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Real-time path planning to dispatch a mobile sensor into an operational area

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ABSTRACT

This paper addresses problems of large planning time and cost uncertainty for informative path planning of a mobile sensor where the location of sensor deployment is different of that of an operational area. The first problem is that the cost has no term dependent on sensor state before arriving at the operational area and it causes large planning time. The information of the state of interest dissipates over time during the planning time and it degrades performance of sensing operation. The other problem is that the cost is dependent on the parameters to be estimated. To assess the cost, the target state in the future should be predicted by integrating the system model based on noisy initial estimate. The limitation of the informative path planning has a greater impact on performance in this specific problem. A strategy to cope with these problems is to devise a real-time path planning algorithm by using online optimization. The proposed algorithm is divided into two phases; determining the path to the boundary of the operational area and guiding the sensor by an informative potential field in the area. Detailed analysis on performance of the proposed algorithm compared to an optimal solution by nonlinear programming is given. The simulation results have demonstrated that the proposed algorithm can cope with performance degradation observed in the optimal solution.

1. Introduction

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. Multisensor management is formally described as a system or a process that attempts to manage a set of sensors in a dynamic, uncertain environment to improve performance of data fusion [1]. Generally, multisensor management algorithm is about how to make real-time decisions for selection of a sensor set [2–4] and configuration of sensor deployment [5–7]. 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. Difference and relationship between various information measures can be found in [8,9].

A mobile sensor denotes a mobile robot system which is equipped with a sensor to gather information of the environment [10–13]. It is also referred to as a mobile smart object [14] which includes aerial or terrestrial drones exploring an operational area [15,16] since it is a mobile robot system that is more complex than a sensor. The mobile sensor is expected to perform a mission in an operational area, to reduce uncertainty in some quantity of interest at some point in time. A key problem for the mobile sensor network is to make plans for maximizing the information by controlling the mobile sensors after the decision of sensor selection and deployment. It is often formulated as an optimal control problem which can be solved by nonlinear programming (NLP) [17–19]. To avoid explosion in computing complexity in NLP, some studies have addressed this problem by using receding horizon method [20–22] and gradient-based control [8,10,23,24] as real-time solutions. For online motion planning including dynamic and environmental constraints, moreover, framework of the Rapidly-exploring Random Tree (RRT) algorithm [25] has been extended to the multidimensional RRT* [26] and the Information-rich Rapidly-exploring Random Tree (IRRT) algorithm [27–29]. Note that in the previous works the sensors are assumed to be deployed already at an operational area, where the sensors can obtain measurements, before starting planned behaviors.

The purpose of this study is to devise a path planner where the mobile sensor can perform sensing task after arriving at an operational area. The problem is that the initial sensor location is different from the operational area. For applications in dynamic environment, such as search and rescue [14,15,30] and target tracking [8,12,13,31], real-time decision to dispatch a mobile sensor to a region of interest or

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reallocate a sensor in operation to another region can be made. In that sense, we suppose that the mission of a mobile sensor starts with the decision to dispatch, not with the deployment onto 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 RRT-based methods to this problem setup since the state-dependent cost resides at a future time. Even if the optimal solution by NLP 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.

Another problem addressed in this paper is the dependence of the cost function on the parameters to be estimated, as pointed out in [21,32,33]. The path planning algorithms should refer to the predicted target state, not the true state, to assess the future information measure. The target state in the future is obtained by integrating the system model based on noisy initial estimate. The obvious limitation to the informative path planning will have a greater impact on performance of the path planner to the specific problem formulated in this study.

The strategy of this study to deal with these problems is to design a real-time path planning algorithm using online optimization. The proposed algorithm is divided into two phases. Determining the path to the boundary of the operational area through a properly chosen waypoint belongs to the first phase, given a gradient-based control law during the operation in the area as the second phase. The gradient descent method for empirical risk minimization [34] is adopted for online optimization executed on the way to the waypoint to determine the best approach position to the operational area. Feasibility of the proposed algorithm was verified by numerical simulations for an exemplary multisensor-multitarget tracking mission. Detailed analysis on performance of the proposed algorithm compared to that of the optimal solution by NLP will be given. Simulation results have demonstrated that the proposed algorithm can cope with performance degradation observed in the optimal solution caused by large planning time and cost uncertainty.

The rest of the paper is organized as follows. It starts with addressing problem formulation in Section 2. After introducing the formulations for the state of interest and the information measure, the problems to be solved will be discussed. Section 3 describes the proposed path planning strategy in detail. Section 4 introduces a multisensor-multitarget estimation models and sensor dispatch scenarios. The method and results of the numerical simulations will be given in Section 5. Finally, Section 6 presents summary and conclusions.

2. Problem formulation

Fig. 1 describes a workflow of a multisensor management algorithm. This paper focuses on the instance after a decision to dispatch a new sensor is made. The decision is made by a sensor manager, which can be of a ground control station or a high-performance onboard mission computer. The sensor manager is supposed to make plans for a mobile sensor to gather measurements from targets of interest. 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, $\mathscr{C} \in \mathbb{R}^2$, called an operational area. The sensor is supposed to get into the operational area at t_s. After approaching the operational area, the sensor is allowed to gather information until t_f. Fig. 2 shows configuration of the operational area and the initial location of the sensor. A solution to the path planning problem can be obtained by solving an optimal control problem, addressed in Section 2.3. Before discussing the optimal control problem, an estimation model for the state of interest will be given in Section 2.1. The cost to be optimized is defined based on the FIM which will be described in Section 2.2.

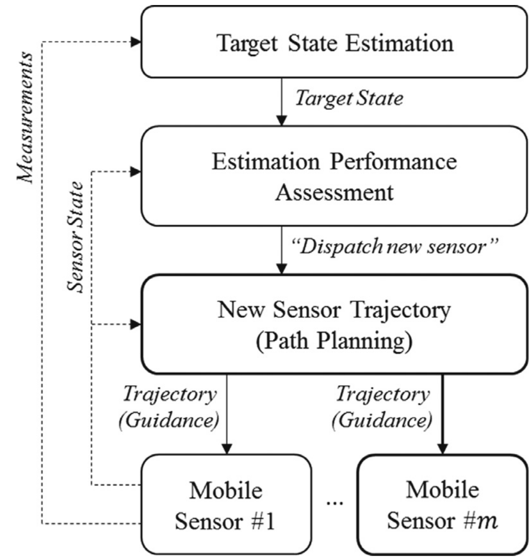

Fig. 1. Workflow of a multisensor management algorithm.

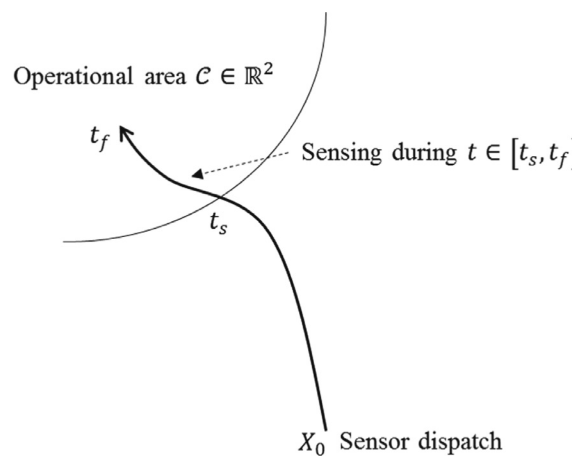

Fig. 2. Operational area and sensor dispatch location.

2.1. State of interest

In this paper, the target system is described as a stochastic vector state space model. Uncertain parameters of interest in the target system are represented by a state vector X_T. The system model for the target state can be expressed as a nonlinear differential equation as

$$\dot{X}_T(t) = f(X_T(t)) + \omega(t) \tag{1}$$

where $\omega(t)$ denotes the zero-mean Gaussian process noise whose covariance is $Q(t)$. One may employ a perturbation method [35] to linearize the system as

$$\delta\dot{X}_T(t) = F(t)\delta X_T(t) + \delta\omega(t) \tag{2}$$

where $F(t) = \frac{\partial f}{\partial X_T}$ is called a state transition matrix. $\delta X_T(t)$ and $\delta\omega(t)$ denote infinitesimal changes of $X_T(t)$ and $\omega(t)$, respectively. The linear system is used to approximate the short-term behavior of a nonlinear system in a simpler form. The long-term behavior can be tracked by some nonlinear estimation scheme.

The observation model which relates measurements to the target state is defined as

$$Z(t) = h(X_T(t)) + \nu(t) \tag{3}$$

where the measurement noise denoted as $\nu(t)$ is a zero-mean Gaussian process with covariance $R(t)$. The linearized observation model is