# Integrating Mobile Robots with Coastal Sensor Networks for Marine Event Response Management

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***Abstract*—The paper presents a novel adaptive control formulation that can be used to determine the operational parameters of both static sensors and mobile robots in a sensor network. The control formulation is posed as an optimization problem to increase the utility of the sensor measurements for improving the prediction accuracy within a dynamic region of interest. The sensor measurements from both the static sensors and the adaptive mobile robots are assimilated into the forecasts of a predictive environmental model in order to improve the assimilated forecast accuracy. We have applied and tested offline this control framework on an existing, functional maritime sensor network, the New York Harbor Observation and Prediction System (NYHOPS). The control formulation enables robotic boats to coordinate their sampling operations with static sensors in the same area. We present results using modeled data from the NYHOPS network to demonstrate how the mobile sensor parameters can be adapted to maximize the accuracy of observing a freshwater plume.**

## I. Introduction

COASTAL zones are dynamic regions, occurring at the interface of the terrestrial, oceanic and atmospheric domains. Due to the large size of these regions and due to the difficulty in accessing offshore locations for data sampling, networks of environmental sensors are being deployed in many coastal regions [1,2] to continuously measure ocean conditions and transmit the data to onshore systems for use in a variety of applications. Such systems are called ocean sensor networks. A predictive model of the ocean can provide forecasts of ocean conditions to interested users. However, hydrodynamic model predictions differ from real-world conditions due to reasons such as approximations in the model formulations. Therefore, ocean prediction systems integrate in situ sensor measurements directly into the model outputs in order to increase the prediction accuracy of the ocean conditions forecasts. Typically, the in situ sensors are fixed in location and operate in a fixed mode, i.e., their operational parameters do not adapt to the detected or predicted ocean conditions.

In our work, we consider the New York Harbor and Ocean Prediction System (NYHOPS), a coastal environment monitoring network that operates in the New York Harbor and extends into the New York Bight [1]. Currently, the NYHOPS system integrates sensor data from fixed ocean sensors into a predictive hydrodynamic model of the ocean. However, it is also possible to augment the fixed sensor readings with measurements taken from robotic boats. The main advantage of this ability is that the robotic boats can be directed to specific regions of interest within the larger monitored area. The research challenge is to develop a system in which the operations of the mobile sensing robots are decided within a common framework that includes the operation of the fixed sensors and the regions of interest. In this way, the mobile resources can be utilized as efficiently as possible. For instance, to monitor a freshwater plume on the ocean surface, the robotic boats should be deployed in those regions which have relatively few fixed sensors.

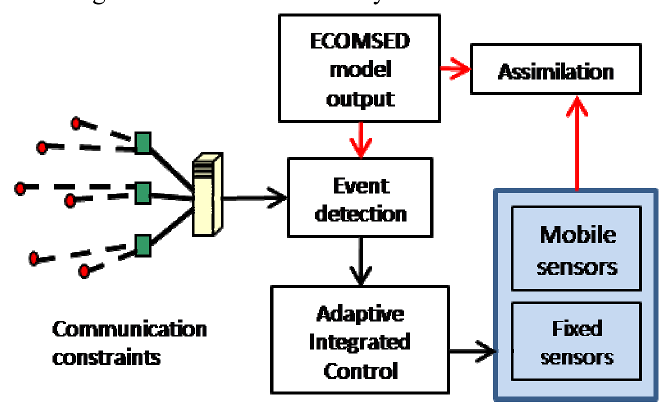


Figure 1: Adaptive control and resource management of sensor web parameters and operations in response to events.

In prior work [3], we have developed a technique to improve the utility of deploying an ocean sensor network by adapting the system parameters that affect the utility of the sensor measurements (sampling rates) and the rate of system resource utilization (energy expenditure rates of sensors and data routes in wireless transmission) such that these two competing factors are optimized (Figure 1). Our approach uses the established mathematical framework of model predictive control (MPC). We showed how this approach could improve the prediction accuracy of the system forecasts. In this paper, we show how the MPC framework can also perform path planning for a fleet of mobile robots. The MPC controller is executed at periodic intervals (6 hours in our simulations) and the resulting coordinated sensing policy is applied in the following time interval. As the robotic boats are modeled as moving over the ocean surface, we assume that the computed paths can be communicated using radio links to the individual boats. Our

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method enables the mobile robots and fixed sensors to coordinate their operations in order to improve the forecast accuracy of a particular event. The method also ensures that the assimilation occurs efficiently by managing the resources of the sensor network in response to dynamic events.

## II. Related Work

Adaptive sampling refers to the explicit control of sensor sampling rates in order to conserve system resources or to respond to changing environmental conditions. This approach has been applied to environmental sensor networks [4-9]. MPC has been used to solve specific problems arising in sensor networks. Bemporad et al. [10] consider a setting where MPC is used as a remote controller that acts on sensors using wireless communication. Arai et al. [11] use MPC to determine a sensor communication schedule in a network of mobile sensors. In environmental sensing applications, mobile sensing robots may have to be operated among a network of fixed sensors. Ogren et al. [12] use a gradient climbing approach to control mobile sensors. Zhang et al. [13] consider adaptive sampling of the environment being monitored using mobile sensors operating with fixed sensors. Paley et al. [14] describe feedback control to coordinate gliders in an ocean monitoring application.

## III. Coastal Monitoring System

The New York Harbor Observation and Prediction System (NYHOPS) is comprised of a network of sensors and a model of the ocean environment to monitor and predict coastal and ocean conditions in the densely populated regions of the Hudson-Raritan Estuary and the New Jersey Atlantic Ocean shoreline [1]. The readings from the sensors are provided to the model of the environment, the ECOMSED/POM model [15]. ECOMSED is a hydrodynamic model that describes the physical properties of the entire water mass in the NY/NJ harbor area using a set of differential equations (representing conservation of mass and momentum, and heat transfer). The inputs to the model are ocean elevation, salinity and temperature at the open and coastal boundary of the model, and weather. The model outputs are elevation, salinity, temperature, and water velocity. The model is run daily and the predictions (along with hindcasts) are displayed as images on a webpage.

## IV. Model Predictive Control for UUVs

Physical sensors that comprise part of an embedded sensing network are limited in their energy and communication resources. If the sensors are always operated at their maximum rates while transmitting all the resulting data across the wireless network, then these resources may be exhausted too early. Therefore, it is important to develop a means of regulating the operation of both the fixed sensors and mobile boats in the network in order to maximize the expected utility of incorporating the sensor data into the system output while still ensuring that the physical limitations of the sensor network are not exceeded.

We utilize a general mathematical control framework called Model Predictive Control (MPC) for regulating the operation of the sensors in the sensor network. MPC is an established technique for controlling complex continuous systems. MPC assumes that a model that describes how the system state responds to control inputs is available. At each iteration, the values of the controlled inputs are obtained by solving an optimization problem that utilizes this state model. Limits on the range of the control, and other domain-specific requirements are specified naturally as equality and inequality constraints in the optimization step. This flexibility in problem specification and the ability to derive optimal control are some of the advantages of this technique. In prior work, we have derived a statistical model to describe the utility of obtaining measurements from spatially separated but fixed sensors at different sampling rates [3]. This statistical model forms the basis for the MPC objective functions. We used the uncertainty in the estimate obtained after optimal fusion of sensor observations as a measure of the utility of the sensor measurements.

We use the formalism of Kalman filters to obtain the uncertainty in the estimate of the true value of the environmental parameter $x_p$ after fusing sensor observations. We assume that the process model and the process noise variance are known *a priori*. For simplicity of the notation, we assume that the sensors can directly observe the environmental variable, $\mathbf{H} = [11 \ldots]^T$. We assume that all the sensors can observe the environment variable but the accuracy of these measurements, as characterized in the covariance matrix $\mathbf{R}$, varies with the sensor distance in addition to the intrinsic errors added by each sensor.

We denote by $P_{t-1}$ the *a priori* estimate variance. The residual variance is then given by $\mathbf{S} = \mathbf{H}P_{t-1}\mathbf{H}^T + \mathbf{R}$ and the updated estimate variance is given by $P_t = (1 - \mathbf{KH})P_{t-1}$. Here $\mathbf{K}$ is the Kalman gain given by $\mathbf{K} = P_{t-1}\mathbf{H}^T\mathbf{S}^{-1}$. If the *a priori* estimate variance is assumed to be infinite (no *a priori* knowledge), then the *a posteriori* estimate variance reduces to $P_t = \mathbf{H}^T R^{-1}\mathbf{H}$. This estimate variance is used as the objective function with respect to a single point $p$. Note that the error covariance matrix is a function of the sampling rates and locations of all the sensors. We extend the definition of the objective function with respect to a region (from a point) by calculating the mean uncertainty over all points in the region of interest $p \in R$.

$$f_I(\mathbf{u}, R) = \sum_{p \in R} \mathbf{H}^T\mathbf{R}^{-1}\mathbf{H}$$

We consider the case where multiple mobile sensors operate in the same area occupied by the static sensors. A constrained optimization problem is defined to provide a means of determining the paths of multiple mobile sensors such that the sensor observations will have a maximal impact on increasing the accuracy of the estimates provided by the integrated sensing system.

Let $P$ denote the number of mobile sensors and let

$\mathbf{x}^{\mathrm{P}}(t) = \left(x_1^{\mathrm{P}}(t), x_1^{\mathrm{P}}(t), \ldots, x_1^{\mathrm{P}}(t)\right)$ denote the state vector of mobile sensor positions at time $t$. The elements of the sensor covariance matrix, $\mathbf{R}$, will change with mobile sensor positions. The variance of a sensor at location $x$ with respect to a local region around $p$ is given by

$$R(x) = \frac{\sigma_s^2 + k_1 d(p, x)}{u_M}$$

Here $\sigma_s^2$ is a measure of the (constant) intrinsic noise in the sensor, $u_M$ the constant sampling rate of a mobile sensor, $k_1$ is a constant of proportionality, and $d(\cdot,\cdot)$ is the distance function. Similarly, the sensor cross-covariance between two sensors at positions, $x_i$,$x_j$, is given by

$$R(x_i, x_j) = \frac{1}{k_2 d(x_i, x_j)}$$

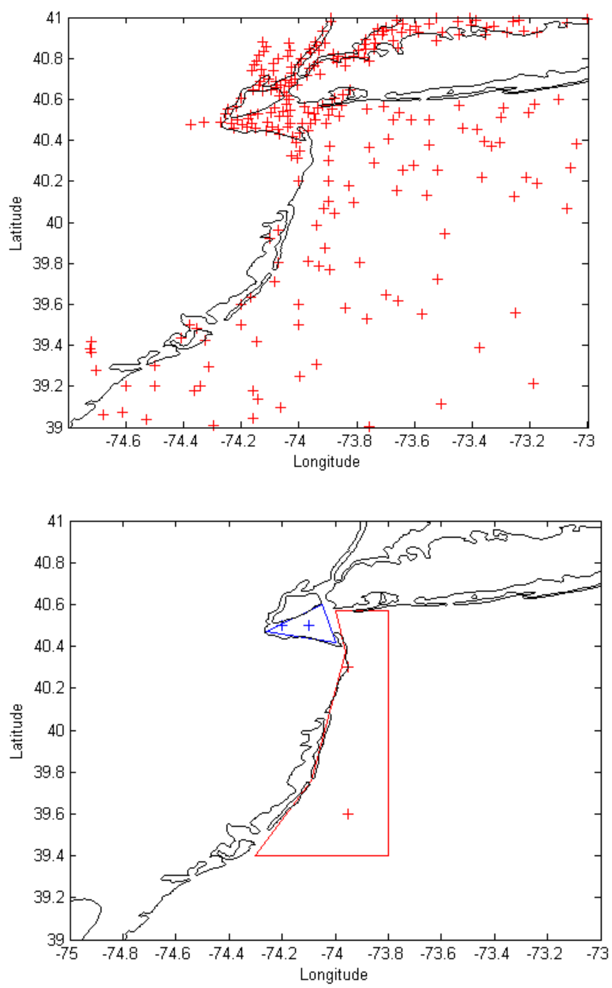


Figure 2: Top: Locations of 250 fixed sensors. Bottom: Navigable areas of the robotic boats and their starting locations.

Let $\mathbf{R}_P(\mathbf{x}^{\mathrm{P}})$ denote the covariance matrix of the mobile sensors with elements as defined above. The objective function with respect to a region of interest $R$ (set of points) is defined as

$$f_P(\mathbf{x}^{\mathrm{P}}, R) = \sum_{p \in R} \mathbf{H}^T \mathbf{R}_p(\mathbf{x}^{\mathrm{P}})^{-1} \mathbf{H}$$

The objective function is extended to the entire prediction horizon, $T$.

$$f_P\left(\mathbf{x}^{\mathrm{P}}(t), \mathbf{x}^{\mathrm{P}}(t+1), \ldots, \mathbf{x}^{\mathrm{P}}(t+T)\right) = \sum_{t'=t+1}^{t+T} f\left(\mathbf{x}^{\mathrm{P}}(t'), R_{Event}(t')\right)$$

The maximum speed of the mobile sensors and navigable areas are modeled as constraints in the optimization problem.

$$d\left(x_p^{\mathrm{P}}(t+k+1|t), x_p^{\mathrm{P}}(t+k|t)\right) \le v_{MAX}\ \forall p = 1,2,\ldots,P, 0 \le k \le T$$

$$x_p^{\mathrm{P}}(t+k|t) \in S_p \forall p = 1,2,\ldots,P, 0 \le k \le T$$

where $v_{MAX}$ is the maximum velocity of a mobile sensor, and sensor $p$ remains within the region defined by $S_p$.

## V. Results

During the week of April 15, 2007 unusually heavy rainfall caused a freshwater flooding event in the New York harbor and surrounding ocean ("Tax day flood"). This caused a freshwater plume to form in the New York Bay and spread out into the open ocean. We simulated the presence of 250 sensors in the modeled area. The locations of the simulated sensors are shown in Figure 2. True ground truth sensor observations are not available at the required resolutions throughout the modeled area. Hence we simulated static and mobile sensor data by subsampling from a high resolution ECOMSED model output. This high resolution model was instantiated with the heavy rainfall parameters. The base model predictions were obtained by intentionally "compromising" the ECOMSED model, i.e., model parameters were set to their historic values instead of real-time observations in order to mimic a model that does not respond to unexpected events. Specifically, we set the flow rates of freshwater into the ocean in the ECOMSED model to their historic median rates. Thus, this compromised ECOMSED model did not predict the freshwater plume but the simulated sensors observed the plume. Event detection was implemented by designating sensors observing surface salinity values that were beyond one standard deviation from the historic mean to be in the region of interest.

We modeled the operation of 4 robotic boats on the ocean surface in the modeled area. In order to reflect the real-life limitation that boats may be deployed close to the coast only, two of the boats were confined to navigate in the Lower New York Bay and the other two along the New Jersey coast. These areas are shown in Figure 2. Figure 3 shows the computed path of the 4 boats. The MPC controller was executed every six hours to plan the paths for all the robotic boats for the following control interval.

The effect of controlling the paths of boats on increasing the accuracy of the ECOMSED model predictions is shown in Figure 4. The plot shows the proportional increase in model accuracy using the model error without sensor data assimilation (RMS error of sea surface salinity of the compromised ECOMSED prediction) as the baseline.

Increasing the number of sensor observations by deploying the boats increases the model accuracy. The relative benefit of using a mobile sensor depends on its location. Figure 4 shows the model accuracy when data from sensors on passing cruise ships (not controlled or modeled in our formulation) is also assimilated into the model. One of the ships moves in the Upper New York Bay, an area where there are few sensors. Hence, assimilating data from this ship leads to a relatively larger increase in accuracy.

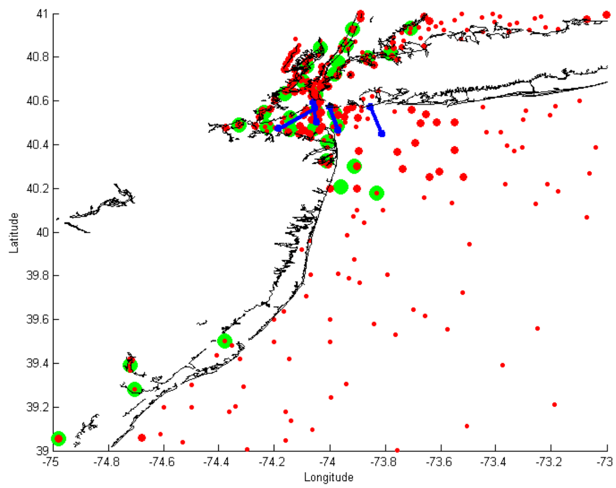


Figure 3: Movement of 4 robotic boats between two consecutive control steps (blue lines). The red dots indicated locations of the fixed sensors with diameter proportional to sampling rates. The green circles indicate sensors that see anomalous readings.

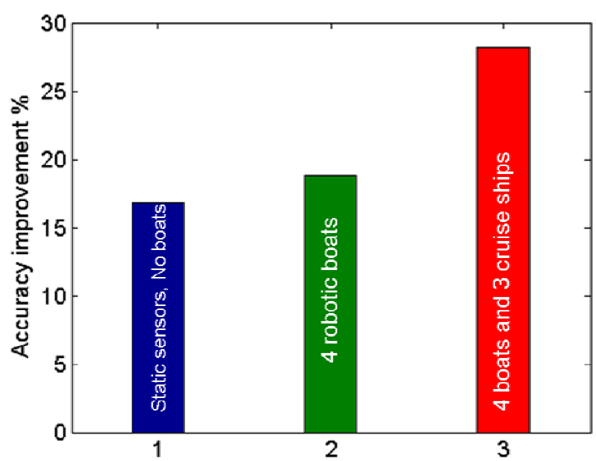


Figure 4: Increase in model prediction accuracy from controlling the paths of robotic boats and assimilating data from passing cruise ships.

## VI. Conclusion and Future Work

The paper demonstrated a framework for sensor control in ocean sensor networks. The technique is general enough that it can determine the optimal paths of mobile sensing robots. The operation of the robotic boats is optimized along with that of the resources of static sensors while ensuring that the system operates within the limits of the system resources. The control technique is adaptive in that the formulation takes into account the changes in the ocean environment.

The MPC resource management algorithms task the robotic boats along with the stationary sensors such that the regions of interest are examined in greater resolution. However, as the energy required to move over water is large, the planned paths for the boats can take advantage of favorable conditions such as a following current and avoid unfavorable conditions. We will implement a model of the energy expenditure of the boats that takes into account the predicted water current to compute this optimized path.

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