Real-Time Path Planning to Dispatch a Mobile Sensor into an Operational Area

Introduction

A mobile sensor denotes a mobile robot system which is equipped with a sensor to gather information of the environment. A representative example of the mobile sensor is an unmanned aircraft with a sensor of any kind to track designated targets. The use of a large number of sensors has become common in data fusion applications to obtain synergistic observation effects. As the amount of data to be processed has increased, emerging interest in research into automatic management of a set of sensors is motivated. Generally, multisensor management algorithm is about how to make real-time decisions for selection of a sensor set and configuration of sensor deployment. The criteria for such decisions are defined on the basis of the accuracy of parameter estimation. Information theory provides a tool of achieving this aim. Information measures such as Fisher information matrix (FIM) and entropic information have been employed to quantify performance of the sensor system.

The purpose of the path planning for dispatch of a mobile sensor is to obtain maximum information of the target state where the mobile sensor can operate sensing task in a circular region, called an operational area, as depicted in Fig. 1. Note that the sensor deployment location is different from the operational area. In making plans for the sensor dispatch, since there is no measurement available right after the dispatch, the cost formulation has no term dependent on sensor state at that time. It is hard to apply the receding horizon and gradient-based methods to this problem setup since the state-dependent cost resides at a future time. Even if the optimal solution is found, the optimal trajectory starting after large planning time may be no longer optimal in the perspective of information. It is because the information of the environment is being dissipated during the planning time. Consuming much time in path planning after the real-time decision to dispatch is not preferable in practice.

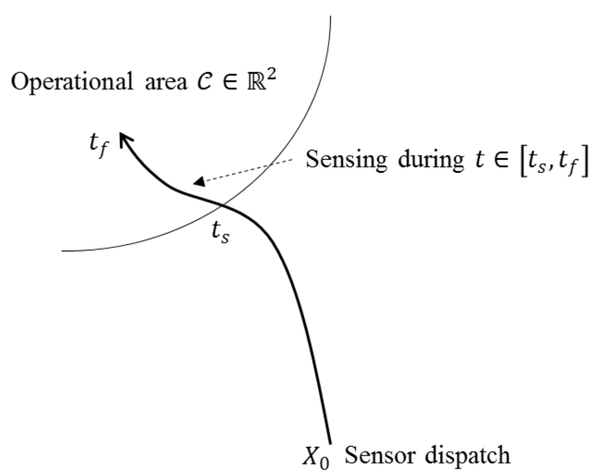

Fig. 1. Operational area and sensor dispatch location.

Problem

Optimal path planning provides a sensor trajectory to obtain maximum information reward. However, solving a nonlinear optimal control problem requires a substantial amount of computational effort. The problem resides in that the sensor management system cannot respond properly to the dynamic environment if the dispatch of the sensor is delayed due to the computation for path planning. The time evolution of the FIM is expressed as below.

$$\dot{J}(t) = \underbrace{-J(t)F(t) - F^T(t)J(t) - J(t)Q(t)J(t)}_{Information\ dissipation} + \underbrace{\mathbb{I}(t)H^T(t)R^{-1}(t)H(t)}_{Information\ gain}$$

where every matrix in the above equation is positive semi-definite. Although the formulation for the cost function assumed that the initial time $t = 0$ is when the sensor is dispatched, the information dissipates over the planning time before the dispatch. Consequently, the optimal solution will give the path for the mobile sensor to obtain maximum information gain based on the dissipated initial information. If the planning procedure takes $t_p > 0$ ant the final time is t_f, the actual performance of the sensing operation is

$$\mathcal{J}(t_f) = -\frac{1}{2}\ln\det\int_{-t_p}^{t_f}\dot{J}(t)dt$$

Given a real-time decision to dispatch a new sensor, consuming much time in planning is not preferable in practice. For simplicity, the following discussions will also define the dispatch time, $t = 0$, as the initial time for path planning.

At the instance of path planning, i.e. $t = -t_p$, only the system model and the target state at that time, $X_T(-t_p)$ are available to path planning algorithms. Therefore, path planning should be done based on the predicted target state for $t \in [t_s, t_f]$, not the true state, evaluated at the planning time. Fig. 2 depicts an exemplary time history of uncertainty of the target state which a path planning algorithm refers to. A path determined by an optimal planning algorithm with erroneous cost evaluation may not be the best solution.

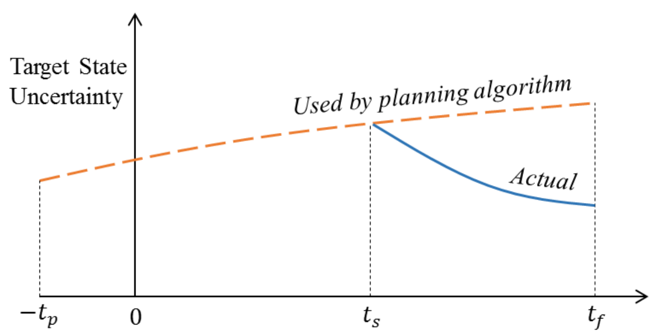

Fig. 2. Time history of target state uncertainty. Dashed line denotes uncertainty of target state predicted at the planning time. Solid line denotes uncertainty of target state estimated by a filtering algorithm.

Proposed Path Planning Strategy

We divided the problem into two phases in order to devise a computationally efficient path planning strategy. Determining the path to the boundary of the operational area belongs to the first phase, given a control law during the operation in the area as the second phase.

The discussion of the proposed method will start by introducing a gradient-descent steering law which is often employed as a suboptimal solution. The gradient of the rate of the information measure is obtained as

$$\nabla \dot{\mathcal{J}}(t) = \begin{bmatrix} \frac{\partial \dot{\mathcal{J}}(t)}{\partial x} & \frac{\partial \dot{\mathcal{J}}(t)}{\partial y} \end{bmatrix}$$

Note that the steering law based on the information potential field depends solely on the spatial coordinates of the sensor. Consequently, the time history of the sensor path during $t \in [t_s, t_f]$ is determined by the starting position of the sensor on the boundary.

Given that the path constructed by the gradient-descent steering law depends on the starting position on the boundary of $\mathcal{C}$, the path planning problem becomes the problem of finding the optimal starting position. In order to further save the planning time, the optimization of the starting position is designed to be executed online. The starting position optimization is based on gradient descent method for empirical cost optimization. The gradient descent is popular for its efficiency in large scale convex optimization and often utilized in online learning.

However, the optimization process still requires computation for executing the gradient descent method before dispatch. The following discussion is about how to further reduce the planning time. The main idea herein is that the optimization can be done online on the way to a properly chosen waypoint. Suppose $[\theta_L, \theta_U] \subset \mathcal{C}_b$ is a set of points at which the mobile sensor can arrive in t_s after dispatch. If a smaller set $[\theta_l, \theta_u] \subset [\theta_L, \theta_U]$ is given, there exists a point outside $\mathcal{C}$, closer to $\mathcal{C}_b$ than X_0, from which the mobile sensor can arrive at any of $\theta \in [\theta_l, \theta_u]$ in the remaining time. We call the point a waypoint and its position is denoted as X_w. After arriving at X_w, the sensor is guided to the optimum θ^*. The waypoint is supposed to have shortest path to the boundary of the operational area to maximize the optimization time. In this paper, Dubins' theory is incorporated to properly choose the waypoint and estimate the optimization time.

Fig. 3 presents a graphical representation of the proposed algorithm.

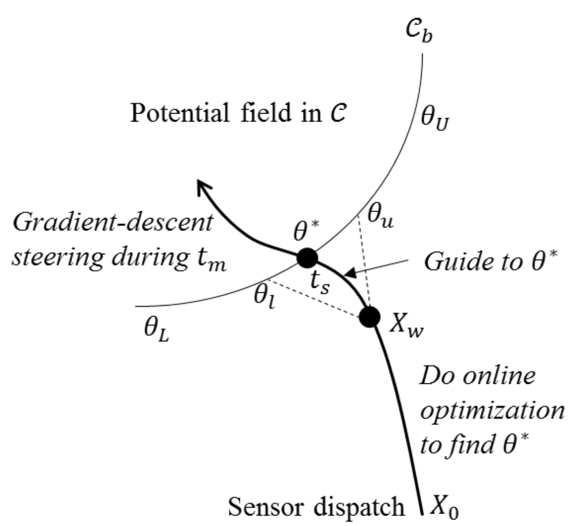

Fig. 3. Graphical representation of the proposed algorithm.

Simulation Result

Suppose a multisensor system is executing a multitarget tracking mission in an operational area. The scenario starts with new 3 targets being detected by some sensor in operation. The sensor manager makes a decision to dispatch a new mobile sensor to track the targets. Specifically, an unmanned aircraft equipped with a sensor system that provides angles and range measurements is supposed to be dispatched.

The solution to the optimal control problem with initial target state uncertainty is denoted as 'optimal' while the optimal solution based on the true target trajectory is denoted as 'reference'. The solution of the proposed algorithm is denoted as 'proposed'. Nonlinear programming (NLP) solver SNOPT of GPOPS-II is used to solve the optimal control problem where the problem is constructed in two phases. The optimized solutions are obtained within two minutes and satisfy optimality criteria with tolerance of 10^{-2}. On the other hand, the proposed algorithm takes less than a second for planning before dispatch.

Assuming solving the optimal control problem requires 10 seconds, the time history of the information indices for a scenario is obtained as Fig. 4. Although the initial target state uncertainty is set equivalent, the information of the targets dissipates during the planning time for the reference and optimal solution. As a result, the proposed method outperforms the optimal solution. We observe that the final cost of the reference solution is degraded as well due to the information dissipation. By the definition of the information index, the lower bound of the volume of the target state uncertainty can be obtained by taking exponential to the information index. If the difference of the information indices between two trajectories is 1, it means the ratio of volume of the target state uncertainty ellipsoids obtained by optimal filtering is $e = 2.7183$.

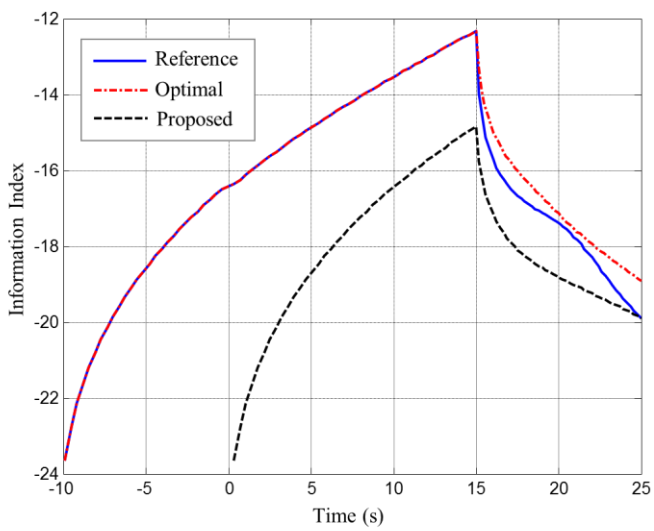

Fig. 4. Time history of information indices.

Conclusion

This paper addressed a real-time path planning algorithm for dispatch of a mobile sensor to an operational area. After presenting the proposed method to cope with the problems caused by large planning time and cost uncertainty, we gave numerical simulation results to verify performance of the proposed method compared to that of optimal solutions. Performance degradation was observed in the optimal solution with erroneous initial target state and large planning time. Requiring less computational effort, the proposed method outperformed the optimal solution.