



## Filtering and Planning for Resource-Constrained Mobile Robots

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The revolution of autonomous vehicles has led to the development of robots with abundant sensors, actuators with many degrees of freedom, high-performance computing capabilities, and high-speed communication devices. These robots use a large volume of information from sensors to solve diverse problems. However, this usually leads to a significant modeling burden as well as excessive cost and computational requirements. Furthermore, in some scenarios, sophisticated sensors may not work precisely, the real-time processing power of a robot may be inadequate, the communication among robots may be impeded by natural or adversarial conditions, or the actuation control in a robot may be insubstantial. In these cases, we have to rely on simple robots with limited sensing and actuation, minimal onboard processing, moderate communication, and insufficient memory capacity. This reality motivates us to model simple robots such as bouncing and underactuated robots making use of the dynamical system techniques. In this dissertation, we focus on four broad themes to solve problems in resource-constrained scenarios: 1) Combinatorial filters for bouncing robot localization; 2) Bouncing robot navigation and coverage; 3) Stochastic multi-robot area patrolling; and 4) Deployment and planning of underactuated aquatic robots.

The striking motivation for the approaches in this dissertation is the global analysis of simple robotics systems. This global analysis of robotics systems leads us to use a dynamical system technique. The dynamical system we use here is the *cell-to-cell mapping* technique (originally introduced by Hsu) (Hsu,

1980, 2013). In the cell-to-cell mapping, the state space is divided into small cells, where each cell is considered a state entity. In our approaches, we utilize two cell-to-cell mapping techniques which are the *simple cell-to-cell mapping* (SCM) and the *generalized cell-to-cell mapping* (GCM). In the SCM, each cell has only one image cell. In the GCM, each cell has several image cells. The GCM is a generalization of the SCM. The modeling of the deterministic behavior of robots leads to the application of the SCM. The formulation of the nondeterministic behavior of robots in terms of the GCM leads to a finite Markov chain. These dynamical system techniques provide the attractors (limit cycles) and domains of attraction from the system behavior which allowed us to develop the filters, controllers, and algorithms for the solutions to localization, navigation, coverage, planning, patrolling, and deployment problems. In the following, the summaries of four contributions in broad research themes are explained.

### Combinatorial Filters for Bouncing Robot Localization

Mobile robot localization is the problem of determining a robot's configuration (position and orientation) in its environment, and it is typically a prerequisite to solving other robotic problems. The motivation of our work is to use a robot with limited linear and angular sensing as a basis for investigating the intrinsic limits of the localization problem. In the first contribution of the dissertation, we focus on a setup that considers a known polygonal environment with obstacles and a robot equipped only with a clock and contact (or bump) sensors called a *bouncing robot*. We consider that the bouncing robot has access to a map of its environment, but is initially unaware of its position and orientation within that environment. This bouncing robot is modeled in a predictable way: the robot moves in a straight line and then bounces from the environment's boundaries by rotating in place counterclockwise through a bouncing angle. The problem of global robot localization is how the robot deduces its con-

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figuration following its modeled behavior. Can this bouncing robot be globally localized without even knowing its initial configuration? Using our setup, we present a global localization method for a bouncing robot (Alam, Bobadilla, & Shell, 2018). Our method finds the limit cycles and their transient trajectories from a known environment using the SCM and generates I-state graphs. We then use these I-state graphs to synthesize filters to solve the localization problem. Our localization filters take less computation time and memory compared to traditional Bayesian filter-based localization approaches (Thrun, Fox, Burgard, & Dellaert, 2001; Fox, 2003; Leonard & Durrant-Whyte, 1991). Figure 1(a) shows two limit cycles generated from our simulation and a corresponding physical experiment for the bouncing robot localization is illustrated in Figure 1(b).

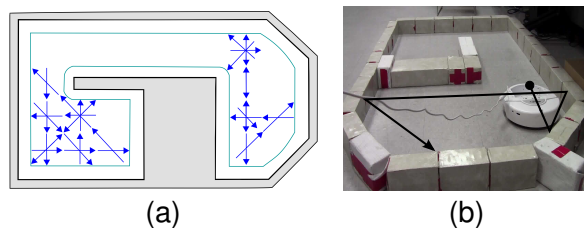


Figure 1: Localization from limit cycles.

### Bouncing Robot Navigation and Coverage

In the second contribution, we use the same bouncing robot model to investigate both the navigation and coverage problems once the localization problem is solved. The problem of navigation is finding a path for a robot between an initial configuration and a goal configuration. The coverage problem of the environment is visiting all locations of interest using one or more robots. How could the simple behavior of the bouncing robot be useful in solving the common robotic problems, such as navigation and coverage, with limited linear and angular sensing? In multi-robot settings, will many such bouncing robots be useful as well to solve the coverage problem? Our proposed solution (Alam, Bobadilla, & Shell, 2017) in this contribution has the following steps: 1) A directed graph is constructed from the environment geometry based on the GCM from the simple bouncing policies. 2) The shortest path on the graph, for navigation, is generated between either one given

pair of initial and goal configurations or all possible pairs of initial and goal configurations. 3) The optimal distribution of bouncing policies is computed so that the actual coverage distribution is as close as possible to the target coverage distribution. A simulation result and a physical experiment of the navigation path between a given pair of initial and goal configurations in the environment are shown in Figure 2. In this contribution, we also create a sampling-based joint trajectory of multiple bouncing robots incrementally to cover the given environment starting from an initial configuration instead of going over all the states in the high-dimensional state space.

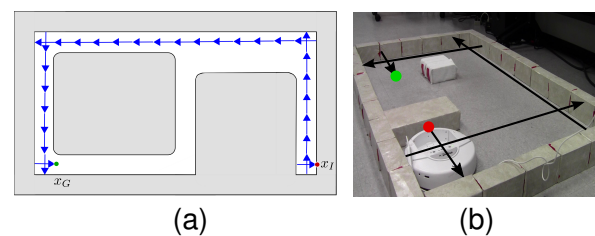


Figure 2: Bouncing-based navigation.

### Stochastic Multi-Robot Area Patrolling

In the third contribution, we investigate the problem of area patrolling in an adversarial situation in which a number of robots as patrollers visit a group of locations of interest in an environment to detect the intrusion of an adversary. In a communication-constrained and adversarial environment, it is a challenging problem for multiple robots to patrol the whole environment by sensing with their limited ability to see. In the multi-robot patrolling problem, what will be an efficient method for robots to patrol an area under the adversarial scenario? How can we remove the need for synchronization and coordination among the patrolling robots? How can the robots with limited visibility be used to patrol an adversarial and communication-constrained environment? Deterministic patrolling strategies could also be learned by an adversary observing them over time. Therefore, we alternately use randomized patrolling strategies based on Markov chains for several reasons: 1) These will make it harder for an adversary to successfully complete an attack and evade its detection due to the unpredictability of the strategies. 2) A randomized motion can be

easily implemented in a mobile robot, since its communication, sensing, and computation requirements are minimal. 3) Efficient algorithms can calculate Markov chains with the desired properties (Ghosh, Boyd, & Saberi, 2008). In this contribution, we propose distributed patrolling strategies for guarding a set of locations in an environment under adversarial attacks (Alam, Edwards, Bobadilla, & Shell, 2015; Alam, 2016) and present a method of finding patrolling policies for multiple patrollers that guard any polygonal environment using limited visibility regions and nondeterministic paths (Alam, Rahman, Bobadilla, & Rapp, 2017). The randomized patrolling policies for patrollers in different environments represented as graphs are illustrated in Figure 3, where the width and color saturation of edges are proportional to the optimal edge weight value or the probability of that edge being chosen by a patroller.

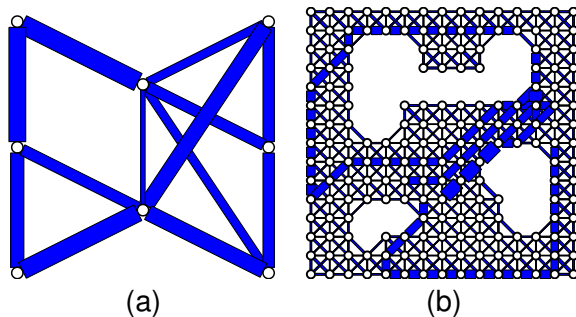


Figure 3: Randomized patrolling policies.

**Deployment and Navigation of Underactuated Aquatic Robots** In the final contribution, we are interested in tackling the problem of deploying multiple underactuated aquatic robots called *drifters* so that their desired long-term trajectories can gather aquatic data visiting all locations on the surface of a marine environment. We also tackle the problems of path planning and finding navigation policy for the drifter. The drifters drift passively with ambient ocean currents. Vertical actuation (buoyancy) enables them to alter their depth and achieve controllability by the use of different current layers in the ocean. How can we model the behavior of the drifter in a marine environment? In addition, the study of a marine environment is a challenging task because of the spatiotemporal variations of ocean phenomena and the disturbances

caused by ocean currents. As such, we must collect data from a marine environment over long periods of time to better assess and understand a marine environment. The uncertainty of the drifter motion due to the disruption of ocean currents and winds needs to be taken into account in our motion model of the drifter. In this contribution, we present a data-driven, deployment and navigation approach for the drifters. We extract the generalized flow pattern within a given region from ocean model predictions, develop a Markov chain-based motion model using the GCM, and analyze the long-term water flow behavior. Based on this long-term behavior of the water flow, we find a minimum number of deployment locations for the drifters in the marine environment (Alam, Reis, Bobadilla, & Smith, 2018). A generated vector field from the Regional Ocean Modeling System (ROMS) (Shchepetkin & McWilliams, 2005) predicted oceanic current data in the Southern California Bight (SCB) region, California, USA, is shown in Figure 4(a). We found attractors and their transient groups or the domains of attraction of the environment as the long-term behavior of the water flow. The initial deployment locations of the drifters based on this long-term behavior are illustrated in Figure 4(b). All possible reachable locations from an initial deployment location of the drifter are determined as its planned, long-term drifter trajectory. An optimal navigation policy is developed to demonstrate the best possible action from any location to a goal location in the environment.

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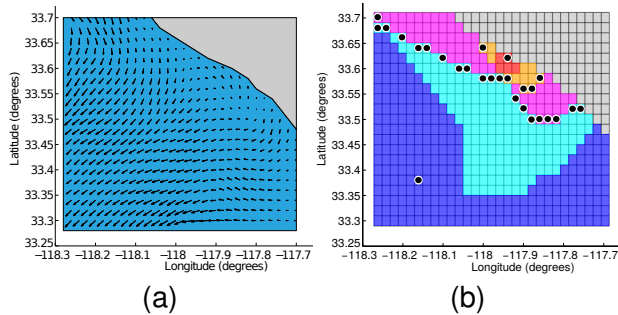


Figure 4: Data-driven deployment: (a) The vector field generated from ROMS current prediction data; (b) Attractors (blue and red regions) and associated transient groups (the cyan region for the blue attractor, the orange region for the red attractor, and the magenta region for both attractors); The initial deployment locations (filled in black circles) for regions of these attractors and transient groups.

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**Tauhidul Alam** received his B.Sc. in Computer Science and Engineering from Chittagong University of Engineering and Technology (CUET), Bangladesh, and his Ph.D. in Computer Science from Florida International University. His research interests span the areas of Robotics, Motion Planning, and Cyber-Physical Systems. In particular, his research aims to devise solutions to the fundamental robotic tasks of localization, navigation, coverage, and patrolling of mobile robots with limited sensing, actuation, computation, and communication.