DATA ASSIMILATION FOR FORECASTING PLUME DISPERSION

Tarunraj Singh[1] , Puneet Singla[1] , Peter Scott[2] , Uma Reddy[1], Gabriel Terajanu[2], and Yang Cheng[1] ,
[1]Department of Mechanical and Aerospace Engineering, University at Buffalo, Buffalo, NY 14260,
[2]Department of Computer Science and Engineering, University at Buffalo, Buffalo, NY 14260.

Introduction: Accidental or deliberate release of toxic chemicals or biological agents in populated areas and the resulting dispersion via diffusion and transport has potentially disastrous consequences. Real-time detection, tracking, and prediction of chemical and biological releases is important for fast response to chemical and biological accidents and attacks. Knowledge about the releases is obtained by fusing data from an array of deployed and possibly mobile sensors and an atmospheric dispersion model. The use of atmospheric dispersion model along with the meteorological model is essential because of the very limited coverage of the sensors in time and space. Gaussian puff based models [1] are often used to make fast release concentration prediction, in which a series of Gaussian shaped puffs are released at the sources and propagated in the atmosphere. Sensors used in dispersion applications usually have imprecise bar readings. The bar readings provide limited information about the true concentration and increase the nonlinearity of the measurement process.

Data assimilation is the science and art of fusing the observations with the model predictions, to get a better estimate. Real-time and operational data assimilation for atmospheric release dispersion, needs to deal with two main problems: high nonlinearity and high state dimensionality. Nonlinearities in the dispersion model and the observation model pose significant challenges for data assimilation techniques. Further, due to continuous release/emissions at the source and potential subsequent puff splitting, the number of puffs and therefore the length of the state vector is not constant, but changes with time. The state dimension may become so high that estimating all states from the sensor data is impossible.

Disperson Model: The atmospheric dispersion model used is based on the RIMPUFF [1] (Riso Mesoscale PUFF) model which was designed to calculate the concentration and doses resulting from the dispersion of airborne particles. It is a Lagrangian mesoscale atmospheric dispersion puff model, which applies both to homogeneous and inhomogeneous terrain with moderate topography on a horizontal scale of up to 50 km, and responds to changing (non-stationary) meteorological conditions [1]. The model simulates the time changing release (emission) of airborne materials by sequentially releasing a series of Gaussian shaped puffs (Figure 1) at a fixed rate on a specified grid. The amount of airborne materials allocated to individual puffs equals the release rate times the time elapsed between puff releases. At each time step, the model advects, diffuses and deposits the individual puffs according to local meteorological parameter values. This model is used as a basis for the present dispersion model, which can be used as a benchmark model for testing various data assimilation techniques.

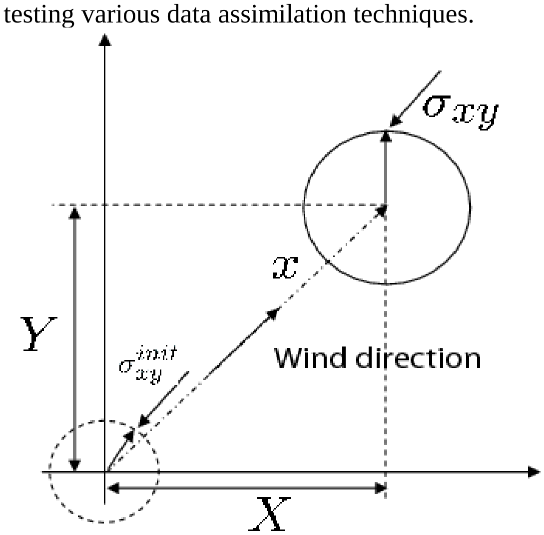

Figure 1: Model Illustration

Sensor Model: Two observation models are used for studying data assimilation performance. The first model is a continuous model, which measures concentration and gives a noisy output with a certain variance R at each sensor location. The second model is based on a model for a simple ion mobility sensor described in [2]. The outputs of the sensor are discrete numbers of bar readings ranging from 0 to 7. These bar readings indicate concentration magnitude [2]; the sensor displays i = 0, . . . , 7, when the "measured" continuous valued concentration magnitude cv is between thresholds Ti and Ti+1. As in [2], the thresholds are assumed to be exactly known. The measured concentration cv is assumed normally distributed about the true concentration c.

Estimation Techniques: Nonlinearities in the system dynamics model and the quantized (bar readings) nonlinear observation models lead to non-Gaussian state distributions. These factors pose significant challenges for data assimilation techniques. Further, due to continuous release/emissions initially and potential subsequent puff splitting, the length of the state vector is not constant, but varies with time. Also, with time, the state dimension may become very high leading to difficulties in the full state estimation. An Extended Kalman Filter and a Particle Filter are designed to test and evaluate the performance of the classical and Monte Carlo based filter.

Results and Discussions : The performance of the estimation techniques is studied for the discussed models using simulated atmospheric dispersion and concentration measurements. The grid resolution over the dispersion region is 200m and sensors are located every 1km along both the axes.

The total simulation runtime is 3600s and sampling interval is 20s. The source location and strength are uncertain. The release occurs for the initial 20% of the simulation time, with a 10% standard deviation. This is implemented as a fraction of the total number of time steps and is modeled as a random variable with mean 0.2 and a standard deviation of 0.02. There is a puff release every three time steps. The nominal value of the wind speed is 5m/s, with a standard deviation of 20%. The wind direction changes from 15 deg to 60 deg after 1800s. The truth is simulated using a perturbed model, taking all these uncertainties into account. The observations are obtained from this truth, using the two sensor models described earlier. Figure 2 illusrtates the concentration dosage from a numerical simulation.

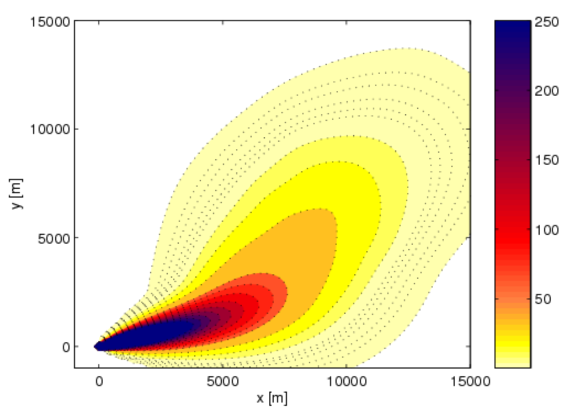

Figure 2: Concentration Dosage

Figure 3 compares the performance of the particle filter (pf), the Extended Kalman Filter (ekf) to a pure forecast of the concentration when the sensor is assumed to provide continuous measurements of the concentration. It is clear that both the filters outperform the model forecast as illustrated by the RMS error summed at numerous grid points.

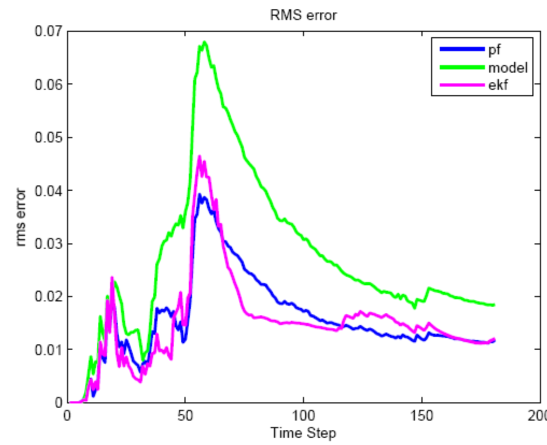

Figure 3: Concentration RMS Error

Conclusions: A test bed is designed to assess the performance of various data assimilation techniques for puff based dispersion models. A two dimensional Gaussian puff based dispersion model is used as a representative model for this purpose. The splitting of puffs which is a characteristic of more complex models is incorporated in the representative model. Two kinds of observation models are used to demonstrate the potential of sampling based filters. A continuous observation model is used to test the performance of Particle Filter against the widely used Extended Kalman filter. It was seen that while both the filters are comparable in terms of estimation performance, Particle Filter offers significant advantages in terms of ease of implementation and memory requirements. Further, Particle Filter can be effectively applied for a quantized observation model, as demonstrated using the probabilistic bar sensor model. The EKF, and other linearization based filters, fail with such sensor models. The application potential of Particle Filter, in the context of variable state dimensionality, high state dimension, non-linearities and quantized observations, is thus demonstrated. The possibilities of incorporating the advantages of other sampling based filters will be explored in the future. The deterministic sampling techniques of the Unscented Filters and the reduced rank representation used in the Ensemble Kalman Filtering techniques hold good potential, towards improving the estimation performance while managing the computational requirements.

References:

[1] Thykier-Nielse S., Deme S. and Mikkelsen T. (1999) Rsio National Lab, Rep RODOES(WG2)-TN(98)-02.

[2] Robins O., Rapley V. and Thomas P. (2005) Int. Conference on Information Fusion.