Cyber-Maritime Cycle: Autonomy of Marine Robots for Ocean Sensing

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Contents

Abstract

Marine robots are playing important roles in environmental sensing and ocean observation applications. This tutorial introduces the overall systems architecture and patterns for data streams that enable autonomy for marine robots in environmental sensing applications. The article proposes the concept of cyber-maritime cycle and surveys its use as a recent development in marine robotics. Supported by communication networks, autonomy can be achieved using at least three feedback loops in a cyber-maritime cycle, each running at different time scales or temporal frequencies. When information is circulating around the cycle, it is transformed between two representations: the Lagrangian view and the Eulerian view. Important functional blocks, such as mission planning, path planning, data assimilation, and data-driven modeling are discussed as providing conversions between the two views of data. The tutorial starts with an overview of enabling technologies in sensing, navigation, and communication for marine robotics. The design of experiment method is then reviewed to plan optimal sensing locations for the robots. The tutorial discusses a class of path planning methods that produces desired trajectories of marine robots while combating ocean current. The lack of an accurate Eulerian map for ocean current will lead to tracking error when robots attempt to follow the planned paths to collect Lagrangian data. The performance of robot navigation can be evaluated through the controlled Lagrangian particle tracking method, which computes trends and bounds for the growth of the tracking error. To improve the accuracy of the Eulerian map of ocean current, a data-driven modeling approach is adopted. Data assimilation methods are leveraged to convert Lagrangian data into Eulerian map. In addition, the spatial and temporal resolution of Eulerian data maps can be further improved by the motion tomography method. This tutorial gives a comprehensive view of data streams and major functional blocks underlying autonomy of marine robots.

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Introduction

Recent developments in autonomous underwater vehicles (AUVs) have enabled the transition from manned systems to unmanned systems in maritime operations. Significant progress has been achieved to increase the endurance of the vehicles. Underwater gliders (Stommel [1989]) such as the Slocum (Webb et al. [2001]), the Spray (Sherman et al. [2001]) and the Seaglider (Eriksen et al. [2001]) are now able to perform missions that last more than a month (Rudnick et al. [2004], Bhatta et al. [2005]). The various kinds of AUVs (reviewed by Yuh and West [2001], Valavanis et al. [1997]) can be broadly viewed as autonomous mobile agents that are able to make decisions to react to environment changes. As marine platforms are becoming more mature and reliable, information technology plays a more important role. The classical perception-plan-action cycle has been adopted by most platforms to achieve various levels of autonomy. Recent developments enhance this cycle by incorporating the latest sensing, computing, and actuation technologies. Furthermore, the last marine robots are supported by the state-of-the-art communication systems.

Marine robots with networking support is especially preferred in environmental sensing and ocean observation applications (Zhang et al.

[2015]). Especially, the use of underwater robotic sensor networks for ocean sampling and surveillance is a perceivable trend (Zhang et al. [2015]). Observations from the vehicles can be combined to detect and measure ocean features more effectively than using single vehicle (Leonard et al. [2007], Curtin et al. [1993]). The effectiveness of robotic sensing networks has recently been demonstrated in a series of experiments supported by the office of naval research (ONR), the national science foundation (NSF) and the national oceanic and atmospheric administration (NOAA). Plans have been laid to construct ocean sampling networks in different regions in the US, such as the National Oceanographic Partnership Program (NOPP) regional ocean observational networks (Frye et al. [2000], Blaha et al. [2000], Roemmich and Owens [2000]). One factor that is key to the effectiveness of the networked robotic sensing systems is the level of autonomy that can be achieved. Higher levels of autonomy usually reduce the amount of human intervention and increase the capability of the overall system. Autonomy is highly desired by maritime systems since the marine environment exhibits many extremes and is hard to predict.

This tutorial article introduces the overall systems architecture and patterns for data streams that enables autonomy for marine robots towards environmental sensing applications. We propose a concept called *cyber-maritime cycle* and survey its use as a recent progress in the marine robotic community. A diagram shown as Figure 1.1 can be used to illustrate the generic structure of a cyber-maritime cycle that will be discussed in this article. It is envisioned that with networking support, autonomy will be achieved using at least three feedback loops, each running at different time scales or temporal frequencies.

- The autopilot loop: This is the inner loop that represents the autopilot control that is implemented inside the embedded computers of a marine robot. This loops runs most frequently.

- The data-driven modeling loop: This loop provides a mapping service of the environment that the vehicles will navigate. Planning algorithms use the data-driven models to generate desired trajectories for the vehicles. This loop runs less frequently than the autopilot loop.

- The geo-scientific modeling loop: This loop supplies measurement data to geo-scientific ocean models. The results produced by the geo-scientific ocean models are used to update the data-driven models. This loop runs less frequently than the data-driven modeling loop.

The arrows in Figure 1.1 represent flow of information. We can view autonomy of marine robots as a result of the circulation of information around the loops, supported by communication networks. This is the reason for us to call the structure a cyber-maritime cycle.

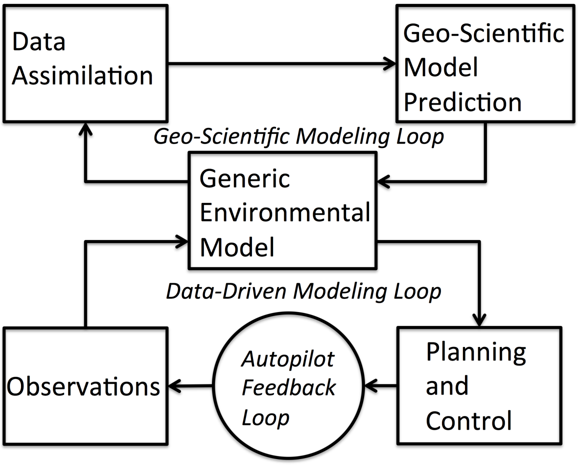

Figure 1.1: The structure of a cyber-maritime cycle for networked autonomy.

The autopilot feedback loop is running at faster time scale and higher frequency than the other two modeling loops. Control laws and navigation algorithms for autopiloting have received sustained interests from the marine robotics community, with many published work (Antonelli [2006], Zhao and Yuh [2005], Fossen [1994], Yuh [1994], Yuh and West [2001], McEwen et al. [2005], Bennett and Leonard [2000], Rosenblatt et al. [2002]) and successful implementations on mature products. Contemporary autopilots are usually implemented by manufacturers of the vehicles and are optimized specifically for different types of vehicles. An autopilot for a commercial vehicle is usually not open for modifications unless special agreements are made with the manufacturer.

The data-driven modeling loop and the geo-scientific modeling loop are often implemented on computing systems that are outside of a marine robot. They require communication or networking support to receive data from the robot and to generate control for the robot. At the network level, the model for vehicle dynamics are often simplified so that the detailed differences of dynamics among vehicles can be ignored. Each vehicle is viewed as a mobile agent with simple particle dynamics, at least conceptually. This abstraction is reasonable since the autopilots are designed to (partially) compensate for the dynamics of the vehicles, so that the vehicles behave like particles with simple dynamics.

The need for autonomy is justified in ocean sensing applications. Close interaction between multiple mobile agents and the geo-scientific models is necessary. Data collected by the mobile sensing agents should be assimilated into the geo-scientific models to be made useful towards improving the accuracy of model predictions. On the other hand, more accurate predictions will help the agents to make correct adaptation decisions and navigate the adversarial ocean environment. In Chapter 2, we will provide more discussions on the nature of data collections performed by mobile sensing agents.

The data-driven modeling loop in Figure 1.1 represents the feedback loop that enables networked autonomy. The blocks in this loop represents the major modules that this article will deliberate on. The "observation" module represents various sensors across multiple agents that generate information about the ocean. The "generic environmental model" (GEM) is a data-driven computational model that convert the data collected by the mobile sensors into a map of the environment to provide immediate navigational support for the mobile agents. More discussion of this module will be provided in Section 5.2. The "planning and control" module represents mission control and navigation methods that generate desired trajectories for the marine robots, and then guide the robots to follow these trajectories to achieve certain sampling patterns. More discussion of this module will be provided in Chapter 3.

The geo-scientific modeling loop in Figure 1.1 represents the need to incorporate principles and insights from geosciences in ocean sensing missions. The "assimilation" module and the "prediction" module together represent two key functions of a geo-scientific model that provides the status of the ocean to be used as templates for data-driven models. The "assimilation" module represents methods that incorporate measurement information into the geo-scientific model, which will be briefly reviewed in Section 5.1. The "prediction" module represents methods that are able to generate predictions for the ocean states for planning purposes.

Not all ocean sensing missions use both the data-driven model and the geo-scientific model. Some field works actually only use geo-scientific models. But there are benefits of using both models. The GEMs can be computed much faster and updated much more frequently than geo-scientific ocean models. Meanwhile, GEMs can provide higher spatial and temporal resolution than geo-scientific models, which lead to more accurate navigation performance, as will be shown in Chapter 4. GEMs will NOT replace the classical geo-scientific ocean models. In fact, GEMs rely on the predictions from the geo-scientific ocean models to initialize and to reinitialize the environment model, as will be shown in Section 5.2. Furthermore, GEMs can be constructed in different ways. Chapter 6 will introduce a method called the motion tomography to construct a class of GEMs.

When information are circulating around the two modeling loops, it is transformed between two representations: the *Lagrangian* view and the *Eulerian* view. For the Lagrangian view, information are represented as data streams along the trajectories of the mobile sensing agents. The data streams are often generated by the sensors onboard mobile agents while they are moving in space. For the Eulerian view, information are represented as data streams at *fixed* spatial locations, as if they are generated by sensors installed at fixed locations. For example, if we imagine spatially distributed data as the height of trees in a forest. Then an Eulerian view of the data will be a spatial map of the tree heights, and the height of each tree increases over time. On the other hand, suppose a person walks along a trail in the forest, then a

Lagrangian view of the the data will be the height of the trees encountered by the person while walking. The main difference between the two views is whether space and time associated with the data streams are coupled (Lagrangian) or decoupled (Eulerian). The "assimilation" module and the GEM transform data from an Lagrangian view to an Eulerian view. Meanwhile, the "planning and control" module transform Eulerian view of data generated by the "prediction" module and the GEM into planned paths for the mobile agents, which are of the Lagrangian view. These two transforms serve as recurring themes for this article.

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