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Multivehicle coverage control for a nonstationary spatiotemporal field[☆]

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ABSTRACT

This paper presents a multivehicle sampling algorithm to generate trajectories for nonuniform coverage of a nonstationary spatiotemporal field characterized by spatial and temporal decorrelation scales that vary in space and time, respectively. The sampling algorithm described in this paper uses a nonlinear coordinate transformation that renders the field locally stationary so that existing multivehicle control algorithms can be used to provide uniform coverage. When transformed back to the original coordinates, the sampling trajectories are concentrated in regions of short spatial and temporal decorrelation scales. For fields with coupled spatial statistics, i.e., the spatial decorrelation scales are functions of both spatial dimensions, the coordinate transformation is implemented numerically, whereas for decoupled spatial statistics, the transformation is expressed analytically. We show that the analytical transformation results in vehicle motion that preserves the vehicle sampling speed (which is a measure of vehicle speed scaled by the ratio of the spatial and temporal decorrelation scales), in the original domain; the sampling speed determines the minimum number of vehicles needed to cover a spatiotemporal domain. Theoretical results are illustrated by numerical simulations.

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1. Introduction

For applications in environmental monitoring with a mobile sensor network, it is often important to generate accurate spatiotemporal maps of scalar fields such as temperature or pollutant concentration, as discussed in Inoue, Kawashima, Fujiyoshi, and Wakatsuchi (2005) and Torres et al. (2008). Sometimes it may also be the case, as in physical oceanography, that it is important to map the boundary of a region, e.g., to find the mass, heat, and salt budget of the domain, as shown in Rudnick and Davis (1988). Either mapping task is especially challenging when sampling resources and/or time is limited. The use of a mobile sensor network provides an effective solution because a limited number of sensors can traverse the field collecting measurements at many space–time locations (Leonard et al., 2010). We address the question of where and when to collect these measurements so as to minimize a standard measure of mapping error used in Paley (2007). In particular, we present a distributed strategy for solving a time-varying environmental mapping problem in which there are two spatial dimensions. We allow for the possibility that the estimated field is nonstationary, i.e., the variability of the field may change in both space and time.

There are several approaches in the literature pertaining to sampling a spatiotemporal field using a mobile sensor network. In distributed parameter estimation, the field is modeled by an underlying process, usually a partial differential equation, for which the parameters are estimated by routing vehicles to maximize an objective function based on optimal experimental design (Demetriou, 2010; Song, Chen, Liang, & Ucinski, 2005; Ucinski & Demetriou, 2004). In Bayesian estimation (Graham & Cortés, 2012a,b; Xu, Choi, Dass, & Maiti, 2012; Xu, Choi, & Oh, 2011), the mean of the field is modeled as a combination of known basis functions and a (partially) known covariance function. A maximum-likelihood, recursive (gridded or particle) filter is used to determine the unknown coefficients of the covariance function as well as regression coefficients for the basis functions. In the coverage-control approach (Kwok & Martínez, 2010; Mathew &

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Mezic, 2009; Song, Feng, Fan, & Wang, 2011; Wang & Hussein, 2010; Zhu & Martínez, 2013), vehicles are routed to maximize the area that the sensor measurements traverse, often using heuristic measures for coverage. Another approach is based on mapping error (Alvarez & Mourre, 2012; Sydney & Paley, 2011), where vehicles are routed to minimize the error in the estimate of the field.

Unlike prior work that focuses on sampling stationary spatiotemporal fields, e.g., Paley (2007); Sydney and Paley (2011), this paper studies the problem of sampling a spatiotemporal field in which the second-order statistics may change as a function of space and/or time, i.e., the field is nonstationary (Higdon, Swall, & Kern, 1999). Some recent works on sampling a nonstationary field focus on coverage control (Cortés, Martinez, & Bullo, 2004; Leonard & Olshevskyi, 2011), where vehicles are controlled such that there are no gaps in the coverage of the field; these works use a heuristic measure of sampling need to measure sampling performance. For example, Leonard and Olshevskyi (2011) sample a time-invariant field by routing vehicles to fixed locations. Sampson and Guttorp (1992) and Schmidt and O'Hagan (2003) estimate the covariance structure of a time-invariant nonstationary field using fixed measurement locations. In Sampson and Guttorp (1992), a coordinate transformation is used to ensure the covariance structure of the transformed field is stationary. The covariance function is parameterized by its characteristic spatial and temporal length scales, called decorrelation scales. The approach in Sampson and Guttorp (1992) is to numerically map the locations of several fixed sampling stations to a new set of coordinates such that the spatial dispersion between locations in the new coordinates is approximately stationary. The new coordinates are found by numerically minimizing a cost function that includes a heuristic measure of stationarity. While not identical, this approach strongly influenced the development of our main result, which extends the coordinate-transform approach to permit mobile sensors. By making additional assumptions about the nature of the nonstationary field, we are able to find an analytical mapping for locations in the new coordinates. We also provide conditions for the existence and invertibility of the coordinate transformation. This work is part of an ongoing effort to apply the Dynamics Data-Driven Application System (DDDAS) to sensor equipped vehicle routing.

The primary contribution of this paper is a multivehicle sampling algorithm that generates trajectories for nonuniform coverage of a nonstationary spatiotemporal field through the use of a nonlinear spatiotemporal coordinate transformation that renders the second-order statistics of the field approximately stationary, a notion we describe as locally stationary. In the stationary domain (the R-domain), we employ a Spanning Tree Coverage (STC) algorithm as described in Gabriely and Rimon (2001) to create a closed path that covers the entire domain. The STC algorithm reduces the (uniform) coverage problem to one spatial dimension, for which the solution described in Paley (2007) and Sydney and Paley (2011) is to space the vehicles evenly around the path. To drive the vehicles to the path, we employ a gradient control. The R-domain trajectories are transformed back to the original, nonstationary coordinates (the r-domain) using the inverse transformation.

As a secondary contribution, we show, for the case of decoupled spatial scales (i.e., where each of two spatial decorrelation scales are a function of only the corresponding spatial dimension) that the control algorithm preserves the steady-state vehicle sampling speed. Sampling speed is the vehicle speed scaled by the ratio of the temporal to spatial decorrelation scales as described in Leonard, Paley, Sepulchre, Frantantoni, and Davis (2007); it is an important metric for determining the minimum number of vehicles required to completely cover the field. To determine the performance of the sampling algorithm, measurements are incorporated into an estimate of the field using optimal interpolation as performed in Bennett (2005) and Eliassen and Sawuer (1954), which also provides a measure of the uncertainty in the interpolated field, i.e., the mapping error. Theoretical results are illustrated in simulation and compared to a uniform coverage algorithm.

The paper outline is as follows. Section 2 formulates the coverage-control problem considered here. Section 3 briefly discusses sampling a one-dimensional stationary spatiotemporal field, which is important for sampling nonstationary fields in two spatial dimensions. Section 4 describes a coordinate transformation that renders a nonstationary field locally stationary in the new coordinates. Section 5 presents a control strategy to drive multiple vehicles to an equally spaced formation along a closed path in the nonstationary field such that there are no coverage gaps. Section 6 summarizes the paper and ongoing work.

2. Problem formulation

Let $A(r_k)$ be the value of an unknown, continuous spatiotemporal field at $r_k \triangleq [x_k,\ y_k,\ t_k]^T \in \mathbb{R}^2 \times \mathbb{R}^+$, which is the space–time location of point k. (We drop the subscript on r to indicate the entire field.) The field is statistically described by its mean $\bar{A}(r_k)$ and the covariance function $C(r_i, r_j)$ between any two points r_i and r_j. A covariance function is a positive-definite function that describes the variability of the field between the ith and jth location, as described in Liebelt (1976). A field is stationary if its covariance function depends only on the difference $r_i - r_j$ and is nonstationary if it depends on r_i and r_j independently. There are a number of choices for the form of $C(r_i, r_j)$, e.g., Matern, rational quadratic, Ornstein–Uhlenbeck and squared-exponential forms as described in Higdon et al. (1999). For the sampling strategy in this paper, we require a covariance function that is a product of a spatial covariance function and a temporal covariance function, i.e., $C(r_i, r_j) = C_s(x_i, y_i, x_j, y_j)C_t(t_i, t_j)$, where C_s and C_t are the spatial and temporal portions of the covariance, which depend on space and time, respectively.

To represent spatiotemporal fields with non-uniform coverage requirements, we adopt a nonstationary squared exponential covariance function of the following form, as introduced in Higdon et al. (1999):

$$C(r_i, r_j) = \frac{|\Sigma(r_i)|^{1/4}|\Sigma(r_j)|^{1/4}}{\left|\frac{\Sigma(r_i)+\Sigma(r_j)}{2}\right|^{1/2}} \exp\left[-\frac{1}{2}(r_i - r_j)^T \times \left(\frac{\Sigma(r_i)+\Sigma(r_j)}{2}\right)^{-1}(r_i - r_j)\right], \tag{1}$$

where $\Sigma(r_k) \in \mathbb{R}^{3\times 3}$ is a positive definite symmetric matrix that is continuous in r_k. We require that $\Sigma(r_k) = \mathrm{diag}\{\sigma_x^2(x_k, y_k), \sigma_y^2(x_k, y_k), \tau^2(t_k)\}$. The square roots of the diagonal elements of $\Sigma(r_k)$ are the spatial and temporal decorrelation scales of the field. The decorrelation scales dictate the spatial and temporal separations between the ith and jth locations at which the covariance function evaluates to $1/e \approx 0.368$. Note, for a stationary field, the decorrelation scales are constant, but for a nonstationary field they may vary in space and time. The Gaussian covariance function (1) is used to derive the coordinate transformation in Section 4, which clusters measurements in space–time regions with shorter decorrelation scales, and spreads measurements where the decorrelation scales are larger. Other covariance functions, e.g., Matern, may contain these decorrelation scales, but they are embedded in a different function, e.g., a Bessel function. The extension of the coverage strategy to the case where $\Sigma(r_k)$ is not diagonal is not considered here.

We investigate the use of a multivehicle sensor network to sample the field $A(r)$ when the covariance function is nonstationary. Specifically, we seek to provide optimal coverage of the field,

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