Bayesian stochastic reconstruction of the atmospheric contamination's source based on the data from field tracer experiment over the Kori nuclear site

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Abstract

Unintentional atmospheric releases of hazardous material pose great risks to human health and the environment, thus it is valuable to develop the emergency action support system, which can quickly identify probable location and characteristics of the release source based on the sensors' network measurements. We apply the approach combining Bayesian inference with Sequential Monte Carlo to the problem of the atmospheric contaminant source localization. We assess the developed algorithms with use of the data from field tracer experiment conducted on 31 May 2001 over the Kori nuclear site. We use the atmospheric dispersion SCIPUFF model as the forward model to predict the concentrations at the sensor's locations. We demonstrate successful localization of the continuous contamination source in the very complicated hilly terrain surrounding the Kori nuclear site.

Keywords: mcmc methods; smc methods; stochastic event reconstruction; bayesian inference

1 Introduction

Knowing gas source and wind field we can apply the suitable atmospheric dispersion model to compute the expected gas concentration for any downwind location. On the other hand, given concentration measurements and knowledge of the wind field and other atmospheric air parameters, pointing the location of the release source and its parameters is vague. This problem has no single solution and can be considered only in the probabilistic frameworks. The issue boils down to the creation the atmospheric dispersion model realistically reflecting the real situation based only on a sparse point-concentration data. This task requires specification of set of model's parameters. In the framework of Bayesian statistics all quantities included in the model are modeled as random variables with joint probability distributions. This randomness can be interpreted as parameter variability, and is reflected in the uncertainty of the true values stated in terms of probability distributions. Bayesian methods reformulate the problem

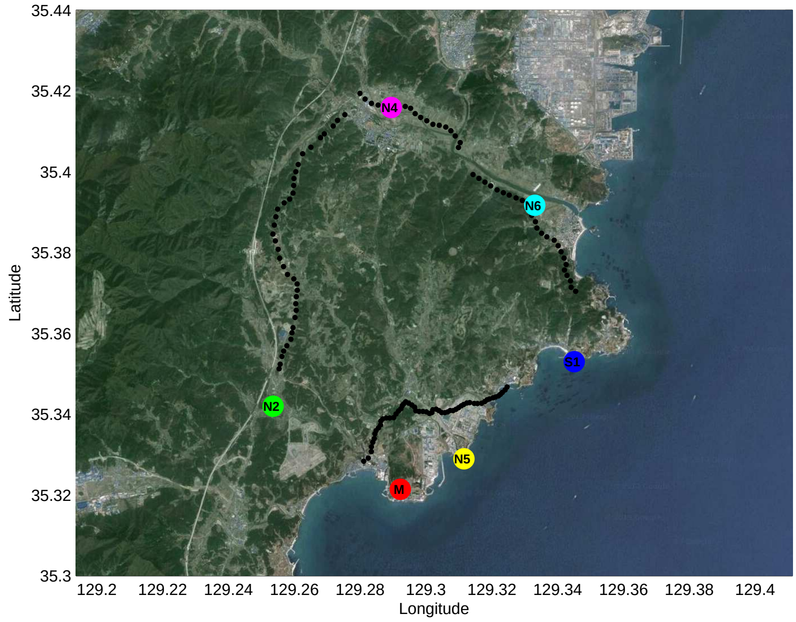

Figure 1: Location of the release point (red dot), sampling points (black dots) and meteorological towers (color dots) during the field tracer experiment conducted on 31 May 2001 over the Kori nuclear site.

into searching for a solution based on efficient sampling of an ensemble of simulations, guided by comparisons with data.

In this paper we present efficiency of the algorithm joining the MCMC and SMC [1, 2] based on the data from field tracer experiment conducted in May 2001 over the Kori nuclear site [3]. The reconstruction of the contamination source for this experiment was challenging due to very complicated wind field's pattern resulting from the hilly terrain and the closeness of the sea coast. As the forward model to predict the concentrations at the sensor's locations we applied the atmospheric dispersion second-order Closure Integrated PUFF Model (SCIPUFF) [4].

2 Bayesian inference

Bayes' theorem, as applied to an emergency release problem, can be stated as follows:

$$P(M|D) \propto P(D|M)P(M) \tag{1}$$

where M represents possible model configurations or parameters and D are observed data. For our problem, Bayes' theorem describes the conditional probability $P(M|D)$ of certain source parameters (model configuration M) given observed measurements of concentration at sensor locations (D) [5].

3 Event reconstruction of the Kori tracer experiment

The Kori site is located at the bottom of the protrusion and is surrounded by the sea on three sides, with bordering land on the north side (Fig. 1). In this terrain the wind field configuration is very complicated. During the experiment the wind direction recorded by the meteorological towers changes significantly direction e.g. at station

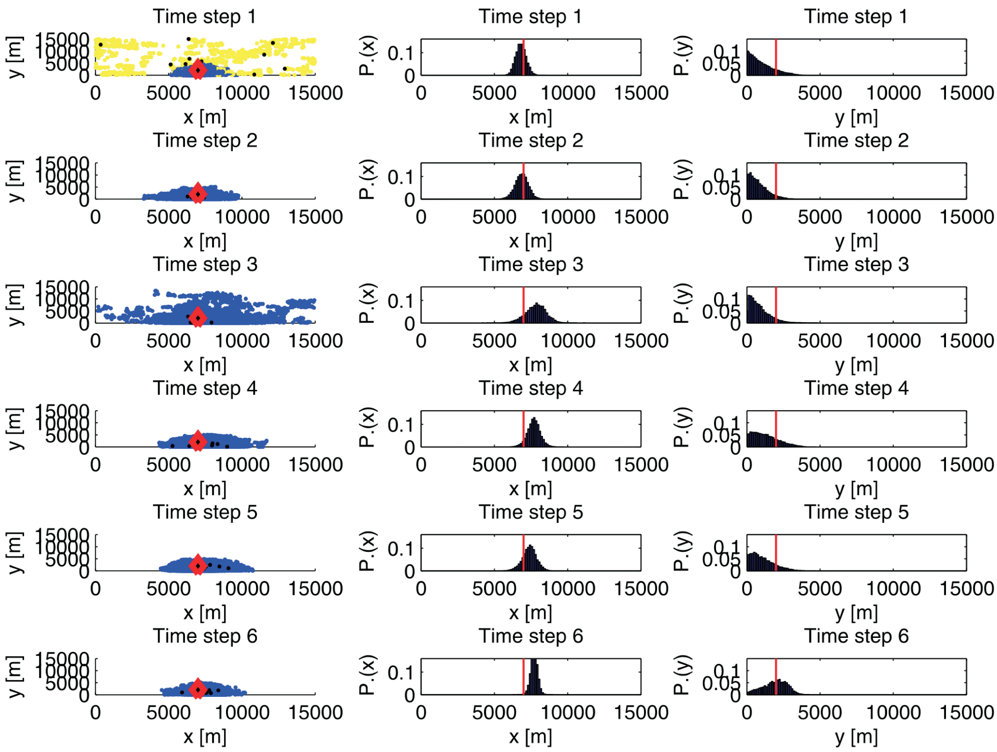

Figure 2: The traces of 10 Markov chains in the location space (x, y) for all 6 time steps (based on 24 sensors). The source location is marked by triangle. The Marcov chain start points are marked by black dot. (The yellow points represent the burn-in factor i.e. 2000 initial samples needed the Markov chain to reach the state when it is sampling from the target distribution).Posterior distribution of x and y parameter in subsequent time steps. Vertical line represent the target value of x and y

$N6$ even for 180° and more than 90° for other towers. A tracer SF_6 gas was released from the meteorological tower M at $58m$ high with average rate $75.79kg/h$. Release started at 12:30 and lasted for 3.5 hours. The sampling of the tracer took place every 10 minutes since 15:00 up to 16:00. The 140 automatic gas samplers were disposed along the traffic roads. However, during this experiment large missing rate of air sampling took place. The main problem of the data is that neighboring sensors record much varying concentrations i.e. at very close location one sensor return the 'zero' concentration and the other high rate. Thus in the scanning algorithm we selected the 24 sensor's data. The parameters scanning algorithm was run with obtaining the first measurements from the sensors. Based on this information we obtain the probability distributions of the searched parameters starting from the randomly chosen set of parameters M (i.e. first we start from the "flat" priori). This assumption reflects initial lack of knowledge about the release. We applied random walk procedure "moving" our Markov chain to the new position. Precisely, we changed each model M parameter by the value draw from the Cauchy distribution. In our calculations we have used 10 Markov chains in each time step. The number of iteration n for each Markov chain was $n = 10000$. Starting from the second time step, as the starting position of the Marcov chains was selected the position drawn from the obtained *'a posteriori'* distributions obtained in the previous

time step (black points at Fig. 2).
Fig. 2 presents the traces of the Marcov chains in subsequent time steps in the source coordinate space (x, y) and the *posteriori* probability distributions. One can see that at the beginning of the reconstruction the considered samples are dispersed over whole domain. Then, in the subsequent time steps when the calculations are updated by the obtained *posteriori* distributions and newly collected sensors data, the accepted samples are starting to focus near the true source location marked by the red diamond and by the red vertical line.

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