navigation to avoid local minima which are generally encountered in potential field based methods. The main features of the underlying method are as follows:

- Adapts to the shape of oil spill thus avoiding unnecessary exploration in oil free area
- Achieves a minimum overlapping cleaning trajectory, resulting in minimization of time and an increase in cleaning efficiency
- Provides complete coverage of the oil spill regardless of its shape
- Dynamically builds up the environmental map when the exact spill location is unknown

The underlying algorithm is validated on the high-fidelity Player/Stage simulator and its efficiency is evaluated by computing the ratio of explored region to the actual oil spill region.

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II. Algorithm for Adaptive Oil Cleaning

Due to dynamic ocean currents and limitations in accuracies of the existing oil detection and localization systems, the exact knowledge of the oil spill location may be incorrect or incomplete. However, with the help of current technologies using satellites, aircrafts, and underwater sensor networks, the best estimation of oil spill area can be obtained. The autonomous vehicle can be assigned an initial starting point to a random spot within the estimated region of oil spill contamination. Subsequently, the oil spill can be dynamically detected (e.g., using onboard sensors [13][14]) and cleaned.

A. Partitioning of the Workspace

The underlying algorithm is based on partitioning of the workspace [15] to form a multiresolution grid that is used for discretizing the decision-making while maintaining the continuous movement of the autonomous vehicle.

The partition establishes a lattice structure of workspace. Let $\mathcal{S} \subset \mathbb{R}^2$ be the workspace and $\mathcal{P} \triangleq \{P_\xi : \xi = 1, 2, \cdots, |\mathcal{P}|\}$ be a partition of $\mathcal{S}$, where $|\mathcal{P}|$ represents the cardinality of the partition set $\mathcal{P}$. Each site in such structure is isomorphic to a grid cell that contains a physical state. Let $\Delta \triangleq \{\delta_j : j = 0, \cdots, |\Delta| - 1\}$ be a finite set of symbols denoting all possible physical states for each grid cell $P_\xi \in \mathcal{P}$. In this paper, set Δ contains four symbols (i.e., $|\Delta| = 4$) representing the three states: i) $\delta_o = P$ (*oil present*), ii) $\delta_1 = N$ (*no oil detected*), iii) $\delta_2 = C$ (*explored with oil cleaned*), and iv) $\delta_3 = U$ (*unexplored*). Then a mapping of Ω: $\mathcal{P} \times \mathcal{T} \rightarrow \Delta$ is defined to assign one symbol from set Δ to each grid cell P_ξ at time $t \in \mathcal{T}$ so that such grid cell contains a state of $q_\xi(t) \triangleq \Omega(P_\xi, t)$, where $\mathcal{T}$ is the time span. Accordingly, the configuration space of the autonomous system at time t is developed as the Cartesian Product:

$$Q(t) = \bigotimes_{\xi=1}^{|\mathcal{P}|} q_\xi(t), \tag{1}$$

where $Q(t)$ is the collective lattice state in the workspace at time t and it has at most $|\Delta|^{|\mathcal{P}|}$ possible state configurations. All grid cells in the workspace are originally defined as unexplored, and when the autonomous system finishes exploration or oil cleaning at a certain site, the corresponding state is then updated after it moves to another grid cell.

Starting from the original workspace of the coarsest level, the number of grids in each dimension are repeatedly divided into two to arrive at finer cells. Specifically, whole workspace is divided along both axis to form 4 coarse cells and then following the same procedure, each of these four cells are further divided into two along each dimension to form 16 cells. Such partitioning procedure is repeated until the size of the grid cell is equal to or slightly greater than the local neighborhood of the autonomous vehicle. Ultimately, a multi-resolution structure is built up that consists of Levels $0, 1, ..., K$, with Level 0 as the finest and Level K as the coarsest partition. Figure 1 shows an example of three level partitioning.

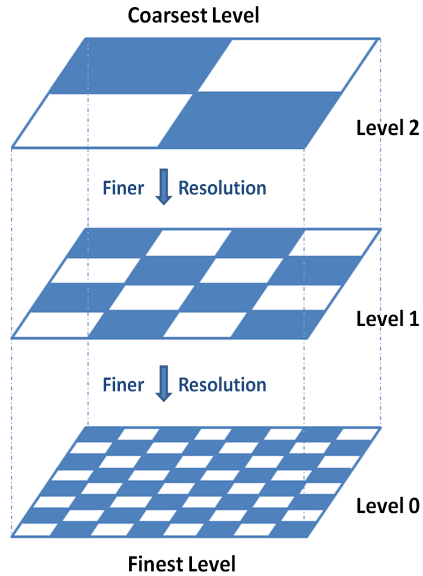


Fig. 1: Multiresolution partitioning of the search area

B. Multi-resolution Navigation Algorithm

This section presents the concept of multi-resolution navigation [16] based on partitioned workspace to provide complete coverage of oil spill. Such multi-resolution navigation algorithm is based on Statistical Mechanics and it can effectively guide the autonomous system out of local extremum that is typically encountered by most potential field based methods.

1) Local Navigation: The local navigation works at Level 0 on the basis of a generalized Ising model [17] as described later. The idea is that, the observed states in the neighborhood changes the resultant energy potential at a grid cell. The autonomous systems in initially assigned a start point inside the oil spill region. Then it starts exploring the region based on an *a priori* assigned potential field that uniformly decreases from left to right. The autonomous system computes potential energy in its local neighborhood and sets the navigation goal as the centroid of grid cell possessing the highest energy. Thus, the autonomous system always move towards the cell in the neighborhood that has the highest potential. As soon as it encounters a cell that has no oil (e.g., a point on the boundary of the oil spill region), it assigns an extremely low potential to that cell. Thus, the autonomous system turns and reaches out to another cell that has the highest potential in the neighborhood inside the oil spill region and thus adapts to the shape of the spill. Thus, detection of a boundary cell causes distortion in the space-time potential field resulting in a decrease in the localized energy. Meanwhile, the autonomous system turns the cleaned cells into low-energy states by cleaning the oil, thus avoiding repetition.

A generalized Ising model with four states is constructed, and the local potential energy $E^{\mathcal{L}}_\xi$ at a site ξ is defined as:

$$E_{\xi}^{\mathcal{L}}(t) = \Psi\left(q_{\xi}(t)\right) + \Phi\left(B_{\xi}(t), q_{\xi}(t)\right) \tag{2}$$

where the first term on the right hand side is called the adaptation term and is responsible for adapting the cleaning trajectory to oil shape. It establishes a forbidden zone along the oil boundary so that the autonomous system may adapt to oil shape and the second term on the right hand side controls the navigation based on *a priori* designed potential function $B_{\xi}(t)$ constructed for back and forth motion. The adaptation function Ψ is defined as:

$$\Psi\left(q_{\xi}(t)\right) = \begin{cases} -\infty, & \text{if } q_{\xi}(t) = N \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Thus, the first term in the right hand side of Eq. (2) consistently keeps the autonomous system away from the boundary of the oil spill region. The function Φ is defined as:

$$\Phi\left(B_{\xi}(t),\ q_{\xi}(t)\right) = \begin{cases} B_{\xi}(t), & \text{if } q_{\xi}(t) = U \text{ or } P \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where the time-varying potential field $B_{\xi}(t)$ is computed at each unexplored cell such that:

$$B_{\xi}(t) = B_{\xi}^{\star} - C_{\xi,\mu}(t) \tag{5}$$

where $B_{\xi}^{\star}$ is the constant potential field constructed offline so that the autonomous system can perform under a back and forth motion. To be specific, $B_{\xi}^{\star}$ is designed such that it contains the same potential on each column site but increases gradually from right to left. Let the current location of the autonomous system at time $t \in \mathcal{T}$ is $p(t) \in \mathcal{P}_{\mu}$, where μ represents the current grid cell index and ξ is any grid cell around μ. Then, $C_{\xi,\mu}(t)$ represents the relative cost potential function that is designed as the total decrease in potential from grid cell of index μ to that of index ξ because of travel and turn costs. It is constructed as:

$$C_{\xi,\mu}(t) \triangleq d_{tr} C_{tr} + \theta_{tu} C_{tu} \tag{6}$$

where C_{tr} and C_{tu} are the traveling cost in a unit time and turning cost of one degree from the heading angle respectively. d_{tr} and θ_{tu} represent the total traveling distance and total turning angle needed towards the goal from the current location following the shortest path.

According to sensor readings, the autonomous system explores the environment with an emphasis on oil and dynamically builds up the environmental map. In local navigation, the autonomous system computes the energy values $E_{\xi}^{\mathcal{L}}(t)$ in the κ-neighborhood $\mathcal{N}_{\kappa}(\mu)$ of its current location ξ and chooses the center of the cell with the highest potential energy as next target. The κ-neighborhood of a current grid $p(t)$ is defined as:

$$\mathcal{N}_{\kappa}(\mu) = \{\nu : max(|\mu_x - \nu_x|, |\mu_y - \nu_y|) \leq \kappa\}, \tag{7}$$

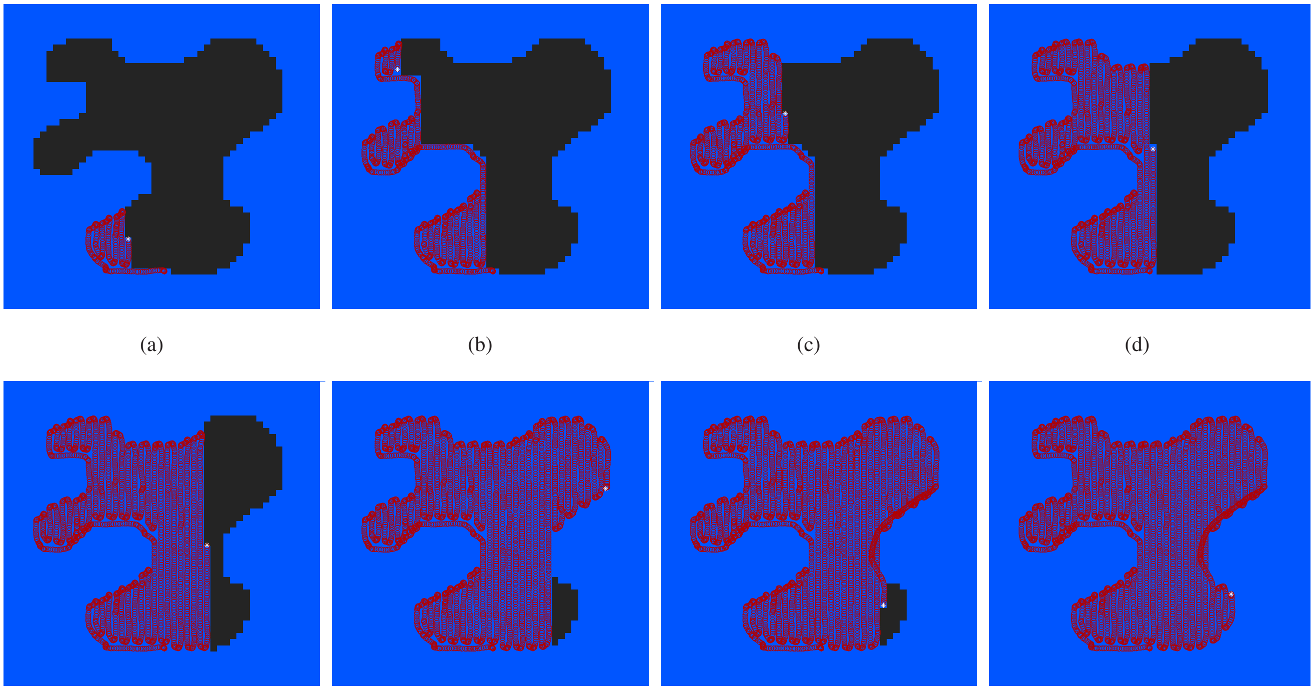
where $\kappa \in \mathbb{N}$ and $\mu_x, \mu_y \in \mathbb{N}$ and $\nu_x, \nu_y \in \mathbb{N}$ denote the x and y coordinates of grid μ and ν, respectively. For this paper, $\kappa = 3$, that generates a 7×7 neighborhood with the autonomous system at the center. The autonomous system computes the values of energy potentials $E_{\xi}^{\mathcal{L}}(t)$, for all $\xi \in \mathcal{N}_{\kappa}(\mu)$ and sets the next wavepoint as the centroid of the cell $\xi^{*}(t)$ that has the highest potential.

2) Global Navigation: Global navigation aims at guiding the autonomous system towards the next available goal if it is trapped in a local minima during local navigation. Such situation may happen when all the points in its local neighborhood are either explored and cleaned or water. In order to resolve this problem, a low-dimensional probability vector is employed to store the dynamic environmental information at the coarse levels. The autonomous system initially starts from Level 0 and moves to the unexplored point with the highest potential energy in its local neighborhood. However, if no unexplored point is available, it enters a coarser level of Level 1 for global navigation. Its local position is then switched into a corresponding global position at Level 1. Besides, each coarse level grid possesses a low-dimensional probability vector, containing the probability of unexplored grids in its subordinate level. Such probability vectors can be easily computed based on finer level grid states and stored. For example at Level 1, the probability vector is assigned based on states of corresponding Level 0 grids. Therefore, the autonomous system calculates the probability vector of its local neighborhoods at Level 1 and the one with the highest probability of unexplored grids is chosen. In such Level 1 grid, the next target is then set as the center of a randomly chosen unexplored Level 0 grid. Once the autonomous system reaches this target, it comes back to the local navigation and proceeds oil cleaning following the usual manner.

If there are no unexplored Level 0 grids contained in its neighborhood at Level 1, the autonomous system will switch to a even coarser Level 2 and perform navigation as explained above and so on until it finds unexplored grids at a finer level. According to given scenario, the autonomous system may switch between local navigation and global navigation for several times during the whole cleaning process. If no unexplored grids at the coarsest level are found, then oil spill at such region has been completely cleaned. This algorithm is less expensive in computation complexity and provides minimum trajectory overlapping. The overlapping trajectory uses the extra energy and time cost, thus, it should be maintained as low as possible even though it is inevitable for its appearance during a cleaning process. The effectiveness of achieving minimal overlapping trajectory is evaluated according to the ratio of explored region to actual oil spill region, and it is defined as:

$$\Lambda = \frac{R_{explored}}{R_{actual}} \tag{8}$$

where $R_{explored}$ is the total area traveled by the trajectory measured by the grid cells explored and R_{actual} is actual oil spill area. In absence of any overlapping trajectory, Λ=1 indi-



(a) (b) (c) (d)

(e) (f) (g) (h)

Fig. 2: Simulation Example of Adaptive Oil Spill Cleaning

cates complete coverage for oil cleaning, while an overlapping trajectory leads to $\Lambda > 1$ due to the presence of local minima.

III. Results and Discussion

The underlying algorithm for adaptive oil spill cleaning is validated on the high-fidelity Player/Stage simulator. Player/Stage is a widely used open source tool for robot and sensor applications [18][19][20]. Player is the robot server which enables modules written independently to connect through transmission control protocol (TCP) communication. Besides, Player can link to either actual robots or Stage, which is a simulator that provides various kinds of robots and sensors working in a two dimensional environment.

The robot starts operation from an arbitrarily selected point where there is oil. The entire workspace is chosen to be slightly larger than the estimated oil spill region, and the predetermined potential field $B^{\star}$ in Eq. (5) is designed offline within such workspace to have a increasing magnitude column by column, with a maximum value of magnitude 25000 at the left most column and a minimum of 500 at the right most column. Under predefined $B^{\star}$, the typical back and forth motion is optimal in terms of minimal number of turns needed for complete coverage. Besides, it is to be noted that, since the autonomous system can dynamically adapt within the oil region, the efficiency and execution time is not subject to the size of the entire workspace.

Figure 2 shows an example of the oil spill cleaning operation in an environment map. The robot is displaced as a white star and the red lines show its operation trajectories. In such scenario the region colored as dark grey and dark blue represents actual oil spill locations and oil-free water, respectively. At the beginning, the robot is assigned to a random point within the oil spill region and starts performing the cleaning process, as shown in Figure 2(a). Furthermore, because the field energy $B^{\star}$ is predesigned with higher value on the left, so if there exists unexplored oil spill on the left hand side of the robot, it will be consistently navigated to the left side until reaching the most left point. Then the robot resumes cleaning in back and forth motion, as indicated in Figure 2(b). Figure 2(f) presents that the robot completes cleaning at a specific region but gets trapped at a local minima. Figure 2(g) shows that in such situation, the global navigation can guide it towards the next available oil target. As the robot continuously cleans up the oil, the corresponding dark grey grids are changed into dark blue, and by the time every point originally covered with oil in the map is visited and cleaned, the entire workspace will be changed all into dark blue which reveals cleaning work completed. Figure 2(h) shows the completion of oil cleaning and the effectiveness of the underlying algorithm.

Figure 3 plots Λ, i.e., the ratio of explored region to the actual oil spill region in the above scenario. When the autonomous system completes oil spill cleaning, the ratio should be no less than 1 so as to guarantee complete coverage. In this scenario, the ratio grows up all the way from 0 to ultimately reach 1.0557 during the entire cleaning operation,

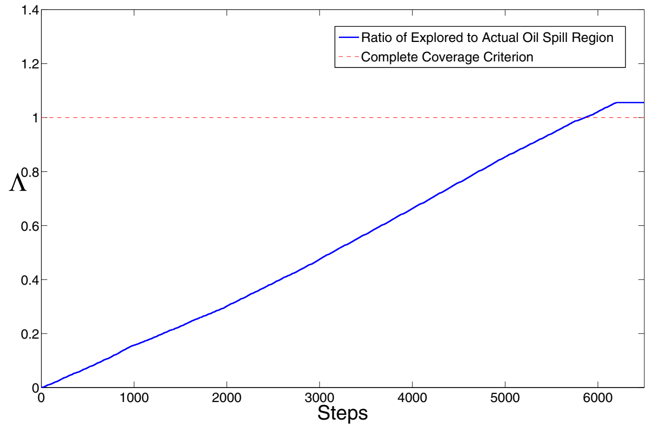


Fig. 3: Ratio of the explored to the actual oil spill region

revealing that the overlapped path has been maintained as low as 5.57%. As shown in Figure 2(g), the overlapping trajectory appears due to the local extremum at the up right corner. In different scenarios, Λ may vary depending on the number and locations of local minima.

IV. Conclusions and Future work

In this paper, an adaptive algorithm using autonomous system under partial information is presented for complete oil spill cleaning. This algorithm provides the complete coverage and cleaning of oil spill with minimum overlapping paths, by employing the intelligent switches between local and global navigation via dynamically updating the state information of the workspace. The local navigation performs at the finest level depending on local decision-making with a decrease in computation complexity, while the global navigation is designed based on probability vectors to prevent the autonomous system from getting stuck into possible local minima. Moreover, through continuously and remotely sensing the oil boundary, such method can dynamically build up an environment map, so that the autonomous system can adapt to oil shape without wasting unnecessary exploration in the rest oil free region. Furthermore, the efficiency of this method has been validated on the widely used high-fidelity Player/Stage simulator.

There are several issues in need of further research before the current method will be acceptable for being incorporated into real-world applications. These research issues include:

- Extension of the algorithm to allow obstacles,
- Extension of the algorithm to consider inaccuracies in remote oil sensing,
- Extension of the algorithm to include environmental uncertainties, and
- Validation of the algorithm on hardware platforms.

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