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Tracking of atmospheric release of pollution using unmanned aerial vehicles

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HIGHLIGHTS

► An algorithm for navigation of UAVs tracking atmospheric release is pro-posed.
► Dynamics of the release is unknown and estimated on-line on a fine time scale.
► Time varying biases of the numerical weather forecast are estimated.
► Assimilation methodology is based on the sequential Monte Carlo.
► Twin experiments performed on a release of radiation with realistic setting.

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ABSTRACT

Tracking of an atmospheric release of pollution is usually based on measurements provided by stationary networks, occasionally complemented with deployment of mobile sensors. In this paper, we extend the existing concept to the case where the sensors are carried onboard of unmanned aerial vehicles (UAVs). The decision theoretic framework is used to design an unsupervised algorithm that navigates the UAVs to minimize the selected loss function. A particle filter with a problem-tailored proposal function was used as the underlying data assimilation procedure.

A range of simulated twin experiments was performed on the problem of tracking an accidental release of radiation from a nuclear power plant in realistic settings. The main uncertainty was in the released activity and in parametric bias of the numerical weather forecast. It was shown that the UAVs can complement the existing stationary network to improve the accuracy of data assimilation. Moreover, two autonomously navigated UAVs alone were shown to provide assimilation results comparable to those obtained using the stationary network with more than thirty sensors.

1. Introduction

Accidental release of a pollutant into the atmosphere is a rare event, however with severe consequences for potentially many people living in proximity of its source. Correct application of the protective measures requires the best possible knowledge about the source and the trajectory of the plume in the atmosphere. Since dispersion of the pollutant in the atmosphere is highly stochastic, every measurement is of a great value. This fact motivated the creation of stable monitoring networks, e.g. around nuclear power plants, and stable and mobile stations for general air quality monitoring that are routinely in operation. The use of airborne measuring stations is less frequent, they are typically assumed to be used only in cases of severe accidents. Since it is too risky to send human-operated aircrafts into the polluted area, these are assumed to be used in the post-accident analysis. With increasing availability of commercial unmanned aerial vehicles (UAVs) arises the question of their use in tracking of accidental atmospheric releases.

In principle, the UAVs have several important advantages. First, they can fly in three dimensional space without spatial restrictions, which contrasts with limits of road vehicles. Second, they can be relatively small and thus they can be deployed in a very short time. Third, as unmanned vehicles they can fly to dangerous zones. Fourth, their movement in the atmosphere is relative to the wind which provides (in combination with GPS) an additional source of information about the wind field.

In this paper, we study the advantages of using UAVs in tracking of an atmospheric release. This task has been considered before using expert system with manually selected rules (Kuroki et al., 2010). Here, we are concerned with fully automatic on-line navigation of the UAVs. We study two potential roles of UAVs: operation in a standalone mode, and operation as a complementary measurements to the existing monitoring networks. Operation in the complementary mode is possible in high profile applications such as radiation accidents, while the standalone mode may be

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interesting for less safety critical applications, such as chemical accidents.

From the methodological point of view, UAVs are mobile sensors that can be relocated at every sampling time. Their navigation is thus an extension of the task of a monitoring network design which has been studied for decades, from early works (Caselton and Husain, 1980) to recent ones (Abida and Bocquet, 2009; Heuvelink et al., 2010). The standard formalism for sensor positioning is the decision theory under uncertainty (Berger, 1985) that poses the task as a minimization problem with respect to the expected future loss function. Previously proposed approaches differ in three aspects: (i) representation of uncertainty, (ii) loss function, and (iii) optimization methods and constraints. The need for uncertainty representation limits the possible selection of the assimilation methodology. For example, traditional methods like point based estimates such as the variational (Jeong et al., 2005; Kovalets et al., 2009) or genetic approach (Haupt et al., 2009; Cervone et al., 2010) are not a natural choice. We need to choose from the methods that model uncertainty using a Gaussian density (Zidek et al., 2000; Abida and Bocquet, 2009), or an empirical density obtained by Monte Carlo trials (Heuvelink et al., 2010; Melles et al., 2011). The choice of the loss functions ranged from entropy (Zidek et al., 2000) to the number of misclassified people (Heuvelink et al., 2010). Since most authors aimed for the global optimum, the most popular choice of the optimization method was simulated annealing, e.g. (Abida et al., 2008; Melles et al., 2011).

A distinct feature of the UAVs as mobile sensors is the need to compute their new locations in real time. This puts practical constraints on the processing time of all elements of the method. As a first step, we relax the requirement of global optimality and seek only a suboptimal solution. We choose to represent the uncertainty via the weighted empirical density, which is provided by the particle filter (Pecha et al., 2009; Hiemstra et al., 2011). We combine both popular loss functions, i.e. the mutual information and the misclassification loss, into a single loss function for improved robustness and flexibility. Computational details of this approach are based on works from the field of UAV navigation (Skoglar, 2009; Hoffmann and Tomlin, 2010; Šmídl and Hofman, 2012b) and recent techniques for efficient Monte Carlo sampling (Šmídl and Hofman, 2012a).

The algorithms were tested in simulated twin experiments. Specifically, we simulate a release of a radioactive pollutant from a nuclear power plant, where the radiation monitoring network (RMN), also known as radionuclide monitoring network, is already in place. In this scenario, we investigate the added value of the UAVs as a complementary means of radiation situation assessment. For comparison, we also investigate the same release without the data from the RMN to investigate the value of UAVs for tracking of releases from less protected sources.

2. Theoretical background

Navigation of the UAVs will be formalized as the task of positioning J sensors, where J is the number of available UAVs. At each time step t, we seek new directions of flight of all UAVs, $\boldsymbol{v}_{1,t+1},\ldots,\boldsymbol{v}_{J,t+1}$, and their speeds $s_{1,t+1},\ldots,s_{J,t+1}$. These form the action variable $\boldsymbol{a}_{t+1} = [\boldsymbol{v}_{1,t+1},\ldots,\boldsymbol{v}_{J,t+1},s_{1,t+1},\ldots,s_{J,t+1}]$. Following the standard decision theory (Berger, 1985), we optimize the expected loss

$$\boldsymbol{a}^*_{t+1} = \arg\min_{\boldsymbol{a}_{t+1}\in\mathcal{A}_{t+1}} E(\mathcal{L}(\boldsymbol{x}_{t:t+h},\boldsymbol{a}_{t+1:t+h})|y_{1:t}), \tag{1}$$

where $\boldsymbol{x}_{t:t+h} = [\boldsymbol{x}_t,\ldots,\boldsymbol{x}_{t+h}]$ is the uncertain future trajectory of the state variable, $\boldsymbol{x}_t$; $\mathcal{L}(\boldsymbol{x},\boldsymbol{a})$ is the loss function mapping the space of all actions and states to the real axis; $\boldsymbol{y}_{1:t} = [\boldsymbol{y}_1,\ldots,\boldsymbol{y}_t]$ are the measured data; $E(\cdot)$ is the operator of expected value with respect to a probability density function $p(\cdot)$ of the random variable in argument of the expectation; $\mathcal{A}_{t+1}$ is a set of all possible actions at time $t+1$.

Framework (1) is very common in the field of network design and targeting of observations. Different methods arise for different choices of the unknown state variable $\boldsymbol{x}_t$, representation of uncertainty in the form of probability density $p(\cdot)$, and the loss function $\mathcal{L}(\cdot)$. In this paper, we will focus on the following variants. Distribution of the pollutant in the atmosphere is described by a parametric atmospheric dispersion model (e.g. the puff model) with unknown parameters. The weather model is based on local correction of the numerical weather forecast model. The state variable $\boldsymbol{x}_t$ is then quite low dimensional, composed of the parameters of the dispersion model and the weather corrections. The uncertainty in all parameters is represented by empirical probability densities (Johannesson et al., 2004). The loss function is based on combination of the misclassification loss (Heuvelink et al., 2010) and the mutual information (Hoffmann and Tomlin, 2010). These elements are now described in detail.

2.1. Atmospheric dispersion model

When the pollutant is released into the atmosphere, it forms a plume which is subject to dispersion. Various parametric models of the pollutant dispersion have been proposed. Here, we focus on approximation of the continuous plume by a collection of puffs (Thykier-Nielsen et al., 1999) for its simplicity. However, no subsequent derivation is based on this assumption and it can be replaced by any other parametric dispersion model. The puff model is formed by a sequence of puffs labeled $k = 1,\ldots,K$, each puff is assumed to approximate a short period of the release of the pollutant at discrete time t. Concentration of the pollutant in a single puff at time τ is given by:

$$C_k(\boldsymbol{s},\tau) = \frac{Q_k}{(2\pi)^{3/2}\sigma_1\sigma_2\sigma_3}\exp\left[-\frac{(s_1-l_{1,k,\tau})^2}{2\sigma_1^2}-\frac{(s_2-l_{2,k,\tau})^2}{2\sigma_2^2}-\frac{(s_3-l_{3,k,\tau})^2}{2\sigma_3^2}\right] \tag{2}$$

where $\boldsymbol{s} = [s_1,s_2,s_3]$ is a vector of spatial coordinates, $\boldsymbol{l}_{k,\tau} = [l_{1,k,\tau},l_{2,k,\tau},l_{3,k,\tau}]$ is the vector of location of the kth puff center, $\boldsymbol{\sigma} = [\sigma_1,\sigma_2,\sigma_3]$ are dispersion coefficients, and Q_k is the released activity in the kth puff. Released activity Q_k is assumed to be unknown, with very flat prior density, e.g. of gamma type

$$\mathcal{G}(\alpha_Q,\beta_Q) \propto Q_t^{\alpha_Q-1}\exp(-Q_t\beta_Q), \tag{3}$$

with parameters α_Q,β_Q. Symbol $\propto$ denotes equality up to normalizing constant. The prior parameters can be designed to match apriori chosen moments, e.g. the mean value, α_Q/β_Q, and the variance, α_Q/β_Q^2.

Illustration of the pollution model is displayed in Fig. 1. Spatial distribution of the pollutant is then fully determined by state variables:

$$\boldsymbol{x}_{pm,t} = [\boldsymbol{l}_{1,t}\ldots\boldsymbol{l}_{K,t},Q_{1,t},\ldots Q_{K,t},\boldsymbol{\sigma}_{1,t},\ldots\boldsymbol{\sigma}_{K,t}]. \tag{4}$$

2.2. Wind field model

We assume that the pollutant is released from a source at known location, $[s_{1,pp},s_{2,pp}]$ and known altitude $s_{3,pp}$, in vector notation, $\boldsymbol{s}_{pp} = [s_{1,pp},s_{2,pp},s_{3,pp}]$. From this point it is advected by the wind field. While it is possible to obtain numerical weather forecast from various sources, its accuracy is usually not sufficient at the