A Dynamic Method to Estimate Source Emission Rate and Predict Contaminant Concentrations

QU Hongquan
College of Information Engineering
North China University of Technology
Beijing, China

PANG Liping
School of Aviation Science and Engineering
Beihang University
Beijing, China

***Abstract*—It is very important to develop a method to predict contaminant concentrations in an enclosed space. The key technology is source emission rate estimation and dynamic concentration prediction. This paper presented a new method to estimate source emission rate and predict contaminant concentrations dynamically. A variable-structural contaminant concentration model was built, and then the Extended Kalman Filter was used to estimate the contaminant source emission rate and predict the concentration based on sensor data. The model of source emission rate could be gotten by applying the least square method to the filtering data of source emission rate. Simulations were done to demonstrate the performance of algorithm. The performance of parameter estimation and state prediction could be improved by using this method, and then the accuracy and speed to predict the air quality trend could also be improved.**

Keywords- identify;Kalman filter;emission rate; contaminant concentration

I. INTRODUCTION

To protect occupants from infectious diseases or possible chemical/biological agents in an enclosed space, such as spacecraft, submarine, airplane and so on, it is critical to identify gaseous contaminant source locations and strengths. It is necessary to forecast current pollution situation and take active measures to against the emergency by using a dynamic method to predict contaminant concentrations. This paper presented a method to realize these, which used both Extended Kalman Filter (EKF) and least square method based on an established variable-structural contaminant concentration model. This method can realize dynamic source strength estimation and real-time concentration prediction, so it can improve response speed to emergent pollution situation in an enclosed space.

II. MODEL OF CABIN CONCENTRATION

The cabin concentration model is given by [1]

$$V\frac{dC}{dt} = G(t) + QxC_{in}(t) - QxC$$

Discretizing the above equation, we get the following equation

$$C(k+1) = \frac{\Delta t}{V}G(k) + \frac{\Delta t}{V}QxC_{in}(k) + C(k)\left(1 - Qx\frac{\Delta t}{V}\right) \quad (1)$$

Where C is concentration (mg/m^3), V is cabin volume (m^3), t is time (s), Q is ventilation rate (m3/s), x is fresh air coefficient, C_{in} is contaminant concentration in fresh air (mg/m^3), G is contaminant source emission rate (mg/s), k is discrete time.

G is very key parameters, and is varied with time [2]. In this paper, we develop a method to estimate source emission rate dynamically and then predict contaminant concentration by using filter arithmetic based on real-time monitoring data. This method considers the uncertain feature of source emission rate G.

The model of certain source emission rate usually follows one of the below forms: linear, polynomial or exponential type. We could establish a multi-model library, and use monitoring and filtering data of source emission rate to identify the unknown model of G.

If we use least square method to identify G, parameters estimation is static process. Its obvious disadvantage is no time-varied character, and this leads to a large delay and low precision [3]. In order to solve above difficult problem, a new method is presented using Extant Kalman Filter (EKF) and least square method together to identify source emission rate and predict cabin contaminant concentration [4].

III. METHOD TO ESTIMATE AND PREDICT

A. Principle of the method

Fig. 1 presents the main algorithm. Contaminant model adopts a variable structure form according to source emission rate G is known or unknown, that is, G term in the model can be modified according to identifying information. A concentration model based on source noise feature is used when the changing pattern of G is unknown, and here the model of G adopts a noise one. When the filtering data are gotten and the changing patter of G term is known with the identifying algorithm, another concentration model based on identified source feature is used, and here the model of G is a certain pattern.

This algorithm includes continuous processing and discontinuous processing as shown in Fig.1.

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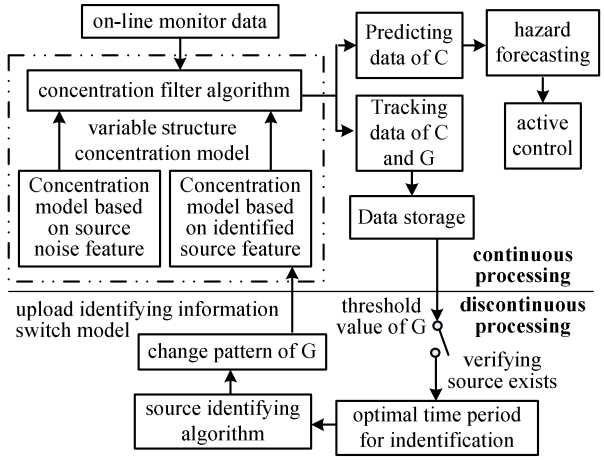

Figure1. Flow chart of source strength identification and concentrations prediction

B. Variable structure concentration model

We recast the model equation (1) and introduce an additive noise, and the system model can be written:

$$C(k)=\left[\frac{\Delta t}{V}G(k)+\frac{\Delta t}{V}QxC_{in}(k)+C(k-1)\left(1-Qx\frac{\Delta t}{V}\right)\right]+n_c(k) \qquad (2)$$

Variable structure means that the *G* term could be switched between structure 1 and structure 2 according to identifying results.

Structure 1 (based on noise feature):

$$G(k)=G(k-1)+n_G(k) \qquad (3)$$

Structure 2 (based on identifying feature, here take polynomial type source for example):

$$G(k)=a_n(k-1)t^n+....+a_0(k-1)+n_G(k) \qquad (4)$$

IV. Filtering and Identifying Algorithm

A. Filtering algorithm

Filtering algorithm is applied to predict concentration and track source emission rate as illustrated in Figure 1. The EKF algorithm is used to real-time track the process, estimate parameter *G* and predict the state *C*. the EKF algorithm is as follows:

$$\hat{X}_{k+1|k}=\Phi\hat{X}_{k|k}$$

$$P_{k+1|k}=\Phi P_{k|k}\Phi'+Q_k$$

$$\begin{bmatrix}\hat{Z}_{k+1|k} & P_{\hat{Z}\hat{Z}} & P_{\hat{X}\hat{Z}}\end{bmatrix}=\begin{bmatrix}h(\hat{X}_{k+1|k}) & H_{k+1}P_{k+1|k}H'_{k+1} & P_{k+1|k}H'_{k+1}\end{bmatrix}$$

$$v_{k+1}=Z_{k+1}-\hat{Z}_{k+1|k}$$

$$S_{k+1}=P_{\hat{Z}\hat{Z}}+R_k$$

$$G_{k+1}=P_{\hat{X}\hat{Z}}S_{k+1}^{-1}$$

$$\hat{X}_{k+1|k+1}=\hat{X}_{k+1|k}+G_{k+1}v_{k+1}$$

Where

$$H_{k+1}=\left.\frac{\partial h(X)}{\partial X}\right|_{X=\hat{X}_{k+1|k}}$$

The application of EKF needs Eq. (2) to (4).

B. Identifying algorithm of G

The identifying algorithm starts when the tracking value of *G* is higher than the threshold value of *G*. The source identification will carry out over the time slice interval, which is between the time that a source is suspected and the time that it is finally isolated. During the source identification process, the main filter in continuous process continues running with a noise model of *G*. At the end of the source identification process, the detected source term will be incorporated into the main mathematical model.

The strategy of method is as follows:

(1) Storage the tracking values of *G* during the continuous processing, at this time the model of *G* term is a noise model.

(2) Optimize the time period for identifying G. This process is very import when the source type is a polynomial type.

(3) Least squares method is adopted to estimate the G term by using the tracking values of *G* in the optimal slice interval.

Upload the identifying result and the source term in the main concentration model will be changed with the detected source term.

V. Simulations

An example is taken to illustrate the method. The volume of an enclosed space is 210 m^3, and ventilation rate is 0.566 m^3/s, and fresh air in ventilation is 56%. Certain initial contaminant concentration is 200 mg/m^3, and then sudden pollution accident happens.

Measurement noises and state noises of state are belonged to Gaussian distribution, and $n_c(k)\sim N(0,10)$, $n_G(k)\sim N(0,10)$, $n_{C_{in}}(k)\sim N(0,20)$. Inlet concentration is 200mg/m^3.

Fig. 2 shows the concentration results. The lines ahead the vertical line represent true values and tracking values of concentration, and the dashed line behind the vertical line represents predicting values. Fig. 3 shows the results of source emission rate *G*. The lines ahead the vertical line represent true values and tracking values of *G*, and the dashed line behind the vertical line represents identifying values of *G*. The root mean square errors (RMSEs) of tracking and true values are shown in Fig. 4.

After obtaining the identifying model of *G*, upload identifying result and the source term in the main concentration model will be changed with the detected source term, so exacter predicting and tracking results would be gotten. The filter method is able to track contaminant concentrations with sufficient accuracy.

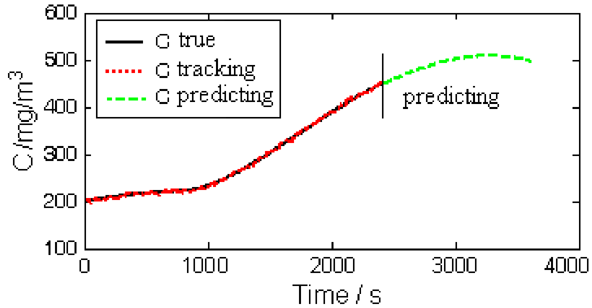

Figure2. True, tracking and predicting values of *C*

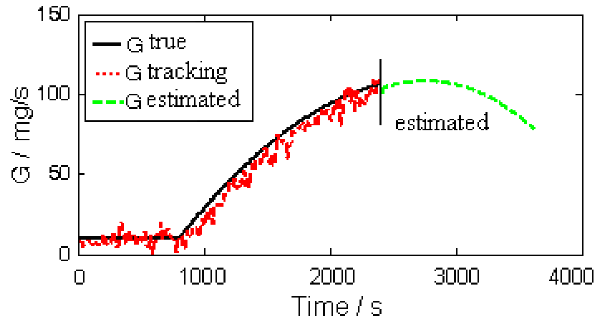

Figure3. True, tracking and estimated values of *G*

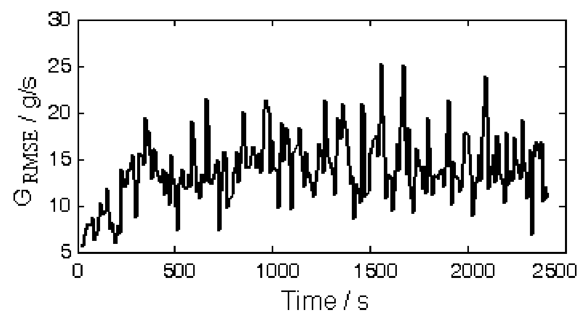

Figure4. RMSE of tracking values of *G*

VI. Conclusions

This paper develops a dynamic method to estimate source emission rate and predict contaminant concentrations in an enclosed space. Based on a variable structure model of concentration, this method uses EKF algorithm in combination with least squares method to realize state prediction and parameter estimation at the same time. This method could realize to track and real-time predict contaminant concentration, and identify source emission rate accurately and efficiently.

The simulations show that the proposed method for identifying source and predicting concentration are feasibility, effectiveness and accuracy. This method will lay a solid foundation for developing an intelligent and integrated airplane management system that can promptly respond to sudden pollution conditions with effective detection, analysis and active control.

Further work will be conducted to explore a suitable algorithm that can track source with both unknown location and release time.

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