Coastal Infrastructure Monitoring through Heterogeneous Autonomous Vehicles

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***Abstract*—Coastal ports represent a fundamental component of a country's critical infrastructure, and their surveillance is essential to enhance resilience against natural and man-made disruptions to their operations. Furthermore, the increasing availability of Unmanned Autonomous Vehicles (e.g., UAVs, UGVs, and USVs) has paved the way for their use in surveillance and patrolling tasks. In this paper, we present a patrolling approach for monitoring ports infrastructure utilizing a group of *heterogeneous* vehicles. Our approach has the following steps: 1) Abstractions that capture the valid motions of the vehicles in a port area are designed; 2) Regions that are visible through line of sight are computed; and 3) An algorithm that finds patrolling cycles to monitor critical port locations with existing energy budgets is developed. We tested our approach through one case study to validate its practical utility.**

I. Introduction

The Maritime Transportation System (MTS) of coastal ports is crucial for a country's economy and enables related industries to flourish. As such, any disruptions on the ports' operations can make a tremendous economic impact. The need to monitor port infrastructure is also motivated by the presence of adversaries that continuously attempt to penetrate a port environment under a predictable surveillance system. Current surveillance operations in ports are carried out with fixed cameras and scheduled patrols by the Coast Guard [1], which are limited by being static and predictable. A port is a large geographical area with several modes of communication (ground, water, and air), making it challenging to observe the entire area simultaneously. Nonetheless, an improved, coordinated port infrastructure surveillance system increases the resilience against any attacks and operational interruptions.

We believe that the most effective way to patrol and monitor a large port area is through a combination of autonomous vehicles' capabilities. In addition, different patrollers, given their different kinematic and visibility profiles, can provide various types of information about a port from several viewpoints using their camera or visibility sensors. Therefore, we utilize an ensemble of heterogeneous patrollers (vehicles or agents), such as unmanned ground vehicles (UGVs), unmanned aerial vehicles (UAVs), and autonomous surface water vehicles (ASVs), to monitor and assess disruptions to ports' critical infrastructure. Our approach develops strategies for a fleet of different autonomous vehicles that exploit their joint visual capabilities in patrolling different regions of a port area, including water, land, and container yard regions.

In practice, patrolling strategies for heterogeneous vehicles may be limited by energy and route constraints. First, the vehicles may have energy limitations (e.g., battery life) that constrain the duration and scope of their patrolling routes. To deal with this issue, it is necessary to develop patrolling routes subject to existing energy capacities. Second, a port area may have several critical locations that must be monitored frequently due to their importance and/or utilization. These locations may vary seasonally depending upon commodity flows. Finally, a port's ability to implement patrolling strategies using autonomous vehicles may vary depending on regulations. For example, ports may need the Federal Aviation Administration (FAA) approval to fly UAVs over port facilities. Furthermore, ports may receive permissions to operate such vehicles in a limited context.

The main contributions of our paper are as follows:

- We devise motion and visibility models for heterogeneous vehicles (UAV, UGV, and ASV) as patrollers in ports.
- We develop an algorithm that integrates vehicle motion and visibility models to find patrolling routes to observe critical port locations for heterogeneous patrollers subject to their energy constraints.

The remainder of the paper is organized as follows. The next section discusses relevant work in environmental patrolling and monitoring. Section III defines the environment model and formulates the problems of our interest. Section IV details our approach for solving the formulated problems. We present our case study in Section V. Section VI concludes the paper with discussion and future directions of our work.

II. Related Work

The coastal infrastructure monitoring task through heterogeneous vehicles is related to the multi-robot patrolling task, a group of regions of interest in an environment is visited repeatedly using multiple robots as patrollers to ensure safety or for monitoring purposes. A common approach for this patrolling task is deterministic based on the optimization of the frequency of visits to different locations in the environment. There have been significant studies for deterministic patrolling [2], [3], [4]. However, these deterministic algorithms could be learned by an adversary observing them over time. To address the limitation of the deterministic patrolling strategies, non-deterministic patrolling algorithms in an adversarial setting were proposed in [5], [6] that attempt to maximize the probability of detecting an adversary while moving randomly. In our previous approaches [7], [8], we have developed patrolling policies in the form of *Markov chains* using convex optimization to minimize the average expected commute time for a set of locations allowing robots to patrol an environment and evaluated the vulnerability of these patrolling policies.

There have been a few studies for the purpose of shipping port monitoring and assessment motivated by the increased security issues in ports. A game-theoretic framework called Protect was deployed by the United States Coast Guard (USCG) for scheduling their patrols in order to protect ports [9], [1]. The authors also did not consider the use of autonomous vehicles and the motion model of these vehicles. Moreover, the Coast Guard cannot patrol some regions of port areas such as nearby forests and have limited visibility capabilities. These limitations create a critical gap in the surveillance system of ports. In [10], an approach measures how disruptions affect the commodity flows for stakeholders and an entire port.

In addition, a group of ASVs can be used on the water surface to monitor ports and harbors from disruptions [11]. In monitoring a port, ASVs can prevent common scenarios, such as hidden bombs, explosives, gas attacks, and so on [12]. Furthermore, ASVs can inspect pipelines for cracks and increase awareness of contraband in the area [13]. An unmanned port security vessel was designed for the use of maritime security and port resilience [14]. Therefore, this paper investigates models and an algorithm to develop patrolling strategies for a robotic team consisting of different types of autonomous vehicles that can collectively monitor water, land, and container yard regions of a large port area with critical infrastructure.

III. Problem Formulation

We examine a 2-D environment where the workspace is a port environment denoted as $\mathcal{W} = \mathbb{R}^2$. Let $\mathcal{O}$ refer to an obstacle region consisting of all locations in $\mathcal{W}$ that lie in one or more obstacles in the port environment. We also assume that a group of heterogeneous autonomous vehicles monitor the environment. Each vehicle is modeled as a point robot. Each vehicle has also an omnidirectional visibility sensor or camera with a particular visibility range. Let r be the visibility range of a vehicle. Different vehicles have different visibility and motion capabilities, coupled with differential and energy constraints. Therefore, we take advantage of different sensing and motion capabilities of heterogeneous vehicles for monitoring of a port area in an adversarial setting. Both obstacles and vehicles are considered as subsets of $\mathcal{W}$. The free space in $\mathcal{W}$ is composed of all navigable locations for vehicles, which is defined as $F = \mathcal{W} \setminus \mathcal{O}$. Let D be the set of critical locations in the environment.

We define x_I as an initial deployment location in F. Let a patrolling route of a vehicle be $\tau : [0, t] \rightarrow F$ such that $\tau(0) = x_I$ and $\tau(t) = x_I$ for a finite time interval t. Let l be the energy budget for a vehicle that represents the maximum length of the route.

To calculate patrolling routes for monitoring port infrastructure, we first build motion map representations for heterogeneous vehicles. In this context, we formulate our first problem.

Problem 1. Building map representations: Given a map of the environment and the types of vehicles, build the representations of the environment F as a set of motion graphs for different types of vehicles.

Once we have the relevant motion map representations, we obtain the patrolling route's visibility locations. To attain that, we formulate our second problem below.

Problem 2. Obtaining the visibility of a patrolling route: Given a patrolling route of the robot τ and a visibility range r for a vehicle, find the set of all locations that the vehicle can observe following that route.

Finally, we generate a set of patrolling cycles utilizing a motion map representation and a vehicle's visibility model. Therefore, we formulate our third problem as follows.

Problem 3. Generating patrolling cycles for visibility-based coverage of critical environment locations: Given an initial location of a vehicle x_I, a set of critical locations D, and an energy budget l, generate a set of patrolling routes or cycles that cover D in F through visibility.

IV. Approach

In this section, we present an information processing pipeline by which a patrolling scheme for heterogeneous vehicles is developed. To solve the problems formulated in Section III, we model the motion and visibility profiles of underwater, aerial, and ground vehicles to ensure that the resulting patrolling strategies can be executed by these vehicles. This information is then used as input to an algorithm for computing patrolling routes. The components of our overall pipeline are detailed in the remainder of this section.

A. Building Map Representations

First, a discrete map representation for a vehicle's motion can be obtained from an aerial view picture of a port area. For each type of autonomous vehicle (UAV, UGV, or ASV), we represent its motion capabilities in the port area as an undirected weighted graph $G = (V, E, w)$. Each vertex $v \in V$ represents a coordinate for a location in $\mathcal{W}$, and it is connected to 8 neighboring locations. The four horizontal and vertical edges have the same weight w_1, and the diagonal edges have a weight of $w_1\sqrt{2}$. The vertices that correspond to untraversable locations in $\mathcal{O}$ are removed from the graph along with all their adjacent edges. The output of this step is a motion graph G for a specific type of autonomous vehicle. Different types of vehicles yield disparate types of motion graphs. For instance, an ASV can monitor water-side coastal port operations, a UGV can monitor land-side operations, and a UAV can monitor container yard regions along with other locations that are not easily traversable such as nearby forests.

B. Visibility Modeling

Next, we model a vehicle's visibility as a circular region with a radius r centered at a vertex v of the graph G. This line of sight visibility is captured by an omnidirectional camera of the vehicle. For each vertex v, the *visibility subgraph* $VG(v, r)$ is all the vertices within a distance r from the center vertex v. Given a vehicle's path that visits k nodes $\tau = (v_1, v_2, \dots, v_k)$, the subgraphs monitored by the path τ can be calculated as $\textsc{VisibleLocations}(\tau, r) = \bigcup_{v \in \tau} VG(v, r)$. These subgraphs can be used to check which locations have been visited while monitoring a number of critical locations.

C. Generating Patrolling Routes

Finally, we generate patrolling routes for a vehicle to monitor critical locations D of the port area through visibility subject to its energy constraint. Algorithm 1 generates a set of patrolling routes (cycles) of a vehicle from its initial location and for its specific energy budget. To achieve this, Algorithm 1 takes as input the motion graph of a vehicle G, the critical port locations (vertices) D, an initial vertex (location) v_s on G, an energy budget l, and a visibility range of the vehicle r. It gives us as output a set of patrolling routes to visit D locations through the cumulative visibility of these routes.

Algorithm 1: $\textsc{PatrollingRoutes}(G, D, v_s, l, r)$

Input: G, D, v_s, l, r – Motion Graph, Critical Locations, Initial Location, Energy Budget, Visibility Range
Output: T – Set of All Patrolling Routes

1 $a \leftarrow v_s$
2 $T \leftarrow \emptyset$ // Initialize the set of patrolling routes
3 **while** $D \neq \emptyset$ **do**
4 $\quad P_1 \leftarrow \textsc{SingleSourceDijkstra}(G, a, D)$
5 $\quad b \leftarrow \textsc{FirstCandidate}(P_1, a, l)$
6 $\quad P_2 \leftarrow \textsc{SingleSourceDijkstra}(G, b, D)$
7 $\quad c \leftarrow \textsc{SecondCandidate}(P_2, b, l)$
8 $\quad \tau \leftarrow \textsc{FindRoute}(a, b, c)$
9 $\quad D \leftarrow D \setminus \{\textsc{VisibleLocations}(\tau, r)\}$
10 $\quad T \leftarrow T \cup \{\textsc{RouteLocations}(\tau)\}$
11 **return** T

We initialize the set of patrolling routes T (line 2). We compute all the shortest paths P_1 using Dijkstra's algorithm from the single source initial vertex $a = v_s$ to all other vertices on G toward critical locations D (line 4). The initial vertex v_s represents the initial configuration of the vehicle x_I. Then, we find the candidate vertices of a patrolling route based on the end vertices of 30% of the longest paths from P_1 within the distance of $l/3$ (line 5). We keep only those candidate vertices from which critical locations of the environments are visible and randomly select the first candidate b from those candidate vertices. Again, we compute all the shortest paths P_2 from the single source first candidate vertex b to all other vertices on G toward critical locations D (line 6). Following the same process as before, the second candidate c is selected from the candidate vertices away from a and b based on the computed paths P_2 and the energy budget l (line 7). Once we have the two candidate vertices b and c along with the initial vertex a, we find the patrolling route τ from the lists of calculated shortest paths P_1 and P_2 and the longest path between a and c within the distance of $l/3$ (line 8). A pictorial representation of a patrolling route (cycle) combining $a \rightsquigarrow b$, $b \rightsquigarrow c$, and $c \rightsquigarrow a$ is depicted in Fig. 1. We exclude the set of visible critical locations along the computed patrolling route τ from D (line 9). We accumulated all the patrolling routes until the remaining visible critical locations are empty. Finally, Algorithm 1 returns the set of all patrolling routes T.

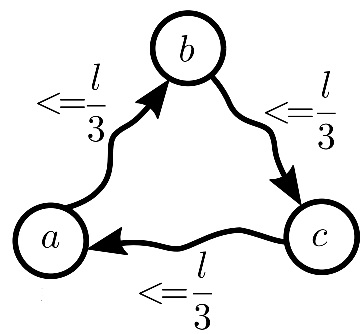

Fig. 1. A patrolling cycle representation with three vertices (locations) within an energy budget l.

V. Results

To validate our approach, we used one study case for monitoring the Port of Caddo-Bossier, LA, USA, using its satellite maps. This study case can serve as a guideline to apply our approach to other port areas. In our study case, we accounted for a set of critical locations and different energy constraints and visibility ranges for UAVs, UGVs, and ASVs.

We gathered preliminary simulation results of patrolling routes for heterogeneous vehicles by developing their motion graphs based on satellite images representing the port environment and then calculating the patrolling routes with their visible locations within specific ranges. The calculated routes took into account critical locations of the port environment for its security and productivity, energy constraints of different vehicles, and their motion graphs. Different sets of patrolling routes for heterogeneous vehicles that monitor critical locations in different regions (water, land, and infrastructure regions) of the Port of Caddo-Bossier area within their energy constraints are illustrated in Fig 2-4. In these figures, red patrolling routes or cycles from green square initial deployment locations cover red square critical locations along with other locations of the port area through blue visible locations or routes themselves.

VI. Conclusion and Future Directions

In this paper, we have considered the problem of monitoring a coastal port environment using a group of heterogeneous

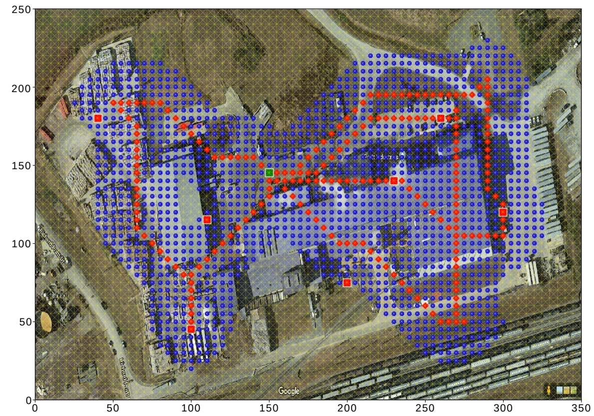

Fig. 2. Three red patrolling routes in the Port of Caddo-Bossier, LA from the green square initial location for a UAV along with its blue visible locations within a certain range covering red square locations on its motion graph.

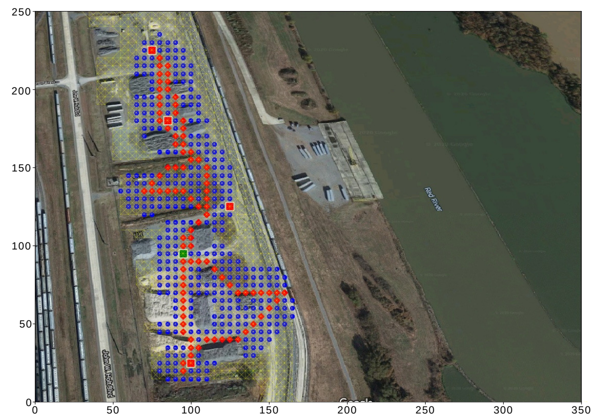

Fig. 3. Two red patrolling routes in the Port of Caddo-Bossier, LA from the green square initial location for a UGV along with its blue visible locations within a certain range covering red square locations on its motion graph.

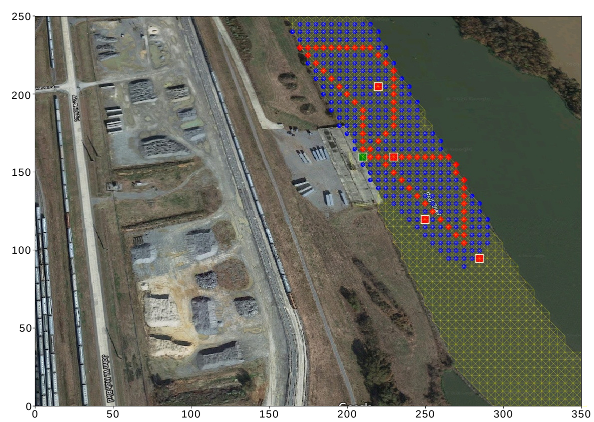

Fig. 4. Two red patrolling routes in the Port of Caddo-Bossier, LA from the green initial location for an ASV along with its blue visible locations within a certain range covering red square locations on its motion graph.

vehicles and presented a system that could be used to plan patrol routes for such vehicles. Our approach constructed motion maps that represent the valid motions of the vehicles, found the regions that are visible through line of sight, and developed strategies to find patrolling cycles for monitoring critical port locations with existing energy budgets. Several directions are open for future work.

In our future research, our patrolling strategies could be synchronized to limit their overlapping areas. We also plan to design richer kinematics and adversary models for heterogeneous patrollers and utilize them for developing patrolling strategies. The developed patrolling strategies will be evaluated to detect an adversary. In addition, we would like to validate our patrolling policies through realistic simulations and physical experiments.

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