

Chapter 6

Statistical Gas Distribution Modeling Using Kernel Methods

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ABSTRACT

Gas distribution models can provide comprehensive information about a large number of gas concentration measurements, highlighting, for example, areas of unusual gas accumulation. They can also help to locate gas sources and to plan where future measurements should be carried out. Current physical modeling methods, however, are computationally expensive and not applicable for real world scenarios with real-time and high resolution demands. This chapter reviews kernel methods that statistically model gas distribution. Gas measurements are treated as random variables, and the gas distribution is predicted at unseen locations either using a kernel density estimation or a kernel regression approach. The resulting statistical

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models do not make strong assumptions about the functional form of the gas distribution, such as the number or locations of gas sources, for example. The major focus of this chapter is on two-dimensional models that provide estimates for the means and predictive variances of the distribution. Furthermore, three extensions to the presented kernel density estimation algorithm are described, which allow to include wind information, to extend the model to three dimensions, and to reflect time-dependent changes of the random process that generates the gas distribution measurements. All methods are discussed based on experimental validation using real sensor data.

INTRODUCTION

Modeling the distribution of gas in an environment aims at deriving a truthful representation of the observed gas distribution from a set of spatially and temporally distributed measurements of relevant variables, foremost gas concentration, but also wind, pressure, and temperature (Lilienthal et al., 2009b). The task of building gas distribution models is challenging mainly because of the chaotic nature of gas dispersal. The complex interaction of gas with its surrounding is dominated by three physical effects. First, on a long time scale, diffusion mixes the gas with the surrounding atmosphere to achieve a homogeneous mixture of both in the long run. Second, turbulent air flow fragments the gas emanating from a source into intermittent patches of high concentration with steep gradients at their edges (Robert & Webster, 2002). Third, advective flow moves these patches. Due to the effects of turbulence and advective flow, it is possible to observe high concentrations in locations distant from the source location. These effects are especially important in uncontrolled environments.

Besides the physics of gas dispersal, limitations of gas sensors also make gas distribution modeling difficult. Gas sensors provide information about a small spatial region only since the measurements require direct interaction between the sensor surface and the analyte molecules. Therefore, instantaneous measurements of gas concentration over a large field would require a dense grid of sensors which is usually not a viable solution due to high cost and lack of flexibility.

Gas distribution modeling (GDM) methods can be categorized as model-based and model-free. Model-based approaches infer the parameters of an analytical gas distribution model from the measurements. In principle, Computational Fluid Dynamics (CFD) models can be applied to solve the governing set of equations numerically. Current CFD methods are computationally expensive and not suitable for realistic scenarios in which a high resolution is required and the model needs to be updated with new measurements in real time. Many other model-based ap-

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