

Chapter 10

Improved Gas Source Localization with a Mobile Robot by Learning Analytical Gas Dispersal Models from Statistical Gas Distribution Maps Using Evolutionary Algorithms

Achim J. Lilienthal
Örebro University, Sweden

ABSTRACT

The method presented in this chapter computes an estimate of the location of a single gas source from a set of localized gas sensor measurements. The estimation process consists of three steps. First, a statistical model of the time-averaged gas distribution is estimated in the form of a two-dimensional grid map. In order to compute the gas distribution grid map the Kernel DM algorithm is applied, which carries out spatial integration by convolving localized sensor readings and modeling the information content of the point measurements with a Gaussian kernel. The statistical gas distribution grid map averages out the transitory effects of turbulence and converges to a representation of the time-averaged spatial distribution of a target gas. The second step is to learn the parameters of an analytical model of average gas distribution. Learning is achieved by nonlinear least squares fitting of the

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analytical model to the statistical gas distribution map using Evolution Strategies (ES), which are a special type of Evolutionary Algorithm (EA). This step provides an analysis of the statistical gas distribution map regarding the airflow conditions and an alternative estimate of the gas source location, i.e. the location predicted by the analytical model in addition to the location of the maximum in the statistical gas distribution map. In the third step, an improved estimate of the gas source position can then be derived by considering the maximum in the statistical gas distribution map, the best fit, as well as the corresponding fitness value. Different methods to select the most truthful estimate are introduced, and a comparison regarding their accuracy is presented, based on a total of 34 hours of gas distribution mapping experiments with a mobile robot. This chapter is an extended version of the conference paper (Lilienthal et al., 2005).

INTRODUCTION

A major problem for gas source localization in a natural environment is the strong influence of turbulence on the dispersal of gas. Typically, turbulent transport is considerably faster compared to molecular diffusion (Nakamoto et al., 1999; Roberts and Webster, 2002). Apart from very small distances where turbulence is not effective, molecular diffusion can thus be neglected concerning the spread of gas. A second important transport mechanism for gases is advective transport due to prevailing fluid flow. Relatively constant air currents are typically found even in an indoor environment without ventilation (Wandel et al., 2003) as a result of pressure (draught) and temperature inhomogeneities (convection flow).

Turbulent flow comprises at any instant a high degree of vortical motion, which creates packets of gas that follow chaotic trajectories (Shraiman and Siggia, 2000). This results in a concentration field, which consists of fluctuating, intermittent patches of high concentration. The instantaneous concentration field does not exhibit smooth concentration gradients that indicate the direction toward the centre of a gas source (Lilienthal and Duckett, 2004b; Russell, 1999). Figure 1 illustrates actual gas concentration measurements recorded with a mobile robot along a corridor containing a single gas source. It is important to note that the noise is dominated by the large fluctuations of the instantaneous gas distribution and not by the electronic noise of the gas sensors. Turbulence is chaotic in the sense that the instantaneous flow velocity at some instant of time is insufficient to predict the velocity a short time later. Consequently, a snapshot of the distribution of a target gas at a given instant contains little information about the distribution at another time. However, under certain assumptions (e.g. that the air flow is uniform and steady) the *time-averaged* concentration field varies smoothly in space with moderate concentration gradients (Roberts and Webster, 2002).

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