It's always smelly around here! Modeling the Spatial Distribution of Gas Detection Events with BASED Grid Maps

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ABSTRACT

In this paper we introduce~~d~~ a novel gas distribution mapping algorithm, Bayesian Spatial Event Distribution (BASED), that, instead of modeling the spatial distribution of the gas concentration, models the spatial distribution of events of *detection* and *non-detection* of a target gas. The proposed algorithm is based on the Bayesian Inference framework and models the likelihood of events at a certain location with a Bernoulli distribution. In order to avoid overfitting a Bayesian approach is used with a Beta distribution prior for the parameter μ that governs the Bernoulli distribution. In this way, the posterior distribution maintains the same form of the prior, i.e. will be a Beta distribution, enabling a simple approach for sequential learning. To learn a field of beta distributions, we discretize the inspection area into a grid map and extrapolate from local measurements using Gaussian kernels. We demonstrate the proposed algorithm for different sensors mounted on a mobile robot and show how qualitatively similar maps are obtained from very different gas sensors.

MOTIVATION

Gas distribution mapping is often treated as the problem of creating a truthful representation of a gas concentration over an area, e.g. [1]. For many practical scenarios it is unrealistic to assume truthful concentrations measurements since most of gas sensing technologies provide non calibrated readings. For example MOX sensors of the same type show differences due to fabrication and are therefore hard to compare. In addition information may come from user reports or other sources, which do not contain information about the concentration. A promising approach to overcome these limitations is to identify events of *detection* or *non-detection* of gas from the sensor output (in this work we use a simple threshold-based approach for event detection). The maps then model the likelihood of detection events at each cell, which is beneficial compared to just modeling the frequency of occurrences as in [2].

ALGORITHM

Given a set of *detection* and *non-detection* events and their respective position, we learn an event map where each grid cell contains the likelihood of observing a *detection* event at that location. The likelihood of a gas event in each cell is best expressed by a Bernoulli distribution

$$p(x|\mu)=\mu^{x}(1-\mu)^{1-x} \tag{1}$$

where x is the variable indicating *detection* (x=1) or *non-detection* (x=0) and μ indicates the likelihood of observing a *detection* event. The maximum likelihood estimation of μ can be obtained in closed form, but is prone to severe overfitting. Hence the parameter is learned from the data through the Bernoulli's conjugate prior distribution, the Beta distribution, see [3], in each grid cell. The beta distribution depends on two parameters a and b

$$p(\mu|a,b)=\frac{\Gamma(a+b)}{\Gamma(a)\,\Gamma(b)}\mu^{a-1}(1-\mu)^{b-1}. \tag{2}$$

a and b can be interpreted as counting variables, representing the number of observed *detection* events and *non-detection* events in each cell. Additionally each cell count of events is updated by fractions of the events in its neighborhood. This fraction is defined by a Gaussian. In case of a *detection* event, all cells' a are updated according to

$$a_i \leftarrow a_i + \exp\left(-d/2\sigma^2\right), \qquad (3)$$

where d is the Euclidean distance between the cell and the actual measurement position, while σ defines the size of the neighborhood. A *non-detection* will trigger the same update, but with b instead of a. All measurements are processed sequentially and integrated into the final map individually without the need of storing all the data. σ can be selected maximizing the conditional log-likelihood of the data through e.g. grid search.

RESULTS

The BASED grid maps have been validated on a data set collected with a mobile robot equipped with a MOX sensor (Figaro TGS2620) and a photo ionization detector (PID). The robot was following a predefined trajectory in a room, where an ethanol source was present. Fixed resistance and concentration thresholds were used as event detectors. The thresholds were chosen to obtain a comparable overall ratio of *detection* to *non-detection* events. In Fig. 1, the likelihood of *detection* events is shown as resulting maps. Despite fundamentally different sensing principles and the use of naïve event detectors, the resulting maps are not only very similar, but consistent with results of other algorithms on the same data [1].

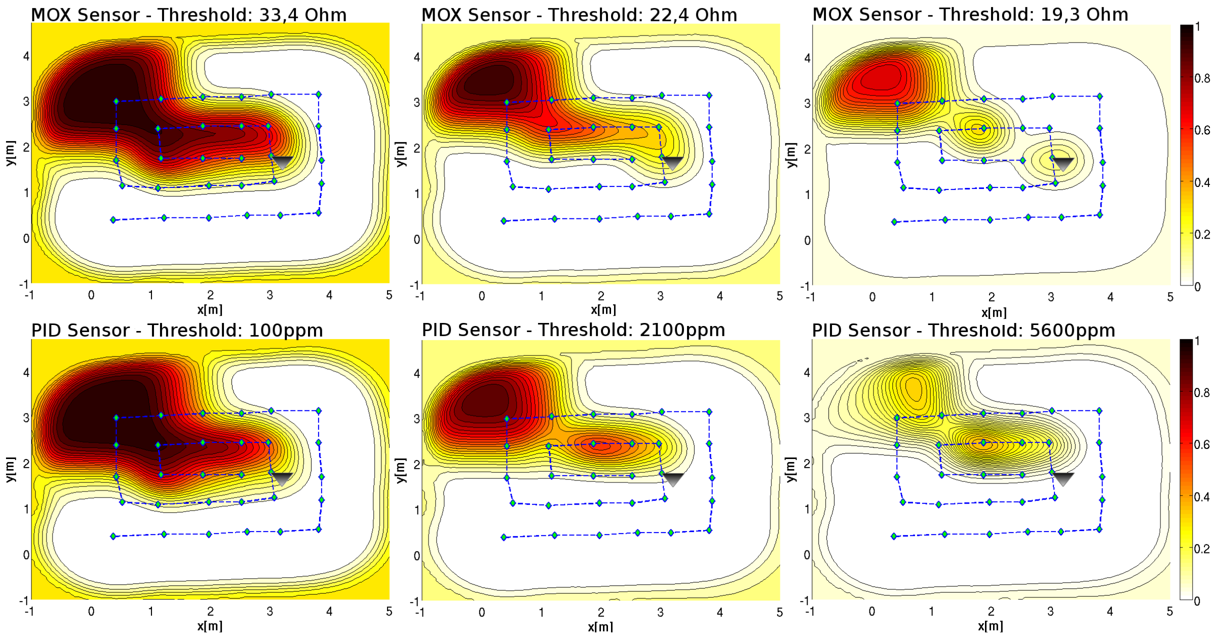

Figure 1: Resulting maps for MOX sensor (upper row) and PID sensor (lower row) for different thresholds of the event detector resulting in 30% *detection* events in the first column, 15% in the second column and 5% in the third column, which is reflected by the prior (color) of areas with no measurements. The blue line represents the robot's path during the experiments. The gas source is marked with a triangle and forms a gas plume towards the upper left corner of the area due to the convective airflow.

Bayesian Spatial Event Distribution grid maps allow the handling of very different chemical sensors in a common framework without the need for calibration. Even inputs which do not contain any concentration information like e.g. human reports can be integrated in BASED.

Reference

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