TD Kernel DM+V: Time-Dependent Statistical Gas Distribution Modelling on Simulated Measurements

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Abstract. To study gas dispersion, several statistical gas distribution modelling approaches have been proposed recently. A crucial assumption in these approaches is that gas distribution models are learned from measurements that are generated by a time-invariant random process which can capture certain fluctuations in the gas distribution. More accurate models can be obtained by modelling changes in the random process over time. In this work we propose a time-scale parameter that relates the age of measurements to their validity to build the gas distribution model in a recency function. The parameters of the recency function define a time-scale and can be learned. The time-scale represents a compromise between two conflicting requirements to obtain accurate gas distribution models: using as many measurements as possible and using only very recent measurements. We have studied several recency functions in a time-dependent extension of the Kernel DM+V[1]. Based on real-world experiments and simulations of gas dispersal (presented in this paper) we demonstrate that TD Kernel DM+V improves the obtained gas distribution models in dynamic situations. This represents an important step towards statistical modelling of evolving gas distributions.

Keywords: time-dependent modelling, statistical gas distribution models, gas dispersial simulation
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METHODS AND RESULTS

To build a time-scale dependent model, we apply an extension of the Kernel DM+V algorithm, which we call TD Kernel DM+V[2]. It combines the spatial extrapolation of the basic Kernel DM+V algorithm with temporal extrapolation weighted by a time-dependent term defined with a time-scale factor. The time-scale is learned together with the other meta-parameters by optimizing the NLPD (Negative Log Predictive Density) value of the predictive model[3]. To evaluate different time-dependent modelling approaches, we have developed a gas dispersal simulation engine[4] which provides ground truth information to evaluate gas dispersion models. Two simulation experiments were performed in

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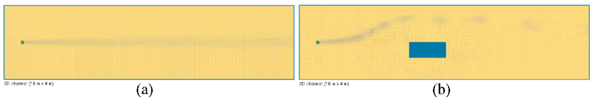

FIGURE 1. Gas dispersal simulation of the two experiments performed in the wind tunnel ($16 \times 4\ m^2$) with the inlet on the left (approx. $1\ \frac{m}{s}$): gas dispersion in (a) predominantly laminar flow with no obstacle and (b) turbulent flow created by placing an obstacle in the tunnel (the blue rectangle). Filled circle indicates an ethanol gas source with emission rate of $1\ s^{-1}$.

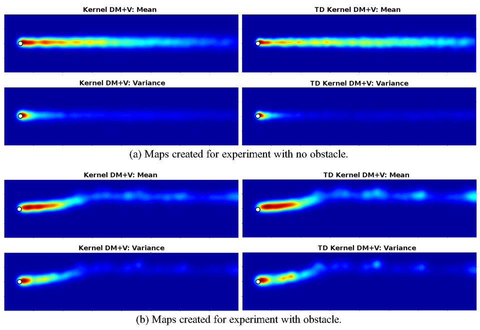

FIGURE 2. Predicative mean (top) and variance (bottom) maps created by Kernel DM+V (left) and TD Kernel DM+V (right) for the experiments: (a) with obstacle and (b) without obstacle shown in Fig 1(a) and Fig 1(b) respectively. White circle indicates the gas source.

a wind tunnel to simulate the gas dispersion under effect of predominantly laminar and turbulent flow, illustrated in Fig. 1(a) and Fig. 1(b) respectively. Measurements in both experiments have been collected at random, fixed locations over the first 16 s. A predictive model is learned by cross-validation over the training set, optimizing the NLPD value. The model is then used to estimate the gas distribution for the 20th s. The corresponding predictive mean and predictive variance using Kernel DM+V (left) and TD Kernel DM+V (right) are illustrated in Fig. 2(a) and Fig. 2(b). The NLPD comparison presented in Table 1 shows a substantial improvement with the proposed time-scale dependent approach.

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TABLE 1. NLPD comparisons of models built with Kernel DM+V and TD Kernel DM+V for the two experiments shown in Fig. 1(a) and Fig. 1(b). More negative NLPD values correspond to better gas distribution predictions. Cell size and Kernel size are in m and time scale factor is in s^{-1}.

Experiment	Kernel DM+V			TD Kernel DM+V			
	NLPD	kernel size	cell size	NLPD	kernel size	cell size	time scale factor
No obstacle	-6.43	0.2	0.05	-14.43	0.16	0.074	0.218
With obstacle	-5.8	0.2	0.05	-11.97	0.209	0.05	0.235