# BASED Grid Maps for Modeling the Spatial Distribution of Gas Detection Events

Erik Schaffernicht, Achim J. Lilienthal*, and Marco Trincavelli

Centre for Applied Autonomous Sensor Systems, Örebro University,

SE-70182 Örebro, Sweden

* Corresponding author

Phone: (+46/0) 19 - 30 3602

Fax: (+46/0) 19 - 30 3463

Email: achim@lilienthals.de

.

*Abstract* - In this paper we introduce a novel gas distribution mapping algorithm, Bayesian Spatial Event Distribution (BASED), that, instead of modeling the spatial distribution of a quasi-continuous gas concentration, models the spatial distribution of gas events, for example 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 $\mu$ 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 as well, enabling a simple approach for sequential learning. To learn a map composed of beta distributions, we discretize the inspection area into a grid and extrapolate from local measurements using Gaussian kernels. We demonstrate the proposed algorithm for MOX sensors and a photo ionization detector mounted on a mobile robot and show how qualitatively similar maps are obtained from very different gas sensors.

**Keywords** - gas distribution mapping, statistical modeling, Bernoulli distribution, beta distribution

# 1 Introduction

Gas distribution mapping is often treated as the problem of creating a truthful representation of gas concentration over an area. For many practical scenarios it is unrealistic to assume accurate concentration measurements. Especially in open sampling systems many gas sensing technologies are very difficult to calibrate due to, e.g., their response characteristics and individual fabrication. In addition, information about the presence of a certain gas may come from user reports or other sources, which do not contain precise information about the concentration. A promising approach to overcome these limitations is to consider as sensor output only events , for example detection or non-detection of a gas. An event could also be a significant concentration change or that the concentration of a pollutant exceeds its legal limit. The definition and computation of those events is sensor dependent and can greatly vary in complexity. To illustrate the concept, we will use in this paper a simple derivation-threshold based event detector for metal oxide (MOX) sensors and a photo ionization detector (PID). The sensors are mounted on a mobile robot, which is used to explore the environment.

The presented mapping algorithm BASED takes its inspiration from Bayesian inference techniques and spatial statistics to learn the distribution of gases in the environment.

A short discussion of previous gas mapping methods is provided in the next section. After this, we will introduce our event concept and sketch methods to extract events from sensor data in Section 3. After extracting such a set of events, Section 4 will present the algorithm to build BASED maps using those events. Case studies and a discussion of the proposed method are provided in Section 5.

# 2 Related works

Gas distribution modelling (GDM) methods can be categorized as *model-based* and *model-free* [1]. *Model-based* methods assume an analytical shape for the gas distribution and infer the parameters of the equations from sensor measurements. The most common *model-based* approaches are Gaussian plume models [2, 3, 4], Gaussian puff models [5], Lagrangian particle models [6] and Computational Fluid Dynamics (CFD). Model-based approaches are often inadequate for real world scenarios since they are either too simplistic to model the real shape of the gas distribution (assuming for example a Gaussian plume model), or require precise knowledge about the boundary conditions (CFD), which in most cases is not available. *Model-free* approaches on the other hand, do no make strong assumptions about the underlying functional form of the gas distribution. Instead, they treat sensor measurements as random variables and derive a statistical representation of the observed gas dispersion from the measurements. *Model-free* GDM is often interpreted as a spatial regression problem with its solutions using Gaussian Processes [7], Kalman Filters [8] or Kernel Regression methods [9]. As a representative of the Kernel Regression approaches, the Kernel DM+V algorithm and its extensions [9] are best known among the *model-free* maps. Yet, all the methods rely on correct concentration measurements from a single calibrated sensor.

The idea of using events to map gases was explored in a rudimentary form before, e.g. in [10], where the authors, however, only record the frequency of events that occur in a specific cell. Instead, we are interested in the probability and distribution of detection events.

Bayesian inference methods to model occurence probabilities using the Bernoulli and beta distributions are well-known techniques in machine learning [11, 12], but have not been applied to spatial estimation problems like gas distribution mapping before.

## 3 Events

The most important feature of the BASED maps is that they take discrete events rather than the quasi-continuous sensor readings. An event $E_i$ is defined as the following tuple

$$E_i = \quad < EventType, EventLocation > \tag{1}$$

*EventType* is the semantic class of the event. For simple gas mapping of a single substance this type is binary and just describes whether the gas was detected in a place or not. For scenarios with more than one gas of interest it describes whether gas 1, ..., gas $n$ or no gas was detected.

*EventLocation* is the 2 or 3-dimensional position of the event in a reference coordinate system. For the considered robotic application, this reference coordinate system and the position in it is provided by the robot's localization system [13], for sensor networks the position of the nodes is considered to be known. We assume accurate localization and do not consider position uncertainty in this paper.

Resorting to events has the advantage of treating every sensor in the same way and thereby it allows the algorithm to easily integrate very different sensor modalities like for example MOX gas sensors, PID sensors and human reports into a single map framework. While the sensor characteristics are largely decoupled from the mapping process itself, it is required to tie the event definition and detection to each sensor seperately. However, it is necessary to ensure that events from different sensors are encoded unambiguously, e.g. only similar conditions will trigger events.

As an example, a very sophisticated approach for event detection using MOX sensors (or any sensor response that can be modeled by exponential functions) is the TREFEX algorithm [14], which detects changes in the sensor response that are caused by gas concentration changes. The resulting change points can be used to distinguish between detection/non-detection events.

A much more simple event detector based on binarization of the sensor signal is used in this work. The (baseline corrected derivative of the) signal is compared to a threshold value and for all times the signal exceeds the limit a detection event is declared, otherwise it is considered a non-detection (e.g. exceeding a certain ppm value for the PID or getting below a certain resistance value for MOX sensors is defined as an event).

# 4 BASED Map Algorithm

Given a set of localized events, the algorithm for BASED maps integrates these events into a grid map. The likelihood of oberserving an event is modeled as a Bernoulli distribution

$$p(x|\mu) = \mu^x(1-\mu)^{1-x}, \tag{2}$$

where x is the variable indicating e.g. detection (x=1) or non-detection (x=0) and $\mu$ describes the likelihood of observing an event. The maximum likelihood estimation of the sample mean $\mu$ can be obtained in closed form, but this approach is prone to severe overfitting [12]. Hence, we use a Bayesian approach where the parameter is learned from the data through the Bernoulli's conjugate prior distribution, the beta distribution (see Fig. 1). The beta distribution depends on two parameters $a$ and $b$

$$p(\mu|a,b) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\mu^{a-1}(1-\mu)^{b-1}. \tag{3}$$

The parameters a and b can be interpreted as counting variables, representing the number of observed events. Whenever an event is detected, $a$ is increased by one and for each non-event $b$ is increased by one. This distribution for $\mu$ is used for predicting the likelihood of a gas detection with the Bernoulli distribution - which is higher for the red curve, because there are more gas detection events in this prior information in the examples of Figure 1.

There are different strategies for initializing $a$ and $b$ [12]. For example, if there is no informationabout the likelihood of detecting gas, both values can be set to 1 or 0. In an offline map building process, where the number of detection $d$ and non-detection $nd$ events is known before attempting to create the map, the ratio $n : nd$ is a reasonable choice. Then the mean of the beta distribution is equal to the overall likelihood of a detection event

$$a = \frac{d}{d+nd}, \quad b = \frac{nd}{d+nd}. \tag{4}$$

Different places will have different likelihoods of gas events and to model this, more then one beta distribution is required. In fact, we define a BASED grid map as $n \times m$ individual cells with a fixed size. Each cell stores the two parameters $a$ and $b$ and hence is represented by its own beta distribution.

The naive way of updating the map is to identify the grid cell in which an event was detected and increment the corresponding parameter $a$ by one in case of an event, else increment $b$. This approach assumes independence of the grid cells. Instead, neighboring cells are expected to have similar probabilities for gas detection events. Hence, each cell count of events is updated by fractions of the events in its neighborhood. This fraction is defined by a kernel function. In case of a detection event, all[1] cells' $a$ are updated according to

$$a_i \leftarrow a_i + K(d, \sigma) \tag{5}$$

where $d$ is the Euclidean distance between the center of cell $i$ and the actual event location[2] $E_j$, while $\sigma$ defines the size of the neighborhood. In this work, we are using the Gaussian kernel $K(d, \sigma) = e^{-\frac{d}{2\sigma^2}}$. A non-detection will trigger the analogous update for $b$

$$b_i \leftarrow b_i + K(d, \sigma). \tag{6}$$

This treatment establishes the ability of BASED maps to extrapolate event measurements to neighbouring cells, where no events are recorded.

All measurements are processed sequentially and integrated into the final map individually without the need of storing all the data. The free parameter $\sigma$ can be selected maximizing the conditional log-likelihood of the data $D$ through e.g. grid search

$$\begin{aligned} \log p(D|\sigma) = \sum_{i=1}^{d+nd} [x_i \log \frac{a_j}{a_j + b_j} \\ + (1 - x_i) \log(1 - \frac{a_j}{a_j + b_j})]. \end{aligned} \tag{7}$$

Eq. 7 sums over every data point available and takes into account the type of event $x_i$ and the predicted likelihood at grid cell $j$ in the map. The conditioning variable $\sigma$ does not appear directly in the right part of the equation, but instead is representated in $a_j$ and $b_j$ (see Eq. 5 and 6).

## 5 Case Study

We validated BASED grid maps 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. At predetermined spots the robot stopped for about 30 seconds. The sensor responses where sampled with 4 Hz, which resulted in 6680 measurements for both sensors. Fixed thresholds were used as event detectors. The thresholds were chosen to obtain a comparable

[1] In practice, it is a good idea to define a cutoff value of e.g. $4\sigma$ around the event's location to reduce the computation time.
[2] Note, that if the event location is not in the center of the cell that cells' count will be increased by less then 1.

overall ratio of detection to non-detection events for the two sensors. In Fig. 2, the mean of the beta distribution in each cell is shown as resulting map. The size of the cells is 5cm $\times$ 5cm and the applied kernel size was $\sigma = 0.35$m (obtained by maximizing Eq. 7).

Despite the different sensing principles and the use of naive event detectors, the resulting maps are not only very similar, but consistent with results of other kernel algorithms on the same data [9]. This shows that despite using two fundamentally different sensors, the event mapping approach handles both the same way and the resulting maps are easily comparable.

# 6 Conclusion

We presented a powerful gas distribution mapping approach that uses a well known statistical concept from the field of machine learning and spatial extrapolation to act as a data aggregation tool that is independent from the actual sensor used. The Bayesian Spatial Event Distribution (BASED) grid maps allow to handle very different chemical sensing modalities in a common framework. Even inputs, which do not contain any concentration information like e.g. human reports can be mapped in BASED. Integration of human reports is an emerging research question from projects that are concerned with information acquisition and decision-making for environmental management. An example is the DIADEM project [1]. Further advantages of the proposed approach include that the computational effort required to build the maps is low and the general concept based on events is easy to grasp.

The algorithm can be extended in several ways. Future work will be dedicated to integrating multiple, different sensors into one map. The extension to more than one gas compound can be achieved by using the multinomial and Dirichlet distribution instead of the Bernoulli and beta distribution. Furthermore, the spatial knowledge dissemination with a Gaussian kernels opens possiblities like including wind measurements in Eq. 5 and 6 as it was already demonstrated with other Kernel algorithms [15]. The same equations can be modified to create a temporal low pass filter in an online mapping process and hence provide dynamic maps of the gas distribution and the changes over time.

## References


[1] S. Asadi, M. Reggente, C. Stachniss, C. Plagemann, and A. J. Lilienthal. *Intelligent Systems for Machine Olfaction: Tools and Methodologies*. IGI Global (**2011**).

[2] J. O. Hinze. *Turbulence*. McGraw Hill (**1975**).

[3] Y. Fukazawa and H. Ishida. In *Sensors, 2009 IEEE* (**2009**), pp. 1721–1724.

[4] W. R. Hogan, G. F. Cooper, M. M. Wagner, and G. L. Wallson. ROD technical report, Raltime Outbreak and Disease Surveillance Laboratory, University of Pittsburh, PA. .

[5] S. Thykier-Nielsen, S. Deme, and T. Mikkelsen. Thechnical report RODOS(WG2)-TN(98)-02, Risø National Laboratory, Roskilde, Denmark .

[6] A. Graff. In *8th international conference on Harmonisation within Atmosperic Dispersion Modelling for Regulatory Purposes.* (**2006**).

[7] C. Stachniss, C. Plagemann, and A. J. Lilienthal. Autonomous Robots vol. 26, (2009), pp. 187–202.

[8] J.-L. Blanco, J. G. Monroy, A. J. Lilienthal, and J. G. Jiménez. In *SAC* (**2013**), pp. 217–222.

[9] A. J. Lilienthal, M. Reggente, M. Trincavelli, J. L. Blanco, and J. Gonzalez. In *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (**2009**), pp. 570–576.

[10] A. Hayes, A. Martinoli, and R. Goodman. Sensors Journal, IEEE vol. 2, (2002), pp. 260–271.

[11] C. M. Bishop. *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer-Verlag New York, Inc., Secaucus, NJ, USA (**2006**).

[12] K. P. Murphy. *Machine learning: a probabilistic perspective*. Cambridge, MA (**2012**).

[13] S. Thrun, W. Burgard, and D. Fox. *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*. The MIT Press (**2005**).

[14] S. Pashami, A. J. Lilienthal, E. Schaffernicht, and M. Trincavelli. Sensors vol. 13, (2013), pp. 7323–8220.

[15] M. Reggente and A. J. Lilienthal. In *Proceedings of IEEE Sensors* (**2009**), pp. 1715–1720.

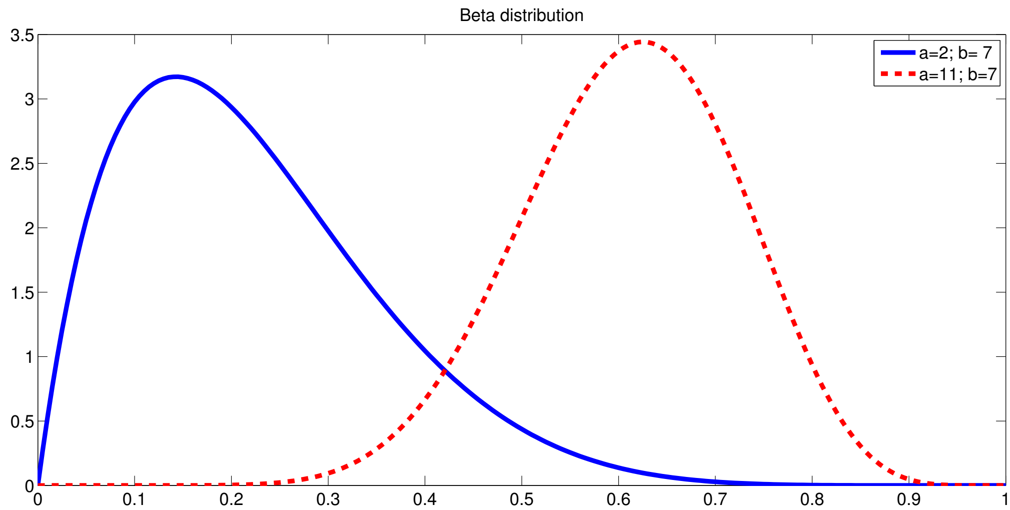


Figure 1: Examples for the beta distribution. The blue curve shows the shape of the distribution in case of very few gas detections ($a = 2$) and a couple of non-detections ($b = 7$). If some additional detection events and no non-detections are recognized ($a = 11$), the distribtion is the red one.

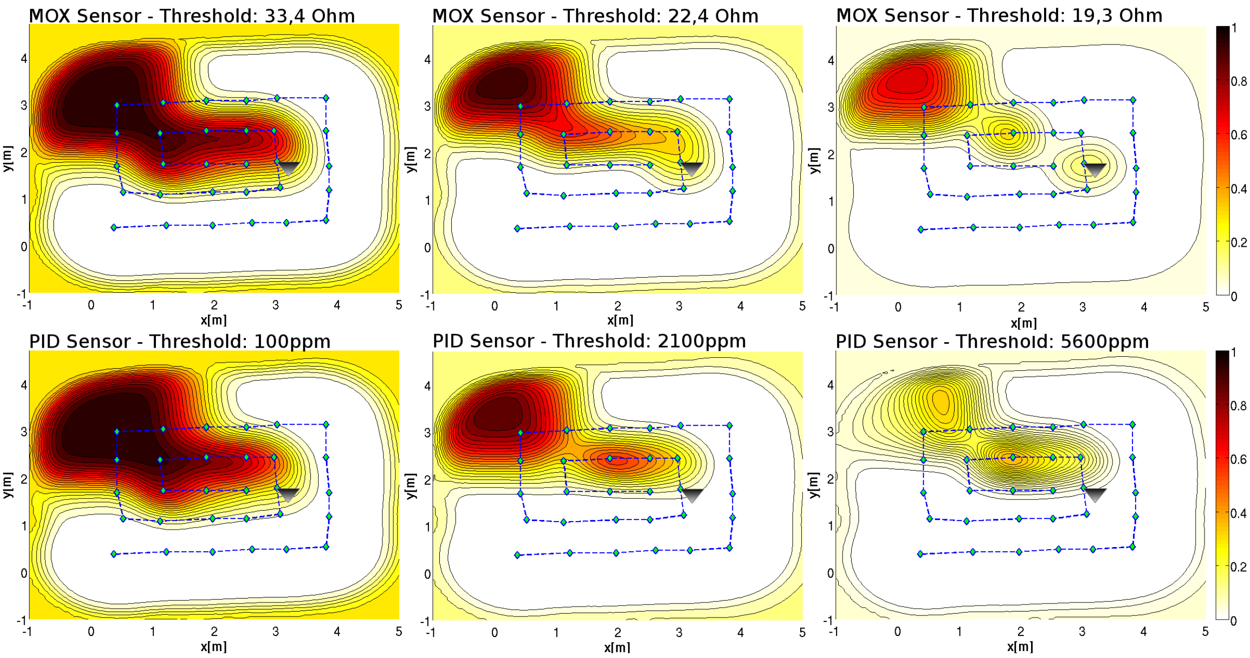


Figure 2: Resulting maps for MOX sensor (upper row) and PID sensor (lower row) for different thresholds of the event detector. If the resistance fell below the given value (MOX sensor) or measured higher ppm values than the treshold (PID), an detection event was declared. The thresholds were chosen to provide a given ratio of detection to non-detection events. This results in 30% of detection events in the first column, 15% in the second column and 5% in the third column, which is reflected by the color (prior) of areas with no measurements (at the edges of the map). The blue line represents the robot's path during the experiments and squares mark stopping positions. The ethanol source is indicated with a triangle and forms a gas plume towards the upper left corner of the area due to the convective airflow.