Inference Grids for Environmental Mapping and Mission Planning of Autonomous Mobile Environmental Robots

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Abstract: Mobile sensing platforms provide a new modality for exploring the natural world. Robotic vehicles can be quickly deployed to new areas of interest and can have their sensor payload configured to the specific natural and environmental processes to be investigated. Building integrated sensing architectures that coordinate the operation of stationary networks and mobile platforms will allow researchers to take advantage of the strengths of both modalities, opening up new opportunities for scientific research and environmental monitoring. Among the various challenges to be faced, there are two key interrelated issues that are common to autonomous mobile platforms: the representation and modeling of natural processes using the sensor data being collected, and the use of this information to provide guidance, navigation and control for the mobile platforms. Both are addressed using a stochastic lattice-based framework for robot mapping, planning and control called the Inference Grid. In this paper, we will review our work on environmental robotic platforms, discuss how Inference Grids are used for natural process representation as well as for planning and control of autonomous robot vehicles, and show selected experimental results from field tests.

Keywords: environmental robotics; environmental research and monitoring; robotic science platforms; aerobots; Inference Grids.

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1. Introduction

Sensor networks with geographically stationary nodes can provide long-term observation of areas of interest with modest power and bandwidth requirements, at low to moderate complexity and cost. However, the sensor payload available at each node of a stationary network is limited and pre-configured prior to installation. Furthermore, these networks cannot be easily moved to another area when a new event occurs.

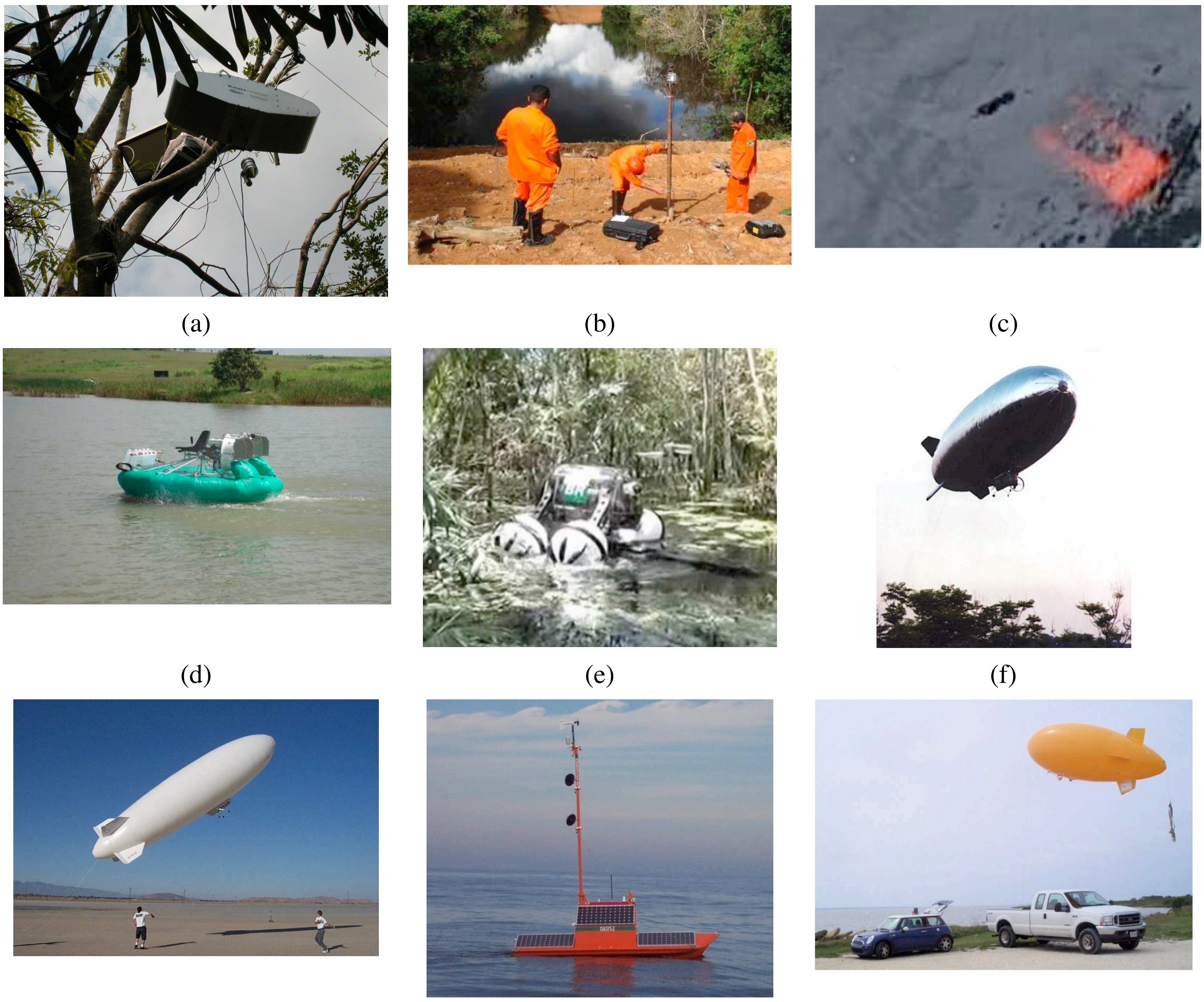
Mobile sensing platforms, on the other hand, can potentially be quickly deployed to new areas of interest and can have their sensor payload configured to the specific natural and environmental processes to be investigated. The drawback is that mobile platforms are also inherently more complex and expensive, and have greater power and bandwidth requirements. Building integrated sensing architectures that coordinate the operation of stationary networks and mobile platforms will allow researchers to take advantage of the strengths of both modalities, opening up new opportunities for scientific research and environmental monitoring.

The use of mobile sensing platforms for sensing a changing world faces several challenges. While robotic systems have provided very successful platforms for scientific research elsewhere in the Solar System (such as the Mars Exploration Rovers or the planned Mars Science Laboratory), it is noteworthy that the use of robot explorers on Earth is still in its infancy. Underwater remotely operated vehicles (ROVs) are being used extensively, and some groups have deployed fixed-wing unmanned aerial vehicles (UAVs) and autonomous underwater vehicles (AUVs) for atmospheric or oceanographic science data acquisition. However, very little has been done in exploring terrestrial environments and non-oceanic biota with other types of robotic vehicles.

Driven by a common interest in exploring the natural world, the authors have been developing and deploying a variety of sensing systems over the last fifteen years [5]. These include stationary sensor networks, remotely operated underwater vehicles, autonomous airships, ocean surface robot boats, and amphibious robot vehicles (Fig. 1). Some of these systems have been deployed in the Brazilian Amazon rainforest, while others are being tested in the Chesapeake Bay, the Mohave Desert, or in Campinas, Brazil.

In this paper, we discuss two key interrelated issues that are common to the systems we are developing: 1) the representation and modeling of natural processes using the sensor data being collected, and 2) the use of this information to provide guidance, navigation and control for the mobile platforms. Both are addressed using a stochastic lattice-based framework for robot mapping, planning and control called the Inference Grid.

Figure 1. Stationary and mobile sensing platforms. (a) A Kwata sensor node deployed from a tree in the Amazon floodplain and used to measure environmental variables and water height and (b) The Kwata-Erosion system, used to measure changes along a riverbank in the Amazon. (c) A ROV vehicle used to explore the bottom of the Rio Negro (Black River). (d) An experimental prototype of a robot hovercraft for Amazon research. (e) An amphibious rover for exploring the Amazon floodplain. (f) The AURORA robotic airship, developed for environmental monitoring applications [3, 4, 5]. (g) The JPL aerobot, an autonomous robotic airship, during tests in the Mohave desert [2]. (h) A NOAA-funded OASIS robot ocean surface research vessel during tests in the Chesapeake Bay [1]. (i) A JPL/CMU aerostat that operates jointly with the OASIS robots for detection of harmful algal blooms (HABs). Systems (a) and (b) were developed by R. F. Tavares Filho and A. Pavani Filho, and are commercialized through the SOLBET company, Brazil; (c) and (d) were developed by R. F. Tavares Filho and A. Pavani Filho at CTI, Campinas; (e) was developed by Ney Robinson, CENPES/Petrobras, Brazil; A. Elfes led the development of (f) while at CTI, Campinas, and of (g) at JPL; G. Podnar, CMU, leads the development of the coordination and control architecture for (h) and (i).



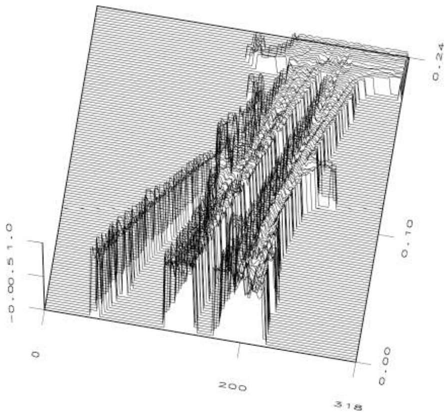
2. Modeling of Natural Processes and Robot Control Using Inference Grids

Observation of natural processes is limited by spatial and temporal sensor footprint, coverage, resolution, sampling rate, and measurement uncertainty. Markov Random Fields (MRFs) provide a natural formulation to represent spatially and temporally distributed observations, and are used extensively in the Inference Grid framework. We use a discretized version of MRFs, called a spatio-temporal Markov Random Lattice (ST-MRL), to encode the data obtained by the different sensors and agents. Each cell in the lattice corresponds to a spatial volume and a time slice, and stores a stochastic vector with the state estimates of the various processes that have been measured at the given location and time interval. Efficient estimation methods are used to update the lattice as new observations flow in from the various sensors and platforms being used [7]. Examples are shown in Figs. 2 and 3.

Associated with the ST-MRL we also maintain additional stochastic lattice-based layers for inference and decision, which are used to plan and control the activities of the robot platforms [4,]. These layers include vehicle navigation cost and risk to reach an area of interest; hypotheses of scientific events to be explored further; information metrics such as entropy to determine how the knowledge of a natural process is evolving, and where critical information is missing; and others. The augmented informational structure that incorporates both the ST-MRL and the information-theoretic inference and decision layers is called an Inference Grid (IG) [6]. An example is shown in Fig. 3.

Figure 2. Airborne identification and tracking of a road. (a) Imagery collected from the Aurora autonomous airship [4] (see also Fig. 1 (f)) is used for spectral identification and tracking of a road for environmental monitoring purposes. (b) A stochastic Inference Grid showing the spatial probabilities of road detection.

(a)



(b)

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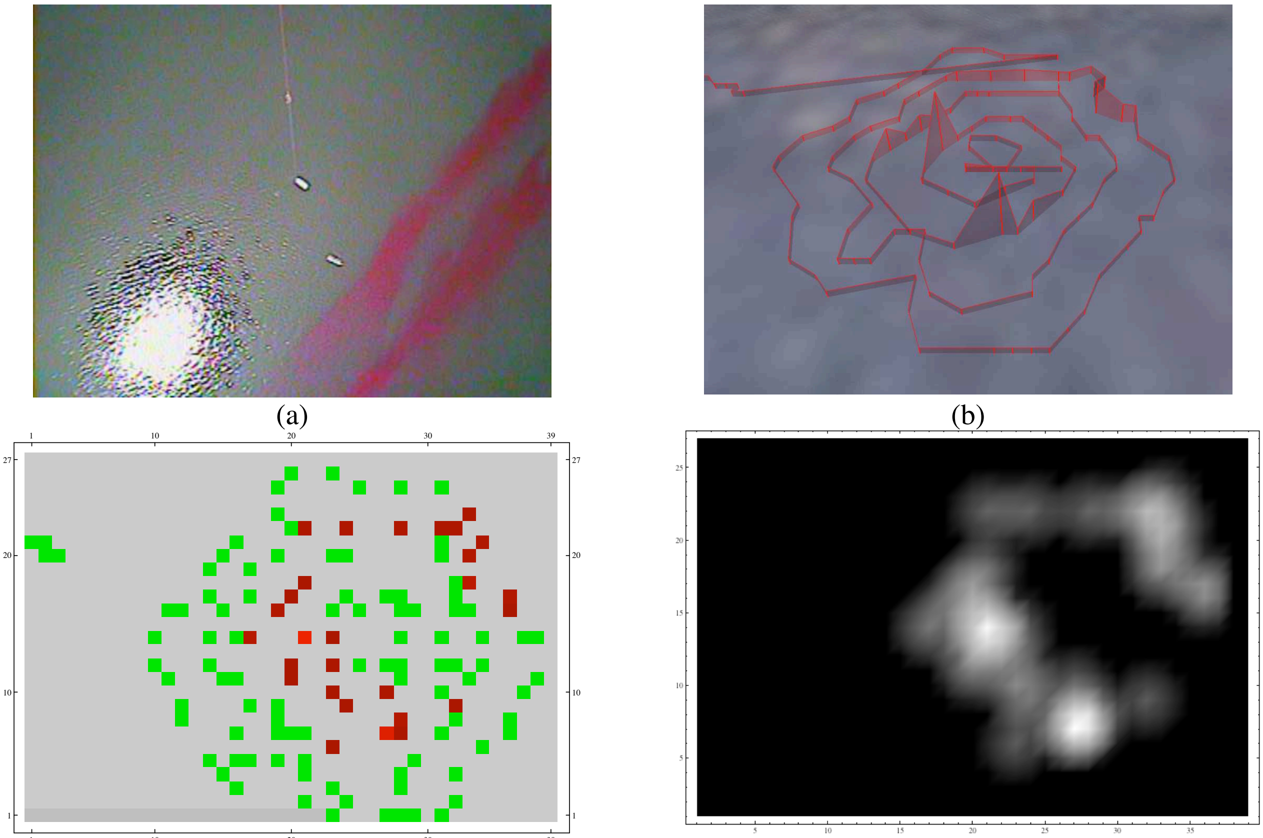
Figure 3. Identification and characterization of harmful algal blooms using the OASIS robot boats (Fig. 1 (h)) and the TAOSF coordination architecture [1]. Pane (a) shows an aerial view from the aerostat (Fig. 1 (i)) of the test area in the Chesapeake Bay; the OASIS robot boat platform (Fig. 1 (h)) is in the lower part of the image, close to the rhodamine dye tracks that serve as a surrogate for algal blooms during field testing. (b) The search pattern executed by the OASIS boat to find the surrogate algal bloom. (c) An Inference Grid showing the areas with high probability of dye presence (in red), high probability of dye absence (in green), and high entropy or lack of information (in grey). (d) An Inference Grid with inferred hypotheses of algal blooms (dye tracks). The areas of high entropy are used to replan the search pattern of the boat [1].



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

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