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Efficient Environmental Monitoring Using Cost-Aware Path Planning

Junghun Suh and Songhwai Oh

Department of Electrical and Computer Engineering and ASRI,
Seoul National University, Seoul 151-744, Korea
E-mail: {junghun.suh, songhwai.oh}@cpslab.snu.ac.kr

Abstract: This paper presents an efficient environmental monitoring strategy that considers the information gain along the trajectory of a robot. In order to monitor environmental parameters such as temperature and chemical concentration, an estimation method based on Gaussian process regression is used. The goal of this paper is to model accurate spatio-temporal phenomena by reducing the uncertainty over the surveillance region. A cost-aware path planning based environmental monitoring is desirable for mobile sensor networks since robots are coordinated to follow a trajectory with the maximum accumulated information gain, as well as the traveling distance. The proposed method with respect to different sampling methods is demonstrated in simulations.

Keywords: Environmental monitoring, Gaussian processes, Cost-aware path planning.

1 INTRODUCTION

As today's society becomes increasingly eco-conscious, a study on environmental changes has been actively conducted in recent years. Especially, after a set of natural catastrophic disasters, such as floods, tsunami, and earthquakes, significant enhancements have been made in the area of environmental monitoring. In order to monitor the environmental phenomenon, large amounts of data measurements over the whole surveillance region is required, and thus it has led to the development of the autonomous robotic systems. When compared to stationary sensor networks, mobile agents provide superior performance by increasing sensing coverage both in space and time, so a mobile sensor network is suitable for monitoring environmental parameters. Since it can acquire information while exploring over the sensing area, a navigation method which intelligently reduces uncertainty in the estimation of environmental parameters is required.

In our approach, a spatio-temporal Gaussian process (GP) is considered to specify the model representing the environmental phenomenon. A Gaussian process (or Kriging in geostatistics) is a nonparametric regression method which has been used to estimate and predict complex physical phenomena [1].

In [2], Gaussian process regression is used to predict the spatial phenomenon of interest and a theoretical foundation of Gaussian process regression with truncated observations is derived. Moreover, mobile robots are used to estimate environmental parameters of the field and coordinate towards the location with the most information gain based on a gradient descent method. However, the navigation strategy is performed without considering the information gain along the trajectories of robots.

In this work, we propose an efficient explorative navigation method, which represents an extension of the swarm navigation method proposed in [2]. In particular, an efficient navigation strategy using a cost-aware path planning method presented in [3] is considered for environmental monitoring. For locations with the most information, we apply not only the information gain but also the Upper Confidence Bound (UCB) under the Bayesian optimisation framework proposed in [4]. From the simulation results, we demonstrate the performance of the proposed method.

The remainder of this paper is structured as follows. In Section 2, we briefly review Gaussian process regression and a cost-aware path planning algorithm. Section 3 explains the efficient explorative navigation for environmental monitoring. The results from simulation are presented in Section 4.

2 PRELIMINARIES

2.1 Gaussian Process Regression

A Gaussian process (GP) is a generalization of any finite number of random variable sets having a Gaussian distribution over a space of function. If $z(X)$ is a GP, where $X \in D \subseteq \mathbb{R}^n$, it can be fully described by its mean function $\mu(X) = \mathbb{E}(z(X))$ and covariance function $K(X,X') = \mathbb{E}[(z(X) - \mu(X))(z(X') - \mu(X'))]$, respectively, as follows

$$z(X) \sim GP(\mu(X), K(X,X')). \quad (1)$$

We can represent the data $Y = [y_1, y_2, \ldots, y_n]^T \in \mathbb{R}^n$ measured at location $X = [X_1, X_2, \ldots, X_n] \in D$ as $y_i = f(X_i) + w_i$, where w_i is a white Gaussian noise with variance σ_w^2. For a new location X_*, based on the measured data Y, the predicted value of $z(X_*)$ has the Gaussian distribution with mean and variance as shown below:

$$\hat{z}(X_*) = K_*^T (K + \sigma_w^2 I)^{-1} Y \quad (2)$$

$$cov(\hat{z}(X_*)) = k(X_*, X_*) - K_*^T (K + \sigma_w^2 I)^{-1} K_*, \quad (3)$$

where $K = [K_{ij}]$ is the kernel matrix with (i, j) entries $K_{ij} = k(X_i, X_j)$, $K_* = [k(x_1, x_*), \ldots, k(x_n, x_*)]^T$, and $cov(z(X_*))$ is the covariance of the estimated value $\hat{z}(X_*)$

[1] and it measures the uncertainty we have about the new location X_* and can be used in mobile sensor networks for exploration.

In this paper, we use the squared exponential as a kernel function,

$$k(X,X') = \sigma_f^2 \exp\left(-\frac{1}{2\sigma_l^2}\sum_{m=1}^{n}(X_m - X'_m)\right), \tag{4}$$

where σ_f and σ_l are hyperparameters of the kernel.

2.2 Cost-Aware Path planning

A cost-aware path planning (CAPP) algorithm developed in [3] is an efficient navigation strategy which finds the minimum cost path of a robot from one location to another, provided that the surveillance region can be represented by a cost map. It extends the rapidly exploring random tree (RRT) [5] algorithm by applying the cross entropy [6] method when extending motion segments as a local planner extends the RRT tree. The CAPP algorithm is shown in Algorithm 1. The algorithm shares the overall structure of RRT but it uses rejection sampling to choose a random point x_{rand} based on the cost map C.

The tree $\mathscr{T}$ initially contains only one point x_0. After finding the nearest point x_{near} of x_{rand} in the tree $\mathscr{T}$, a modified version of the cross entropy (CE) based path planning algorithm is applied to extend the tree. The modified CE method finds the minimum cost path, which selects a trajectory with the minimum cost, which is a sum of costs accumulated along the trajectory and the terminal cost, among candidate trajectories. With this two layers of filtering, a minimum cost path from x_{near} to x_{rand} is obtained. The algorithm terminates when the tree $\mathscr{T}$ reaches the goal region x_{goal}.

The CAPP algorithm can reach the goal region because it shares the overall structure of RRT, unlike a CE based method. On the other hand, while a solution from RRT is not finely tuned to minimize the cost, the proposed algorithm enjoys fine tuning of control over a continuous control input space using the cross entropy based optimization.

Algorithm 1 A cost aware navigation strategy

Input: Start position x_0 and goal position x_{goal}; Cost map $C : \mathscr{X} \to \mathbb{R}^+$

Output: Minimum cost path from x_0 to x_{goal}

1: Choose a sample point x_{rand} over state space based on rejection sampling.
2: Find a point in the tree $\mathscr{T}$ which is nearest to x_{rand} according to the distance metric.
3: Apply the modified cross entropy method in order to extend the tree $\mathscr{T}$ based on the cost map C.
4: Repeat steps $1-3$ until tree $\mathscr{T}$ reaches x_{goal}.

3 EFFICIENT ENVIRONMENTAL MONITORING

The efficient environmental monitoring strategy is shown in Algorithm 2. The algorithm is an extension of the explorative navigation strategy developed in [2], which coordinates a group of mobile agents to reduce the predictive variance of the surveillance region while maintaining a certain distance between each pair of agents using consensus and flocking. By using the cost-aware path planning method explained in Section 2.2 when coordinating toward the location with the largest information gain, we can reduce the cost of a robot along its path, which is more desirable than the simple gradient descent navigation method in [2]. In order to sample the location with the most information, [2] picks a location with the highest predicted variance which represents the largest information gain. In this paper, we also applied a different sampling method, Upper Confidence Bound (UCB) [4]. UCB is defined as follows:

$$UCB(x) := z(x) + \kappa\sigma(x), \tag{5}$$

where $z(x)$ and $\sigma(x)$ are the mean value and variance for the prediction at location x, respectively. κ is a tuning parameter which represents the exploration-exploitation trade off. The location which maximizes the value of UCB is selected as a location with the most information gain. By considering the predicted value of the environmental field, the region with a high value of $z(x)$ is selected more often. As a result, it provides more efficient monitoring strategy over the surveillance region.

Algorithm 2 Efficient environmental monitoring strategy

Input: Number of stationary sensors N; Positions of stationary sensors $\mathbf{x_s}(t_k)$; Initial position of the robot $q(0)$; Resolution r

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while true do
    Let x be the location with the most information.
    Select x depending on the sampling method
    Set x to the goal position x_goal and the current positions of the robots to the initial position x_0.
    Apply Algorithm 1 and find the trajectory to x_goal.
    while true do
        k = k + 1 (update the current time)
        Let A(t_k) be the measurements from stationary sensors, i.e., A(t_k) = [y_1(t_k) ··· y_N(t_k)] and y(q(t_k)) be the measurement from the robot.
        Compute predicted variances at evenly divided locations at resolution r using A(t_k) and y(q(t_k)).
        Apply control to follow the trajectory.
    end while
end while
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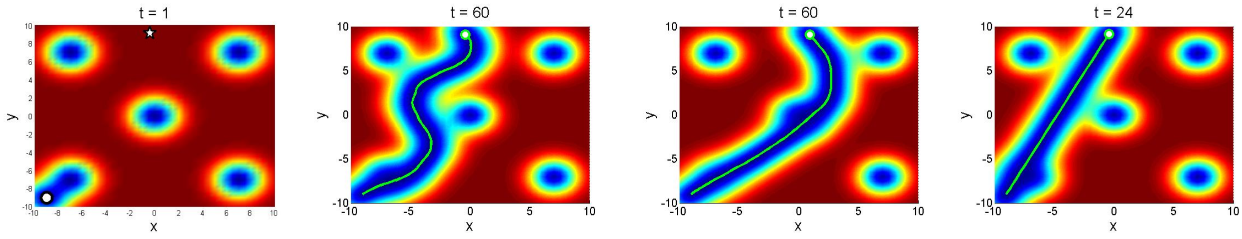

Fig. 1 Environmental field used in simulation and trajectory found from different path planning algorithms. The color represents the variance of the environmental field. The blue color represents low variance and the red color represents high variance. Each green line represents of trajectory obtained from CAPP, basic RRT, and gradient descent in 1(b)-1(d), respectively.

4 SIMULATION RESULTS

In order to study the performance of our environmental monitoring strategy, we first apply different path planning methods such as cost-aware path planning (CAPP), the gradient descent method, and the basic RRT to the explorative navigation strategy. We generated the static environmental field to be monitored. This field is constructed using (4), where $\sigma_f^2 = 1$ and $\sigma_l^2 = 2$. We placed five stationary sensors over this field and collected measurements from the stationary sensors at each time with measurement noises ($\sigma_w = 0.2$). We first compared cost-aware path planning (CAPP) against the basic RRT and gradient descent for the static environmental field. Figure 1 shows the variance of the environmental field over the surveillance region and the trajectory based on each algorithm toward the location with the highest uncertainty from the initial location. High variance is represented by red and low variance is represented by blue. The white circle represents the initial position and a star represents the goal position. Since we placed the stationary sensors over the field, the variance around the sensors are low at the initial time as shown in Figure 1(a). Trajectories obtained from CAPP, basic RRT, and gradient descent method are shown in Figure 1(b)-1(d), respectively. Since the speed of the robot for the gradient descent method is determined depending on the gradient over the field, the arriving time to the goal position is the shortest while the other algorithms gives longer trajectories. As can be seen from Figure 1, the trajectory found by the CAPP passes through the region with high variance, while the other two methods pass through the region with the sensor. Mean square errors are shown as a function of the traveled distance in Figure 2. MSE of the CAPP becomes the least as the traveled distance increases. But MSE is not different from the CAPP and the gradient descent method at the begining. This is due to the fact that there exist many regions with high variance, so the path planning algorithm does not have an effect on reducing MSE at the beginning.

We also conducted simulations with a different sampling method based on the environmental field used in previous simulations. Mean square errors are shown in

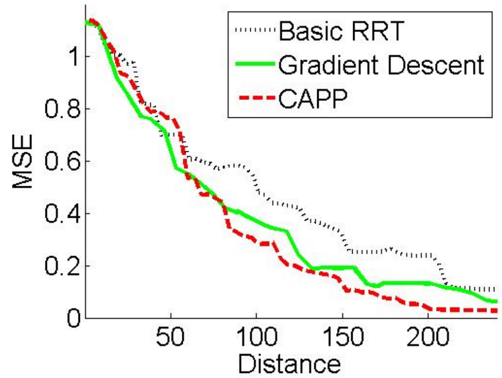

Fig. 2 Mean square errors are shown as a function of the traveled distance. Legend: basic RRT (black), gradient descent (green), and CAPP (red).

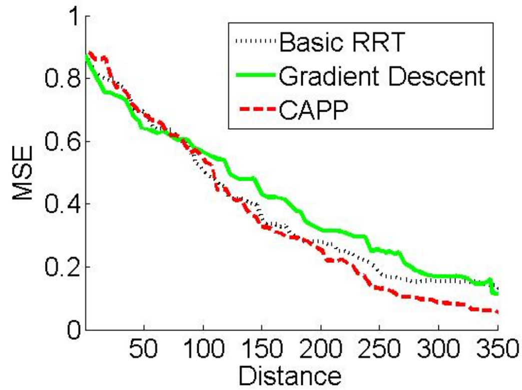

Fig. 3 Mean square errors for UCB based navigation strategy.

Figure 3 when the UCB based navigation strategy is applied for sampling the location with the maximum information gain. Again, the CAPP is the best performer.

5 CONCLUSION

In this paper, we have proposed an efficient environmental monitoring strategy using cost-aware path planning algorithm. The environmental field over the surveillance region is modeled by a Gaussian process. The proposed strategy enable robots to coordinate toward the location with the most information by following the trajectory with the maximum accumulated information gain. We have shown through simulations that applying a cost-aware path planning algorithm is the best performer for decreasing the estimation error over the surveillance region in terms of distance travelled by a robot.

6 ACKNOWLEDGEMENT

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