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Online Estimation of 2D Wind Maps for Olfactory Robots

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***Abstract*—This work introduces a novel solution to approximate in real time the 2D wind flow present in a geometrically known environment. It is grounded on the probabilistic framework provided by a Markov random field and enables the estimation of the most probable wind field from a set of noisy observations, for the case of incompressible and steady wind flow. Our method delivers reasonably precise results without falling into common unrealistic assumptions like homogeneous wind flow, absence of obstacles, etc., and performs very efficiently (less than 0.5 seconds for an environment represented with a 100x100 cell grid). This approach is then quite suitable for applications that require real-time estimation of the wind flow, as for example, the localization of gas sources, prediction of the gas dispersion, or the mapping of the gas distribution of different chemicals released in a given scenario.**

I. Introduction

Wind is the bulk movement of air. It is an important environmental phenomena in our world, playing a crucial role in the dispersion of volatile chemical substances in air, concretely, driving the advection component of the general advection-diffusion transport equation of fluid dynamics [1]. Since in most real applications advection has a strong predominance over molecular diffusion, having knowledge of the existing wind patterns is paramount for many artificial olfaction related tasks. Examples include gas source localization [2], [3], classification of volatile chemical substances [4], [5] or gas distribution mapping [6], [7]. According to how the wind data is predicted, existing works can be arranged in two major groups: those based on computational fluid dynamics (CFD), and those which assume unrealistic conditions to make the problem more tractable. The former involves solving the Navier-Strokes equations numerically, providing an accurate estimation of the wind flow but at the expense of both a high computational burden (not being suitable for online applications) and the need of expertise for handling the many parameters for running a simulation. On the other hand, many works simplify the problem by considering very specific and simple scenarios such as wind tunnels, homogeneous and steady-state wind, or the absence of obstacles in the environment. Our interest is in the estimation of wind flow in real time by an olfactory robot and, therefore, neither of these approaches are completely suitable.

In this work we propose a novel approach to estimate the wind flow in a known environment, from a set of sparse and noisy wind measurements (strength and direction). Our proposal is rooted in the probabilistic framework of Gaussian Markov random fields (GMRF), enabling not only the consideration of complex environments (e.g with the presence of obstacles, multiple rooms, different inlets and outlets, etc.) but also providing an uncertainty measure associated to the predicted wind flow. Our proposal can be seen as a real-time approximation of CFD techniques to estimate 2D wind flow in planar environments (i.e. with the same obstacle distribution from bottom to top), under the assumption that the flow is incompressible. Therefore, our algorithm is mostly suitable for indoor scenarios and applications that require real-time performance.

II. Modeling Wind Flow with GMRF

The proposed approach aims at estimating the 2D wind flow from a set of noisy wind measurements $\mathrm{Z} = \{\mathbf{z}_i\}_{i=1}^{K}$, and prior knowledge of the physical environment occupancy (i.e. obstacles, walls, free-space, wind inlets/outlets). We consider a discrete two-dimensional lattice of cells, where a map $\mathrm{W} = \{\mathbf{w}_i\}_{i=1}^{N}$ is modeled as a random field, being N the total number of cells. Each $\mathbf{w}_i$ stands for the wind vector inside the i'th cell with coordinates (x_i, y_i). The goal, then, is to obtain the maximum a posteriori (MAP) estimation of W.

In this work we propose the use of Gaussian Markov random fields, a tool widely employed in other estimation problems on grids [6], [8]. A GMRF consists of a vector of random variables satisfying the Markov conditional independence assumptions, and further following a multivariate normal distribution, that is, each random variable is modeled as a Gaussian distribution $\mathbf{w}_i \sim \mathcal{N}(\boldsymbol{\mu}_i, \Sigma_i)$. This approach formulates the posterior probability distribution $p(\mathrm{W}|\mathrm{Z})$, which we want to maximize, as a decreasing exponential of energy functions defined over the relations of a cell with its neighbours [9]:

$$p(\mathrm{W}|\mathrm{Z}) \propto \exp\{-E(\mathrm{W},\mathrm{Z})\} , \quad (1)$$

where E is the overall energy function that depends on the random variables W and the wind observations Z.

We consider four energy terms or, equivalently, four factors if we refer to its homonymous graphical representation as a factor graph:

- **Energy derived from Observations**: It encodes the observation model $p(\mathbf{z}_k|\mathrm{W})$. Assuming that each observation $\mathbf{z}_k$ is associated only to the nearest cell (denoted as $\mathbf{w}_{i_k}$), we can express this energy function as:

$$E_z(\mathrm{W},\mathrm{Z}) = \sum_{k=1}^{K} \frac{\|\mathbf{w}_{i_k} - \mathbf{z}_k\|^2}{\sigma_z^2} \ , \tag{2}$$

  where σ_z^2 stands for the variance of the sensor noise.
- **Energy derived from the Law of Conservation of Mass**: Following a finite-volume approach, we impose this constraint per cell using a 2D contour composed of its 8-neighbours (see Fig. 1). Assuming that the fluid is incompressible, the mass flux through this contour must be null and, therefore, the associated energy term is expressed as

$$E_m(\mathrm{W}) = \lambda_m \sum_{i=1}^{N} \left(\oint_{C_i} \mathbf{n}(c) \cdot \mathbf{w}(c) \, \mathrm{d}c \right)^2 \ , \tag{3}$$

  where C_i is the countour surrounding the i-th cell, $\mathbf{n}(c)$ is the normal to the contour and $\mathbf{w}(c)$ is the wind velocity evaluated along the contour. Thanks to the simple shape of C_i, these integrals are solved analytically and result in linear functions of the wind vectors W. In turn, λ_m is a weight that controls the importance of this term in the overall energy function defined in Eq. (1).
- **Energy derived from the presence of obstacles**: Since wind cannot go through obstacles/walls, this term imposes that wind at cells surrounding obstacles can only be tangential to them:

$$E_o(\mathrm{W}) = \lambda_o \sum_{i=1}^{N} T(\mathbf{w}_i)^2 \ , \tag{4}$$

  with

$$T(\mathbf{w}_i) = \begin{cases} 0, & \text{if cell } i \text{ has no obstacles around} \\ \mathbf{w}_i \cdot \mathbf{n}_{obs}, & \text{otherwise} \end{cases} \ , \tag{5}$$

  where $\mathbf{n}_{obs}$ represents the normal vector to an obstacle and λ_o is the corresponding weighting factor.
- **Regularization**: We establish a correlation between nearby cells, enforcing that neighbouring cells must have similar wind vectors:

$$E_r(\mathrm{W}) = \lambda_r \sum_{i=1}^{N} \sum_{j \in E_i} \|\mathbf{w}_i - \mathbf{w}_j\|^2 \tag{6}$$

  being E_i the set of neighbours surrounding cell i and λ_r the weighting factor. Thus, this energy controls the smoothness of our estimated wind map.

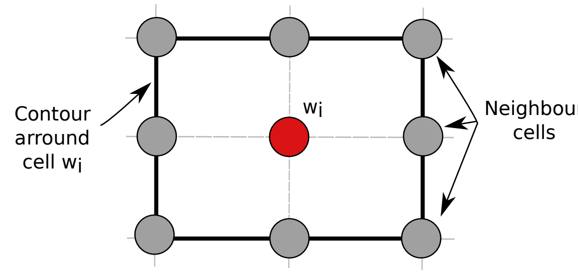

Fig. 1. 2D contour defined over the 8 neighbours of a cell $\mathbf{w}_i$ used to impose the law of conservation of mass.

Finally, by taking the negative logarithm over the posterior in Eq. (1), our MAP estimation problem can be expressed as a simple least-squares minimization, which in our case reads:

$$\arg\min_{W} \{E(\mathrm{W},\mathrm{Z})\} \tag{7}$$

$$E(\mathrm{W},\mathrm{Z}) = E_z(\mathrm{W},\mathrm{Z}) + E_m(\mathrm{W}) + E_o(\mathrm{W}) + E_r(\mathrm{W}) \tag{8}$$

III. Validation Simulations

This section presents two experiments where comparison between the 2D wind flow approximated by our approach, and the solution obtained from CFD (employing the open source OpenFOAM[1] simulator), is provided. The CFD case considers the steady-state solution for an incompressible, turbulent flow employing the k-epsilon turbulence model. Furthermore, all experiments are carried out in a 10×10 m simulated environment with several rooms (see Fig. 2). The values of the model parameters ($\lambda_m, \lambda_o, \lambda_r$) have been empirically tuned in accordance with the environment and the wind flow conditions (strength, turbulence, etc), leaving for a future work the automatic estimation of the optimal values.

The first experiment follows a typical CFD configuration, comparing both approaches for the case where only boundary information is provided. More specifically, we set the wind vectors at the inlet, and assume a constant pressure over all open outlets for CFD. Fig. 2 plots the wind flow as estimated by both approaches for two different inlet-outlet configurations of the environment: (a) when only outlet 1 is open, and (b) when the three outlets are open at the same time (giving rise to multiple wind paths). As can be observed, our approach provides an estimation of the wind flow that strongly agrees with the solution obtained from CFD, having similar wind speeds and direction on most areas. Yet, given we just consider a simplification of the general and complex law of fluid dynamics, differences can be appreciated, specially in areas of low wind speed.

The second experiment presents a more challenging scenario, where there is neither prior knowledge about the state (open/close) of the inlets/outlets in the environment, nor about the wind conditions at the boundary. In simulation, a mobile robot inspecting the environment periodically measures the wind vector with a 2D anemometer ($\sigma_z = 0.32$), and updates the wind map W with each new measurement. Fig. 3 plots a sequence of wind maps corresponding to the belief at different

[1]http://www.openfoam.com/

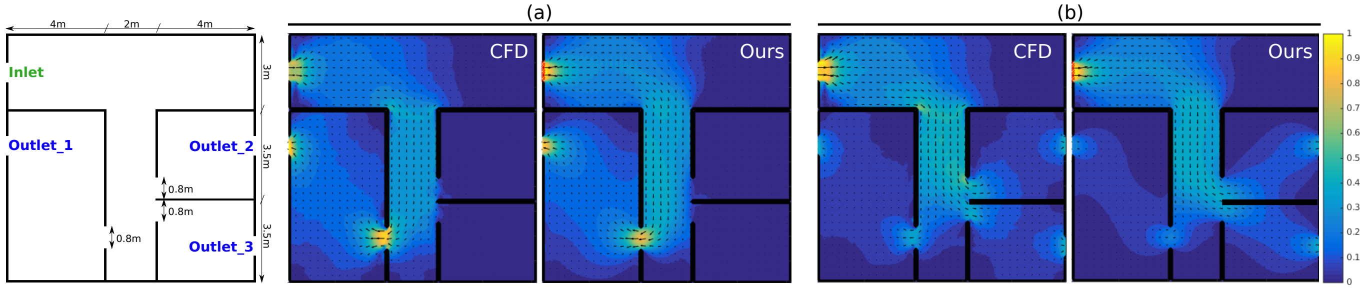

Fig. 2. Wind flow comparison between CFD and the solution provided by our method for two possible scenarios: (a) when only outlet 1 is open, (b) when the three outlets are open. The wind flow is depicted by a contour plot with color proportional to the wind strength, and an arrow field to show the wind direction. Only the wind vectors at the inlet (red) are considered as measurements when running our method.

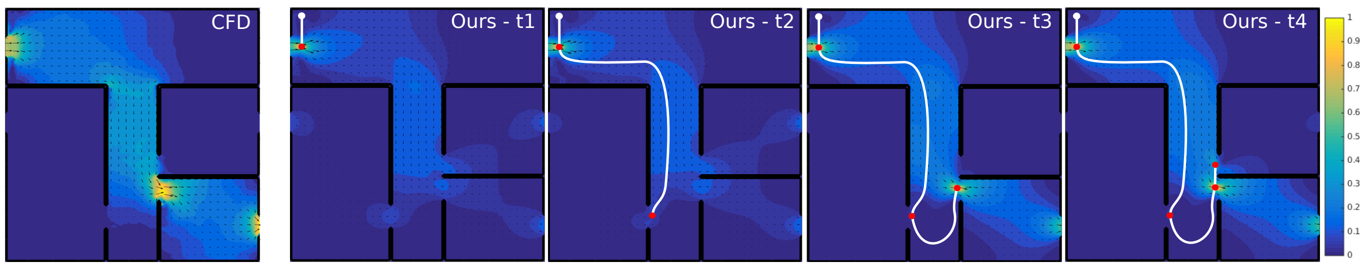

Fig. 3. Wind-maps estimated by our approach at different time steps (t1, ... , t4). A mobile robot inspects the environment measuring the wind conditions at sparse locations (for each new measurement a wind-map is plotted). The white line represents the path followed by the robot, while the red dots show the locations where wind measurements are taken. It can be seen how our estimates rapidly converge to the CFD solution with just a few measurements.

time instants. It can be appreciated how our approach converges to the CFD solution as new observations are considered, especially those located at the room doors. The latter raises a new research question: what is the optimal path to follow in order to obtain a fast and accurate estimate of the wind flow? This question requires a deep analysis of the problem and, therefore, we leave it for future research.

Finally, it must be stressed that for a number of applications related to artificial olfaction (e.g. gas source localization, gas distribution mapping, trail following, etc.) it is more interesting to have a not-so-accurate estimation of the wind flow, but available at a high rate (i.e. real time), rather than the opposite. Our approach represent an ideal candidate for these applications, being significantly faster than its CFD counterpart (less than 0.5 seconds for the presented scenario, in comparison with the 10 minutes of CFD).

IV. Conclusion

We have presented a new approach to approximate the wind flow in a 2D environment from a set of sparse and noisy observations. Our approach is built over the Gaussian Markov random field framework, providing a precise and fast estimate of the average wind flow, as well as being able to explicitly handle uncertainty on the data. Our method has been compared with computational fluid dynamic tools, demonstrating its ability to provide an accurate solution in real time.

As future work we plan to extend our algorithm to 3D environments and to introduce uncertainty in the occupancy gridmap. Thus, we will also model changing environments, where e.g. doors or windows can be open or closed, from a set of wind observations.

V. Acknowledgements

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