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Technical note

# Localisation of a source of hazardous substance dispersion using binary measurements

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ABSTRACT

The problem is to estimate the parameters of a source continuously releasing hazardous material into the atmosphere. The concentration measurements are collected at a number of known locations by a moving binary sensor, characterised by an *unknown threshold*. The paper formulated a solution in the Bayesian framework, using a dispersion model of Poisson distributed particle encounters in a turbulent flow and assuming the environmental parameters (wind velocity, diffusivity, particle lifetime) are known. The method is implemented using an importance sampling technique and successfully validated with three experimental datasets under different wind conditions. In this context, the estimates of the source release rate are not of practical use, being scaled with an unknown constant related to the binary threshold.

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## 1. Introduction

Localisation of a source of hazardous substance release into the atmosphere, is an important problem for national security and environmental monitoring applications (Kendall et al., 2008). Wind, as the dominant transport mechanism in the atmosphere, can generate strong turbulent motion, causing the released material to disperse as a plume whose spread increases with the downwind distance (Arya, 1998). Assuming a constant release of the contaminant, the problem involves estimation of source parameters: its location and intensity (release-rate). Two types of measurements are generally at disposal for source localisation: (i) the concentration measurements at spatially distributed sensor placements; (ii) the average wind speed and wind direction (typically available from a nearby meteorological station).

Many references are available on the topic of polluting source localisation, assuming un-quantised (analog) concentration measurements. Standard solutions are based on optimisation techniques, such as the nonlinear least squares (Matthes et al., 2005) or simulated annealing (Thomson et al., 2007). These methods can be unreliable due to local minima or poor convergence; in addition, they provide only point estimates, without uncertainty intervals. The preferred alternative is the use of Bayesian techniques; they result in the posterior probability density function (PDF) of the source parameter vector, thereby providing an uncertainty measure to any point estimate derived from it. Most Bayesian methods for source estimation are based on Markov chain Monte Carlo (MCMC) technique, assuming either Gaussian or log-Gaussian likelihood function of measurements (Keats et al., 2007; Humphries et al., 2012; Ortner et al., 2007; Senocak et al., 2008). Recently, a likelihood-free Bayesian method for source localisation was proposed in (Ristic et al., 2015a).

Binary sensor networks have become widespread in environmental monitoring applications because binary sensors generate as little as one bit of information. Such binary sensors allow inexpensive sensing with minimal communication requirements (Aslam et al., 2003). In the context of binary sensor networks, an excellent overview of non-Bayesian chemical source localisation techniques is presented in (Chen, 2008). Best achievable accuracy of source localisation using binary sensors has been discussed in (Ristic et al., 2015b).

Prior work in using binary sensor data for emitting source localisation assumes that the detection threshold of the sensor is known. It is a reasonable assumption for a commercial sensor whose sensitivity is specified (for example, in parts per million by volume ($ppm_v$) or grams per cubic meter) by the manufacturer and

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when the sensor is well calibrated. However, we consider at least two scenarios where the detection threshold of a binary sensor may not be accurately known. The first scenario is when a sensor's detection threshold goes off calibration due to environmental conditions such as temperature or humidity or ageing of the sensor. The second scenario is where the sensor is a human rather than a device. For example, imagine a person smelling a strong odour such as due to a gas leak or a decomposing animal carcass. When the person moves around, the smell will be detected in some locations but not in others, producing a binary measurement sequence without knowing the exact value of the threshold in ppm or g/m$^3$. In this paper, we develop a Bayesian algorithm that carries out source parameter estimation based on such *binary concentration measurements* where the sensor threshold is unknown. A Monte Carlo technique, importance sampling, is applied to calculate the posterior PDF approximately. The method is successfully validated using three experimental datasets obtained under different wind conditions.

## 2. Models

### 2.1. Dispersion model

To solve the source localisation problem described above, we propose a solution formulated in the Bayesian framework which relies on two mathematical models: the atmospheric dispersion model and the concentration measurement model. A dispersion model mathematically describes the physical processes that govern the atmospheric dispersion of the released agent within the plume. The primary purpose of a dispersion model is to calculate the mean concentration of emitted material at a given sensor location. A plethora of dispersion models are in use today (Holmes and Morawska, 2006) to account for specific weather conditions, terrain, source height, etc. In this paper, we adopt a dispersion model of "particle encounters" in a turbulent flow based on Lagrange statistic (Vergassola et al., 2007). The model is computationally fast because an analytic expression for the mean rate of particle encounters is available. During a certain sensing period, a sensor experiences a Poisson distributed number of encounters with released particles. The binary nature of measurements indicates that a sensor reading of binary "1" or a "positive detection" corresponds to the number of such encounters exceeding a particular threshold.

If a binary sensor with a particular threshold makes positive detections (binary "1") at some locations and zero detections (binary "0") at other locations due to a source of a certain release rate, the measurements at these locations will be the same even if both the source release rate and the sensor detection threshold were scaled up or down together by the same amount; it is the ratio between the source release rate and the sensor threshold that determines which sensor locations will have positive or zero readings. Therefore, when we estimate the source parameters using binary data from a sensor whose detection threshold is unknown, we can estimate only a scaled version of the source release-rate, where the scaling coefficient remains unknown. Nevertheless, the source location, which is actually the parameter of main interest, can be estimated. Without loss of generality, in our experiments, we assumed the sensor to output binary "1" if it encounters at least one particle during a sensing period and output a binary "0" otherwise.

Let us adopt a two-dimensional coordinate system in which the source is located at $(x_0, y_0)$. The (scaled) source release rate is $Q_0$; its unit is the number of particles per second. The particles released from the source propagate with combined molecular and turbulent isotropic diffusivity $D$, but can also be advected by wind. We assume the released particles to have an average lifetime of $\tau$ (before they are absorbed). While the wind speed is typically available from meteorological data from a nearby measuring station, we use this speed as the prior guess for a Bayesian estimate of the true, effective wind speed affecting the advection of particles. Accordingly, let us assume that the mean wind speed is $V$ and the mean wind direction coincides with the direction of the $x$ axis. We denote the PDF of the wind speed by $\pi(V)$. A spherical sensor of small size $a$ at a location with coordinates $(x, y)$, non-coincidental with the source location $(x_0, y_0)$, will experience a series of encounters with the released particles.

The parameter vector we wish to estimate consists of the source coordinates $(x_0, y_0)$, the source release rate $Q_0$, and the wind speed $V$. Let us denote it by $\boldsymbol{\theta} = [x_0\ y_0\ Q_0\ V]^\top$. The rate of particle encounters by the sensor at the $i$th location (where $i = 1,\ldots,M$) with coordinates $(x_i, y_i)$ can be modelled as (Vergassola et al., 2007):

$$R(x_i, y_i|\boldsymbol{\theta}) = \frac{Q_0}{\ln\left(\frac{\lambda}{a}\right)} \exp\left[\frac{(x_0 - x_i)V}{2D}\right] \cdot K_0\left(\frac{d_i(\boldsymbol{\theta})}{\lambda}\right) \tag{1}$$

where $D$, $\tau$ and $a$ are known environmental and sensor parameters,

$$d_i(\boldsymbol{\theta}) = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \tag{2}$$

is the distance from the source to $i$th sensor location, $K_0$ is the modified Bessel function of order zero, and

$$\lambda = \sqrt{\frac{D\tau}{1 + \frac{V^2\tau}{4D}}}. \tag{3}$$

Environmental parameters $D$, $\tau$ and $V$ can be captured by a single non-dimensional parameter $Z = V^2\tau/D$.

### 2.2. Measurement model

The stochastic process of sensor encounters with released particles is modelled by a Poisson distribution. The probability that sensor at location $(x_i, y_i)$ encounters $z \in \mathbb{Z}^+ \cup \{0\}$ particles ($z$ is a non-negative integer) during a time interval $t_0$ is then:

$$P(z; \mu_i) = \frac{(\mu_i)^z}{z!} e^{-\mu_i} \tag{4}$$

where $\mu_i = t_0 \cdot R(x_i, y_i|\boldsymbol{\theta})$ is the mean number of particles at $(x_i, y_i)$ during $t_0$. Equation (4) represents the full specification of the likelihood function of parameter vector $\boldsymbol{\theta}$, given the sensor encounters $z$ counts at the $i$th position.

However, because the actual sensor is binary, the measurement model is

$$b_i = \begin{cases} 1, & \text{if } z = 1, 2, 3, \ldots \\ 0, & \text{if } z = 0. \end{cases} \tag{5}$$

Note that $b_i$ is a Bernoulli random variable with the parameter

$$q_i(\boldsymbol{\theta}) = \Pr\{b_i = 1\} \tag{6}$$

$$= \sum_{z=1}^{\infty} P(z; \mu_i) \tag{7}$$

$$= 1 - P(0; \mu_i) \tag{8}$$

$$= 1 - e^{-\mu_i}. \tag{9}$$

The likelihood function for the sensor when it is at the $i$th

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