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Decentralized Dynamic Data-Driven Monitoring of Atmospheric Dispersion Processes

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Abstract
Online state and parameter estimation of atmospheric dispersion processes using multiple mobile sensor platforms is a prominent example of Dynamic Data-Driven Application Systems (DDDAS). Based on repeated predictions of a partial differential equation (PDE) model and measurements of the sensor network, estimates are updated and sensor trajectories are adapted to obtain more informative measurements. While most of the monitoring strategies require a central supercomputer, a novel decentralized plume monitoring approach is proposed in this paper. It combines the benefits of distributed approaches like scalability and robustness with the prediction ability of PDE process models. The strategy comprises model order reduction to keep calculations computationally tractable and a joint Kalman Filter with Covariance Intersection for incorporating measurements and propagating state information in the sensor network. Moreover, a cooperative vehicle controller is employed to guide the sensor vehicles to dynamically updated target locations that are based on the current estimated error variance.

Keywords: DDDAS, Reduced Order Models, Decentralized State Estimation, Cooperative Vehicle Controller

1 Introduction

Environmental monitoring of pollutant dispersion due to chemical leaks is an important task in disaster response. It is essential to repeatedly estimate characteristic state variables and important process parameters on-line in order to be aware of the current hazardous situation. The task is usually solved using a sensor network from which measurements are incorporated into a suitable model of the underlying process. As static sensor networks are very inflexible

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in a dynamically changing environment, the use of robotic systems is increasingly considered in this context [8, 15]. Vehicles are equipped with sensors and computing units and measure the process state at different locations of the problem domain. Instead of moving along fixed trajectories, the sensor vehicles are intended to adapt their movement on-line, depending on the current estimate and its uncertainty. This leads to the concept of Dynamic Data Driven Application Systems (DDDAS) [3, 5]. The collected data is directly integrated into the system model and the vehicle movement and further measurement process is based thereupon. In this way, a changing environment can be observed by a relatively low number of self-adapting robots moving to positions where measurements are highly profitable.

A number of DDDAS approaches in the context of monitoring atmospheric dispersion have been proposed in recent time. While on the one hand complex optimal control problems subject to process/vehicle dynamics and estimation statistics are considered for finding optimal trajectories [22, 24], more efficient suboptimal methods splitting the estimation part from the trajectory planning part [6, 19] are described on the other hand. However, all these approaches rely on a centralized structure of the sensor network. All measurements are sent to a central supercomputer, which assembles the current estimate, calculates control inputs for the vehicles and sends this information back to the sensor platforms. Obviously, such approaches are not robust due to a central point of failure and demand for vast communication ranges. Moreover, they lack scalability and modularity.

It is much more desirable to design a decentralized strategy where information is processed and exchanged locally without the utilization of a central computing node. Although several general concepts for decentralized estimation and control strategies have been developed in the last years [11, 16, 17], further research regarding amongst others the considered model types or coupling with vehicle control is required to apply these strategies. Decentralized approaches related to plume detection and information gathering were presented in [7, 23]. Due to the reduced on-board computation power and real-time requirements, all these approaches do not consider a partial differential equation (PDE) model of the underlying process since its solution requires a lot of time and high computational power. On the other hand, PDEs model physics and dynamic behavior of the process and are necessary to obtain a detailed and accurate forecast of the process. The use of PDE-models in the considered real-time context is, thus, highly advisable, but also highly challenging.

The present work is aimed to present a decentralized dynamic data-driven system for plume estimation that is based on the forecasts of a PDE-model. Pursuing, extending and distributing the methods presented in previous work [10, 20] on centralized systems, a DDDAS is proposed that is able to monitor pollutant dispersion in a distributed way with cooperating sensor vehicles and the aid of a PDE model. To meet the limited computational capacity, reduced order models are applied. Proper Orthogonal Decomposition of a snapshot set consisting of radial basis function as well as noise impulse response snapshots reduces the large dimension of the original problem drastically. Every sensor node uses and maintains such a reduced model and incorporates its own measurements into the model using a Kalman Filter. Furthermore, sensors share information (estimates and their error covariances) with other sensors located within the communication range using Covariance Intersection. Based on the error covariance of the obtained estimates, every node identifies new informative measurement locations. A Mixed Integer Linear Program is solved by each vehicle in a Model Predictive Control fashion to obtain its new control input so that the group of sensors cooperatively achieves reaching their target locations.