Environmental Monitoring using Autonomous Aquatic Robots

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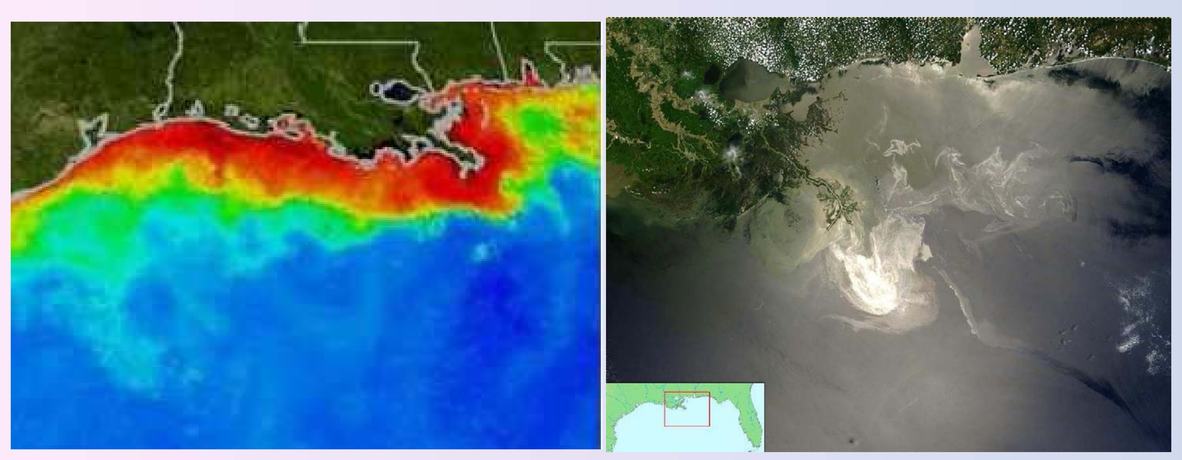
Introduction

In recent years, due to significant progress in sensing, communication, and embedded-system technologies, many research activities have been focused on the areas of mobile sensor networks and multi-agent systems.

Mobile sensor networks can be used to monitor environmental variables such as temperature, pH, salinity, toxins, and chemical plumes.



(a) (b)

Figure 1: (a) Dead zone created by algal blooms in the Gulf of Mexico (NASA). (b) The oil slick as seen from space by NASA's Terra satellite on May 24, 2010 (Photo courtesy of NASA).

In modeling a time-varying, environmental scalar field (or a spatio-temporal process), a finite set of basis functions is often used so that a scalar value $\mu(\nu,t)$ at position ν and time t can be represented by

$$\mu(\nu,t)=\sum_{j=1}^{n_x}\psi_j(\nu)x_j(t)=\psi^T(\nu)x(t),$$

Where $\{\psi_j(\nu)\}$ is a finite set of basis functions and $x(t)$ is a time-varying coefficient vector, which is modeled by a linear time-invariant system with a stochastic input w_1

$$\frac{dx(t)}{dt}=Ax(t)+w_1(t).$$

When a small number of mobile sensing robots monitor a possibly unstable environmental process in a large surveillance region, several important problems arise. One of them is how to design a sampling strategy for robotic sensors such that a good quality of the estimation is always being maintained. On the other hand, the lifetime of the robotic sensor network has to be maximized for this resource-constrained scenario.

The down-sampled system

We consider a down-sampled system with the accumulated sampled-data measurements over a period, which is defined by

$$y_i := \mathrm{col}(y(Ni+1), y(Ni+2), \cdots, y(Ni+N)) \in \mathbb{R}^{Nn_y}.$$

We obtain the down-sampled system with collective measurements

$$x_{i+1}=F_i x_i + G_i u_i,$$
$$y_i = H_i x_i + v_i.$$

The optimal estimator for this down-sampled system can be given by a Kalman filter.

$$\hat{x}_{i+1|i}=F_i\hat{x}_{i|i-1}+K_i(y_i-H_i\hat{x}_{i|i-1}),$$
$$P_{i+1|i}=F_iP_{i|i-1}F_i^T+G_iQ_iG_i^T-K_iR_{e,i}K_i^T.$$

Therefore, we use the KF predictor updates for the down-sampled system to obtain the estimates of $x(Ni)$ and the estimation error covariance based on the measurements $\{y(0),y(1),...,y(Ni)\}$.

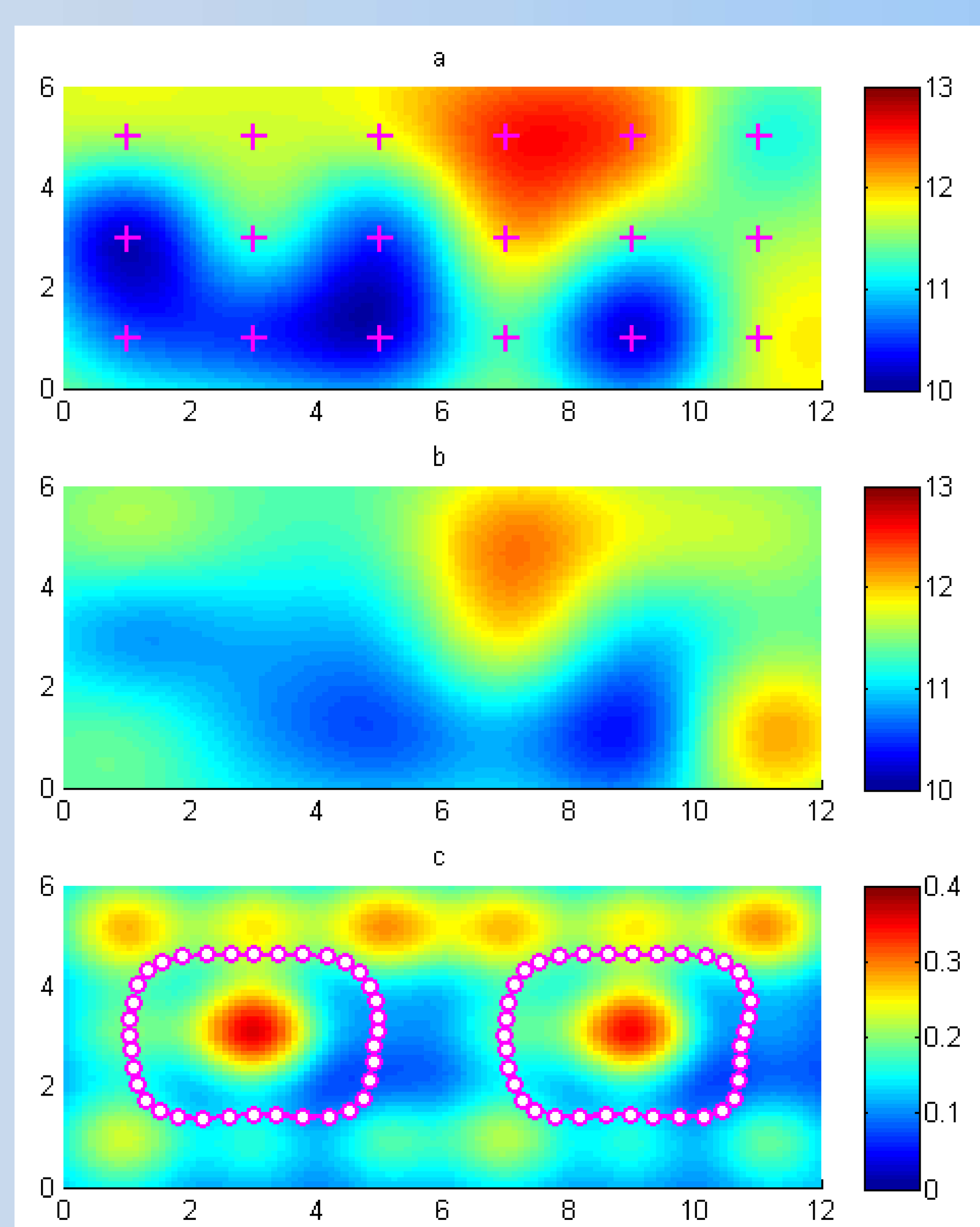


Figure 2: (a) The simulated true temperature field is shown. The purple pluses represent the target points and also the centers of radial basis functions. (b) The estimated temperature field is shown. (c) The estimation error variance field is shown. The CCW trajectory of simulated sampling points is shown in purple solid lines with white dots. The trajectory for both agents starts from three o'clock

Optimal Sampling Strategies

Let $r=\mathrm{col}(r_1,\cdots,r_N)\in\mathbb{R}^{2n_yN}$ denote a sampling position vector whose position entries are associated to the sampling times $t_{Ni+1},\cdots,t_{Ni+N}$ over a period. The sampling position vector r also serves as a collection of way points which robotic agents track and take measurements at over a period.

To optimize the sampling strategy, we consider mixed optimization for minimizing two conflicting cost functions such as the estimation error variances at target positions $q^{target}:=\{q_j^{target}|j=1,\cdots,n_T\}$ and another one for maximizing the lifetime of the robotic sensor network.

The cost function at iteration $i+1$ is given by

$$J^{i+1}(r)=\lambda J_1^{i+1}(r)+(1-\lambda)J_2^{i+1}(r),$$

where $\lambda\in[0,1]$ is the weight factor. $J_1^{i+1}(r)$ is the estimation performance cost function defined by the averaged estimation error variances at target positions at period $i+1$ using observations up to period $i+1$ and $J_2^{i+1}(r)$ denotes the traveling energy cost function of the sensor network.

$$J_1^{i+1}(r)=\frac{1}{n_T}\sum_{\nu\in q^{target}}\mathbb{E}\left[(\mu(\nu)-\hat{\mu}(\nu))^2\right]$$

$$J_2^{i+1}(r)=\alpha\left(\frac{\|r_N-r_1\|^2+\sum_{k=1}^{N-1}\|r_k-r_{k+1}\|^2}{Nh}\right)$$

We consider the following greedy policy which minimizes the cost function in the next iteration.

$$r[i]=\arg\min_{r\in DS} J^{i+1}(r),$$

where $r[1],\cdots r[i]$ are sampling position vectors for periods *1, ..., i* . *DS* is the set of all possible r in which $\{F,H(r)\}$ is detectable.

The estimation performance cost J_1 and the energy cost J_2 are conflicting cost functions since robotic sensors need to sample many different points to improve the quality of the estimate, which requires a lot of traveling and energy dissipation. A trade-off can be obtained between the conflicting cost functions J_1 and J_2 e.g., the achieved value of J_1 decreases while that of J_2 increases as λ increases.

Experiment

We have built our own aquatic surface robots equipped with various sensors for localization and water quality monitoring. The robot is capable of monitoring the aquatic variables in an autonomous manner while could be remotely supervised by a central station as well.

Figure.3: The aquatic robot is shown.

Acknowledgment

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Conclusions

- We developed a practical solution to an environmental monitoring problem in a large region by a small number of robotic sensors.
- Optimal sampling strategies were developed to maximize the estimation quality and the lifetime of the robotic sensors.
- A trade-off between these two conflicting objectives has been presented.
- The effect of the sampling parameters such as the number of measurements, weighting factors, and the sampling time interval has been reviewed.
- the simulation and experimental results have been provided by our aquatic surface robot in an outdoor swimming pool with controlled hot water flux.