

Using Local Wind Information for Gas Distribution Mapping in Outdoor Environments with a Mobile Robot

Matteo Reggente and Achim J. Lilienthal

AASS Research Center, Örebro University, SE-701 82 Örebro, Sweden

Email: matteo.reggente@oru.se and achim@lilienthals.de

Abstract—In this paper we introduce a statistical method to build two-dimensional gas distribution maps (Kernel DM+V/W algorithm). In addition to gas sensor measurements, the proposed method also takes into account wind information by modeling the information content of the gas sensor measurements as a bivariate Gaussian kernel whose shape depends on the measured wind vector. We evaluate the method based on real measurements in an outdoor environment obtained with a mobile robot that was equipped with gas sensors and an ultrasonic anemometer for wind measurements. As a measure of the model quality we compute how well unseen measurements are predicted in terms of the data likelihood. The initial results are encouraging and show a clear improvement of the proposed method compared to the case where wind is not considered.

I. INTRODUCTION

Environmental monitoring is important to protect the public and the environment from toxic contaminants and pathogens in the air. The EU (framework directive 1996/62/EC) has imposed strict regulations on the concentration of many airborne environmental contaminants, including sulfur dioxide, carbon monoxide, nitrogen dioxide, and volatile organic compounds, which originate from vehicle emissions, power plants, refineries, and industrial and laboratory processes, to name but a few. Typically these gases are being monitored by stationary networks of sensors located in strategic positions that send the pollution values to a central station for data processing [1]. A mobile robot equipped with an “electronic-nose” (“m-nose”) can act as an autonomous wireless node in a monitoring sensor network. Due to their mobility, self-localization capability and the ability to adaptively select sampling locations, sensor nodes carried by mobile robots offer a number of important advantages compared to stationary sensors, among others: higher and adaptive monitoring resolution, source tracking, first aid and cleanup of hazardous or radioactive waste sites, compensation for inactive sensors, and adaption to the dynamic changes of the environment. Ideally, the environmental monitoring function is integrated in an existing mobile robot application. An example is the EU project “DustBot” that develops autonomous robots which simultaneously clean pedestrian areas and monitor the pollution levels [2].

Gas distribution modelling is the task of deriving a truthful representation of the observed gas distribution from a set of spatially and temporally distributed measurements of relevant variables, foremost gas concentration and wind but

also pressure, and temperature, for example [3], [4]. Building gas distribution models is a very challenging task. One main reason is that in many realistic scenarios gas is dispersed by turbulent advection. Turbulent flow creates packets of gas that follow chaotic trajectories [5]. This results in a concentration field that consists of fluctuating, intermittent patches of high concentration. In principle, CFD (Computational Fluid Dynamics) models can be applied, which try to solve the governing set of equations numerically. However, CFD models are computationally very expensive. They become intractable for sufficiently high resolution in typical real world settings and depend sensitively on accurate knowledge of the state of the environment (boundary conditions), which is not available in practical situations. We propose an alternative approach to gas distribution modelling. Instead of trying to solve the fluid dynamics equations known from physics, we create a statistical model of the observed gas distribution, treating gas sensor measurements as random variables.

An issue that has not been considered so far in statistical gas distribution modelling is to include wind information when building the gas distribution map. Due to the strong influence of advective transport, local airflow is a very important parameter for gas dispersal. The major contribution of this paper is an extension of the Kernel extrapolation method for distribution mapping (Kernel DM+V [4]) so that wind information is taken into account during the creation of the map. In the proposed method, spatial integration of the point measurements is carried out by using a bivariate Gaussian kernel. The kernel can be interpreted as modelling the information content about the statistics of the gas distribution with respect to the point of measurement. By correlating the shape of the kernel with the wind measurements we model the information content depending on the direction and magnitude of the wind. Thus, the proposed method incorporates the information provided by wind measurements about where a sensed patch of gas is likely to have come from and where it tends to move to.

After a discussion of related work in Sec. II, the Kernel DM+V/W algorithm to include wind information when creating gas distribution maps is introduced (Sec. III). Next, the set-up of the monitoring experiments is described (Sec. IV) and an evaluation of the proposed approach in terms of the predictive data likelihood is presented (Sec. V). We conclude with a summary and suggestions for future work (Sec. VI).

II. RELATED WORK

In natural environments, advective flow dominates gas dispersal compared to slow molecular diffusion. Since the airflow we encounter is almost always turbulent, the gas distribution becomes patchy and meandering [6]. Few publications on gas distribution consider the influence of turbulent wind. Addison et al. [7] propose a method for prediction the spatial pollutant distribution within a street canyon. The method is based on a Lagrangian stochastic particle model superimposed on a velocity and turbulence field, which is assumed to be known.

Statistical gas distribution modeling tries to avoid making strong assumptions about the environmental conditions. However, even under conditions that can be modeled by a stationary random process, gas concentration has to be measured for a prolonged time (in the order of minutes) at each location in order to obtain a reliable measure of the concentration mean [8]. Compared to the corresponding demand on sampling density (in time and space), sampling will be always sparse in realistic applications. In order to obtain nevertheless a truthful statistical representation of the gas distribution, several gas distribution modelling approaches have been proposed in the area of mobile olfaction. Again, analytical models have been used. Ishida et al. [8] apply a description of the time-averaged effect of turbulence as diffusion (eddy diffusivity) under the assumption of a stable uniform airflow field. An alternative are interpolation methods [3], [4], [9] that provide a statistical representation of the gas distribution without assuming a pre-defined functional form of the distribution. The approach presented in this paper is based on kernel extrapolation which treats sensors measurements as random variables. As an extension of the Kernel DM+V algorithm in [4] we present the Kernel DM+V/W algorithm, which uses information about the local airflow in addition to gas sensors measurements to compute a statistical gas distribution model. The kernel extrapolation methods have also been extended recently to scenarios where multiple odor sources are present [10] and to the three-dimensional case [11].

Most experiments in the domain of airborne chemical sensing with mobile robots were carried out in small controlled environments. In most of the cases, uniform strong airflow fields were artificially created. Otherwise, small areas in larger rooms were carefully chosen to have constant airflow [12]. In this paper, we present experiments with a gas-sensitive mobile robot in an outdoor scenario.

III. KERNEL DM+V/W ALGORITHM

In this section we introduce the basic ideas of the Kernel DM+V/W algorithm, which is an extension of the algorithm described in [4] that models the distribution mean and the corresponding variance. The general gas distribution mapping problem addressed is to learn a predictive two dimensional model $p(r|\mathbf{x}, \mathbf{x}_{1:n}, \mathbf{r}_{1:n})$ for the gas reading r at location \mathbf{x} , given the robot trajectory $\mathbf{x}_{1:n}$ and the corresponding measurements $\mathbf{r}_{1:n}$. To study how gas is dispersed in the environment we consider measurements from metal oxide

sensors and anemometer readings. The central idea of kernel extrapolation methods is to understand gas distribution mapping as a density estimation problem addressed using convolution with a Gaussian kernel. The first step in the algorithm is the computation of weights $\omega_i^{(k)}$, which intuitively represent the information content of a sensor measurement i at grid cell k :

$$\omega_i^{(k)}(\sigma_0) = \mathcal{N}(|x_i - x^{(k)}|, \sigma_0). \quad (1)$$

The weights are computed by evaluating a Gaussian kernel \mathcal{N} at the distance between the location of the measurement x_i and the center $x^{(k)}$ of cell k . Using Eq. 1, weights $\omega_i^{(k)}$, weighted sensor readings $\omega_i^{(k)} \cdot r_i$, and weighted variance contributions $\omega_i^{(k)} \cdot \tau_i$ are integrated and stored in temporary grid maps:

$$\Omega^{(k)}(\sigma_0) = \sum_{i=1}^n \omega_i^{(k)}(\sigma_0), \quad (2)$$

$$R^{(k)}(\sigma_0) = \sum_{i=1}^n \omega_i^{(k)}(\sigma_0) \cdot r_i, \quad (3)$$

$$V^{(k)}(\sigma_0) = \sum_{i=1}^n \omega_i^{(k)}(\sigma_0) \cdot \tau_i, \quad (4)$$

where

$$\tau_i = (r_i - r^{k(i)})^2 \quad (5)$$

is the variance contribution of reading i and $r^{k(i)}$ is the mean prediction of the cell $k(i)$ closest to the measurement point x_i . From the integrated weight map $\Omega^{(k)}$ we compute a confidence map $\alpha^{(k)}$ which indicates high confidence for cells for which a large number of readings close to the center of the respective grid cell is available. The confidence map is computed as

$$\alpha^{(k)}(\sigma_0) = 1 - e^{-\frac{(\Omega^{(k)}(\sigma_0))}{\sigma_\Omega^2}} \quad (6)$$

where σ_Ω is a scaling parameter that defines a soft margin which decides whether the confidence in the estimate for a cell is high or low. By normalising with the integrated weights $\Omega^{(k)}$ and linear blending with a best guess for the case of low confidence, we finally obtain the map estimate of the mean distribution $r^{(k)}$ and the corresponding variance map $v^{(k)}$:

$$r^{(k)}(\sigma_0) = \alpha^{(k)} \frac{R^{(k)}}{\Omega^{(k)}} + \{1 - \alpha^{(k)}\} \bar{r}, \quad (7)$$

$$v^{(k)}(\sigma_0) = \alpha^{(k)} \frac{V^{(k)}}{\Omega^{(k)}} + \{1 - \alpha^{(k)}\} v_{tot}. \quad (8)$$

The second terms in these equations contain the best estimate, which is used for cells with a low confidence, i.e. for cells for which we do not have sufficient information from nearby readings, indicated by a low value of $\alpha^{(k)}$. As the best guess of the mean concentration \bar{r} we use the average over all sensor readings. The estimate v_{tot} of the distribution variance in regions far from measurement points is computed as the average over all variance contributions.

A. Local Wind Integration

Now we consider the case that information about the airflow is available and describe how wind information is integrated into the gas distribution mapping process by adjusting the shape of the Gaussian kernel. As described in Section IV we can only obtain reliable wind information when the robot is stopped. In this case the symmetric, univariate Gaussian in Eq. 1 (see Fig.2.a) is replaced by an elliptic, bivariate Gaussian with the semi-major axis stretched along the wind direction (see Fig.2.c). The bivariate normal distribution is governed by a mean vector μ (the point of measurement) and a 2×2 covariance matrix Σ . This covariance matrix is computed according to an instantaneous estimate of the local airflow at the sensor location \vec{v} as follows:

- To describe the length of the semi-major and semi-minor axis of the ellipse (a , b) in terms of the kernel width σ_0 of the symmetric Gaussian (see Eq. 1) we set the constraint that the area of the ellipsis remains constant, i.e.

$$\pi\sigma_0^2 = \pi ab. \quad (9)$$

The semi-major axis a is stretched out according to the wind intensity. We assume a linear dependency as

$$a = \sigma_0 + \gamma|\vec{v}|. \quad (10)$$

By combining Eq.(9) and (10) we obtain the length of the semi-minor axis:

$$b = \frac{\sigma_0}{1 + \gamma|\vec{v}|/\sigma_0}. \quad (11)$$

The equations (10) and (11) describe the relation between the estimate of the wind intensity and the eigenvalues of the covariance matrix (see Fig.2.b). The parameter γ in Eq.(9) is assumed to be constant and set heuristically in this paper.

- Finally, the covariance matrix is rotated so that the semi-major axis is aligned with the wind direction (see Fig.2.c)

$$\Sigma_R^{-1} = R^{-1}\Sigma^{-1}R \quad (12)$$

where R is the rotation matrix and Σ_R^{-1} is the inverse of the rotated covariance matrix.

If no reliable information about the local airflow is available (in our set-up this is when the robot is driving), the radially symmetric Gaussian kernel with width σ_0 is applied, which corresponds to the case when zero wind is measured.

The Kernel DM+V/W algorithm depends on four parameters: the zero-wind kernel width σ_0 , the cell size c , the confidence scaling parameter σ_Ω , and the stretching coefficient γ . The kernel width governs the amount of extrapolation on individual readings and the cell size determines the resolution at which different predictions can be made. The confidence scaling parameter defines a soft margin on the confidence estimate, which is used to decide whether sufficient information is available to estimate the concentration mean and variance for a given grid cell. The stretching coefficient is related to the certainty about the wind estimate and to the duration

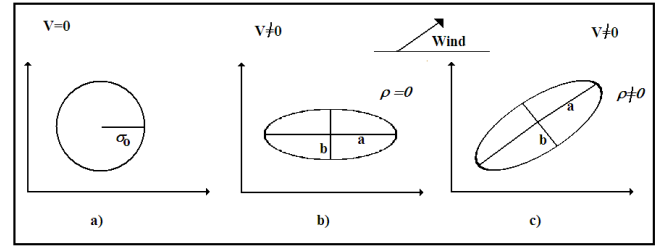


Fig. 2. Modification of the kernel shape. a) Zero wind or no information about the wind: the contour of the normal distribution is radially symmetric. b) Wind intensity: the kernel shape is stretched proportionally to the wind intensity. c) Wind intensity and direction: the bivariate Gaussian kernel is rotated according to the wind direction.

over which the local airflow \vec{v} can be assumed constant. An example that shows how a single gas sensor reading is convolved onto a gridmap is given in Figure 1 for the case of a radially symmetric Gaussian kernel (blue dashed in the left part of the figure) and a wind re-shaped kernel (red solid line). For both cases, those cells that have a distance of less than 3σ from the point of measurement are indicated on the right side of Fig. 1 by a surrounding strong border. It is evident that a different set of cells is affected by the same measurement and that the weights (Eq. 1) will be different.

IV. EXPERIMENTAL SETUP

An ATRV-JR robot equipped with a SICK LMS 200 laser range scanner (for localization) and an “electronic nose” was used for the monitoring experiments (see Fig.3, top). The “electronic nose” comprised different Figaro 26xx gas sensors enclosed in an aluminum tube. These tubes are horizontally mounted at the front side of the robot and actively ventilated through a fan that creates a constant airflow towards the gas sensors. This lowers the effect of external airflow or the movement of the robot on the sensor response and guarantees continuous exchange of gas in situations with very low external airflow. In this work, we address the problem of modeling the distribution from a single gas source. With respect to this task, the response of the different sensors in the electronic nose is highly redundant and thus it is sufficient to consider the response of a single sensor (here: TGS 2620) only.

In order to measure the airflow, an ultrasonic anemometer (Young 81000) was used, which has a range from 2 cm/s up to 40 m/s and a resolution of 1 cm/s. The placement of the anemometer had to be a compromise between the desire to measure the airflow as close to the gas sensors and as undisturbed as possible. In the presented experiments it was mounted above the top of the robot in order to minimize the influence of the fan of the “electronic nose”, the advective flow created by the heated metal oxide sensors, and the body of the robot itself. The information content of the wind measurements is decreased by the distance between the gas and the wind sensor. It was one of the goals of this investigation to find out whether despite the large distance between gas and

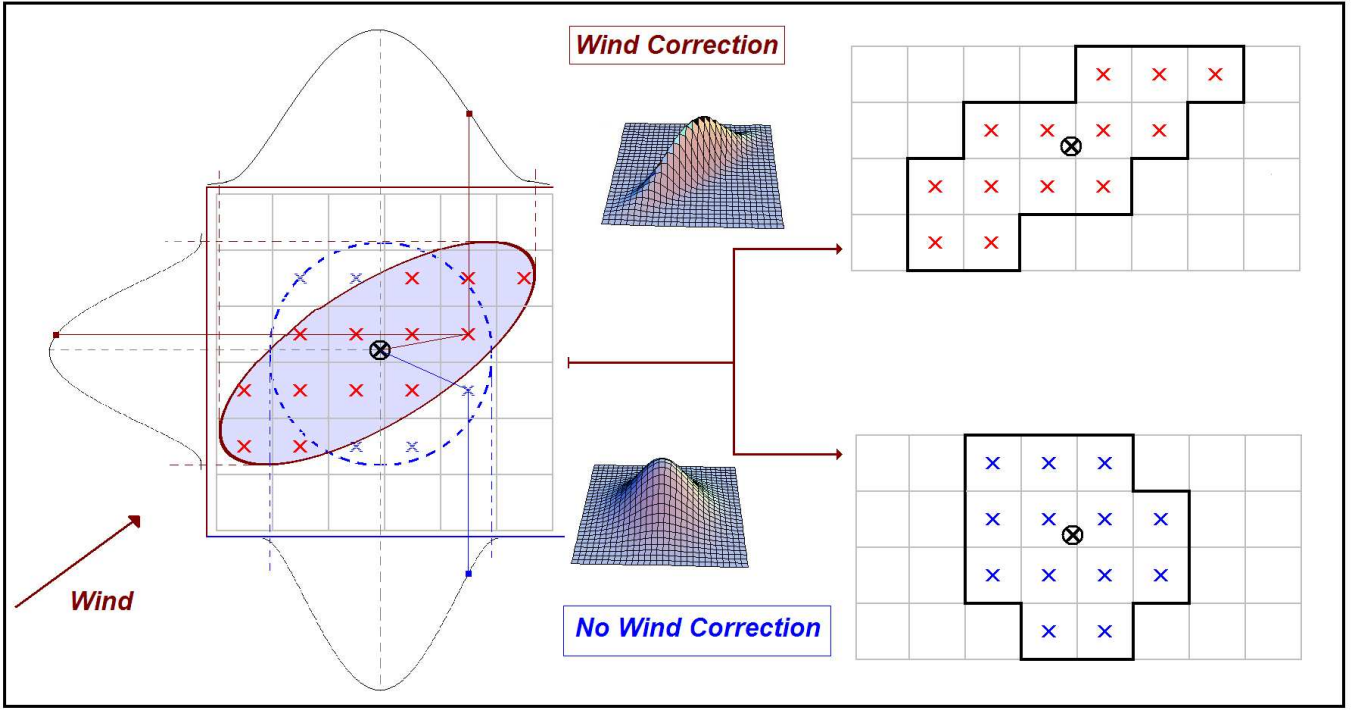


Fig. 1. Discretisation of the Gaussian kernel onto a grid. Left side: Model of the information content of a gas sensor reading (the sampling location is depicted in the center by a black \otimes) in the case of a radially symmetric Gaussian kernel and bivariate Gaussian kernel, respectively. The blue dashed circle represents the contour of the kernel in absence of wind and the red solid line shows the elliptic contour of the kernel for the case of non-zero wind. Right side: strongly affected cells are surrounded by a strong border.

wind sensor the wind measurements still provide sufficient information to obtain better gas distribution maps.

The robot software is based on the Player robot server [13], a control interface that simplifies access to standard robot sensors and actuators.

The scenario selected for the gas distribution mapping experiments is an outdoor region of approx. 8×8 m^2 that is a part of much bigger area. The gas source was a small cup filled with ethanol and it was placed on the floor roughly in the middle of the investigated area (see Fig.3, bottom). In the experiments, the robot followed a predefined sweeping trajectory (repeated two times) covering the area of interest. Along its path, the robot stopped at predefined positions (waypoints) and carried out a sequence of measurements on the spot for 30s. The robot was driven at a maximum speed of 5cm/s in between the stops. The reason for stopping the robot at each waypoint to collect wind measurements is due to the difficulty in compensating for the shaking of the anemometer when the robot is moving.

In order to avoid calibration issues, we model the normalised sensor response $r_i \in [0, 1]$

$$r_i = \frac{R_i - \min\{R_j\}}{\max\{R_j\} - \min\{R_j\}}. \quad (13)$$

We make the assumption that the sensor response is caused by a single target gas, i.e. we do not consider problems related to interferences or simultaneous mapping of multiple odours. In

principle the proposed method can be extended to the case of multiple different odor sources as described in [10]. Finally, we assume perfect knowledge about the position x_i of a sensor at the time of the measurement. To take into account the uncertainty about the sensor position, the method in [14] could be used.

V. RESULTS

Knowledge of the exact gas source position and the correlation with the maximum in the map has been considered as a way to evaluate gas distribution models. However, the maximum of a gas distribution does not necessarily have to correspond to the true location of the gas source. An alternative way to evaluate to which degree a model captures the true properties of the gas distribution is to evaluate how well unseen measurements are predicted by the distribution model. To do this we split the dataset D into disjoint sets D_{learn} and D_{eval} . We use D_{learn} to train the model and then compute the likelihood of unseen measurements as the average negative log predictive density (NLPD) over the n' samples in D_{eval} as:

$$NLPD = -\frac{1}{n'} \sum_{i \in D_{eval}} \log\{p(r_i|x)\} = \quad (14)$$

$$\frac{1}{2n'} \sum_{i \in D_{eval}} \left\{ \log v^{(k(i))} + \frac{(r_i - r^{(k(i))})^2}{v^{(k(i))}} \right\} + \log(2\pi).$$

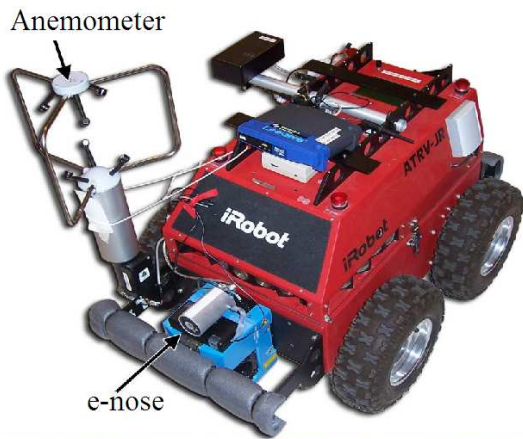


Fig. 3. The mobile robot “Rasmus” (top) and a snapshot during a pollution monitoring mission in the experimental environment (bottom).

Since we want to maximize the likelihood of the data points our goal is minimize the NLPD in Eq.(14). In order to evaluate whether the Kernel DM+V/W algorithm improves the model, we have calculated the NLPD with and without wind correction in the outdoor scenarios described above. We used the first half of the dataset to learn the hyper parameters and the corresponding model and the second half to evaluate the model, then the second half to learn and the first to evaluate. Due to the difficulty of measuring wind precisely when the robot is moving, we considered gas sensors and anemometer readings only when the robot was stopped and only gas sensor readings when the robot was driving. The value of the cell size c and the kernel width σ_0 were optimized by cross validation over D_{learn} . The parameter γ was empirically set to 1.0 and the soft parameter σ_Ω was tied to the selected kernel width σ_0 using $\sigma_\Omega = \mathcal{N}(0, \sigma_0)$.

The results are outlined in Figure 4. The bar-plots show the absolute difference of the obtained NLPD ($\Delta(NLPD) = (NLPD_{DM+V} - NLPD_{DM+V/W})$). Positive values correspond to an improved model when the method proposed in this paper is used. The upper part of Fig. 4 shows results obtained from data sets that contain periods where the robot was driving and periods where it was stopped (Drive&Stop trials). The bottom part shows results from data sets that contain only

TABLE I
STATISTICAL EVALUATION

Trial Type	Wilcoxon Signed Rank test, p value
Drive&Stop	0.0234
Stop	0.0312

those parts of the data where the robot was stopped (Stop trials). It is evident that the DM+V/W algorithm improved the resulting gas distribution model (only one time it performed worse than without considering wind information). The results of a paired Wilcoxon signed-rank test confirm this observation at a confidence level of 95% (see Table I).

A qualitative result is shown in Fig. 5 that shows three gas distribution maps. In the top map the DM+V algorithm without wind extension is used. The middle and bottom maps are obtained using the proposed DM+V/W algorithm, with the difference that in the bottom map, the wind measurements are rotated by 90 degrees. In the right part of the map plots in Fig. 5, the computed NLPD values are shown (obtained by averaging over predictions of measurements from the second part of the trial by a model learned from the first part, and vice versa). In all three gas distribution maps the global maximum of the distribution mean is found in the proximity of the gas source (which is indicated by a white \otimes). In examining the top map, please note that there are two disjoint areas where the concentration of gas is high. In the middle map, which was obtained with the algorithm proposed in this paper, the two areas are less disjoint and the modelled distribution of the gas is more uniform. A possible intuitive explanation for the improved NLPD value corresponding to this map is that the expected plume structure is captured most clearly. In the bottom map, where an error in the direction of the wind was introduced, two separate local maxima are formed and the distribution does not exhibit a clear plume shape. A comparison of the resulting map with the result shown in the middle of Fig. 5, emphasizes the importance of correct wind information for the proposed algorithm.

VI. CONCLUSION AND FUTURE WORK

Gas distribution modelling with a mobile robot in an uncontrolled environment is a challenging field of research. This is mainly due to the chaotic nature of the dispersed gas that is affected by the turbulent nature of the wind. Utilization of mobile robots to monitor pollution has a number of advantages reflected by an increasing interest in this field in the last ten years. In this paper we introduce a statistical method to build two-dimensional gas distribution maps that takes into consideration the influence of wind in the dispersion of gas (Kernel DM+V with Wind = Kernel DM+V/W). The mapping technique extends the Kernel DM+V algorithm by a bivariate Gaussian weighting function to model the information provided by gas sensor measurements. The proposed method is evaluated using a mobile robot equipped with an “e-nose” and an ultrasonic anemometer. Experiments in an outdoor

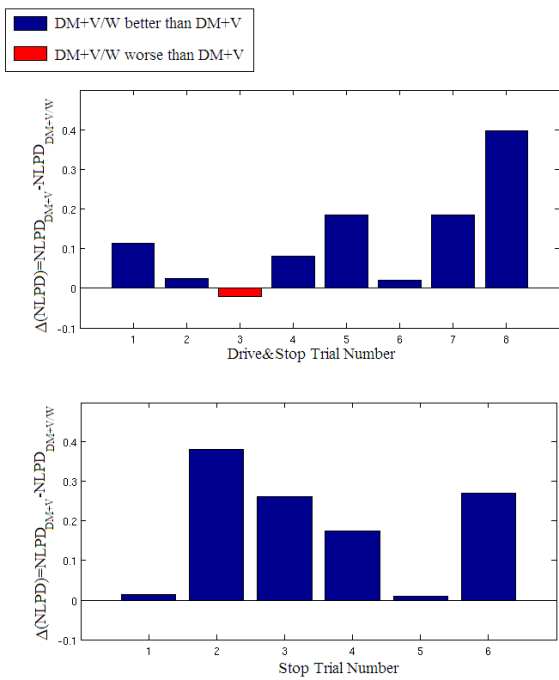


Fig. 4. Top: Drive&Stop trials. Bottom: Stop trials. Bar-plot: $(\Delta(NLPD) = (NLPD_{DM+V} - NLPD_{DM+V/W}))$. Positive values correspond an improvement of the model using Kernel DM+V/W.

environment are presented and evaluated with respect to the ability of the obtained model to predict unseen data. The results are encouraging, showing a clear improvement when using the proposed method.

Future work will first aim at a set-up where the distance between the wind and the gas sensors is smaller. We also investigate the possibility to learn the stretching coefficient γ from the data. Another interesting extension is to integrate the proposed method with a 3D modelling approach based on data acquired with gas sensors mounted at different heights.

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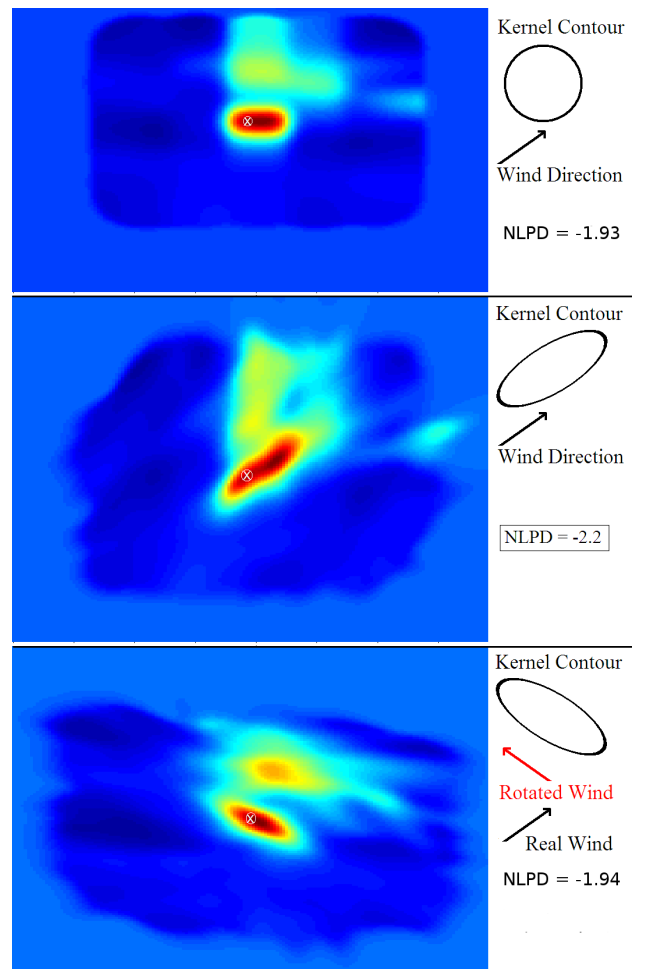


Fig. 5. Gas Distribution Map. Top: DM+V algorithm. Middle: DM+V/W algorithm. Bottom: DM+V/W with "wrong" wind measurements (true wind measurements rotated by 90 degrees).

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