Fusion Approach for Real-Time Mapping Street Atmospheric Pollution Concentration

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***Abstract*—The real-time mapping of street atmospheric pollution concentration does play an important role because its knowledge is crucial for strategy-makers to make more effective control strategies to decrease urban atmospheric pollution and improving urban atmospheric environment. Combining the conventional methods (e.g. the dispersion model prediction and neural network prediction) and mobile measurement technology (e.g. the GMAP vehicle) which their characteristics are complementary, a linear model is proposed and then a fusion approach called weighting filter derived from the concept of Kalman filter. Moreover, a self-tuning regulator is introduced to adjust the parameters of filter for the changing noise statistical characteristics over time which mainly caused by season switch. The performances of asymptotic stability and asymptotic optimality are both mathematically proven. Finally a simulation test is conducted to verify this approach.**

I. Introduction

With the increase in number of vehicle and outmigration of high-pollution factories, traffic emission has become the leading factor to cause urban atmospheric pollution. Researches among a general population provide strong confirmation that living near a major traffic road will increase the risk of wheezing illness, lung disease and deep van thrombosis a lot for the residents' long-term exposure in traffic emission pollution [1]–[3]. So it is necessary to take controls to improve the urban atmospheric environment.

The real-time mapping of street atmospheric pollution concentration does play an important role because its knowledge is crucial for strategy-makers to make more effective control strategies to decrease urban traffic pollution and improving urban atmospheric environment [4]. Fortunately, the sensors to measure traffic and weather conditions which are two primary factors determining pollution concentration, is distributed on almost every main traffic road especially in a mega-city. And the development on intelligent traffic technology enable us to implement this mapping with these existing data [5], [6]. But some problems still exist as shown below. Various pollutants interact themselves in various complicated chemical reactions. For example, when emitted into urban atmosphere, the pollutant CO has a stable behavior to not change its structure by chemical reactions with other pollutants. On the contrary, the pollutant NO reacts with O_3 to form NO_2, the pollutant NO_2 can be reverted to NO by sunlight energy. Secondly, besides the two primary factors as mentioned before, the traffic emission pollution depends on quite many other factors such as vehicle characteristics, geographic environment and street structure. What is more, using deterministic dispersion models to predict street atmospheric pollution concentration is rather difficult for the complex topography and heat phenomena [4].

The conventional method be referred as indirect prediction method is popular currently which uses the existing data (e.g. traffic volume) to map street atmospheric pollution concentration. The dispersion model relates pollution concentration by emission rate, vehicle characteristics, traffic and meteorology conditions within one equation, it has been widely used in many cities during the past decades. Operational Street Pollution Model (OPSM) developed by Berkowicz et al. [7], [8] were applied on many roads in Copenhagen and its surrounding areas to map street atmospheric pollution concentration, demonstrating that this model is effective in pollution assessment by comparison between the measurement data and simulation data. Similar works were done by Kukkonen et al. [9] and Wang et al. [10] in Helsinki and Beijing, all the results support that the OPSM model is effective in mapping street atmospheric pollution concentration.

The Neural Network (NN) technology is another promising indirect prediction method to map street atmospheric pollution concentration, which can approximate arbitrarily highly nonlinear functions with only little information hiding the nature of these relationships. Gardner et al. [11] developed a multi-layer perceptron (MLP) NN model to hourly relate pollution concentration by meteorological condition parameters in Central London, which showed that using NN model

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to establish the relationship between pollution concentration and meteorological condition parameters performs better than using the ordinary least squares (OLS) model and first-order autocorrelation (AR) model developed by Shi et al. [12] at the same location. Similar works were done using various improved NN models in Athens of Greece [13], Santiago of Chile [14] and Perugia of Italy [15]. The NN technology to map pollution concentration has been proven valuable in terms of the researches' results, but the question whether the NN models developed on one road can still perform well on another road, namely the transferability, remains in many researches. Zito et al. [4] developed a methodological approach to achieve the transferability of neural models on other roads, and this approach does not depend on the geometry of the road intersection in particular.

Instead the indirect prediction method, the direct measurement method may perform better in this program. But distributing every road a fixed sensor will cost quite a lot, making this method can not be applied till now. Two excellent scientists from Environment Protection Agent, Thoma and Hagler, proposed the so called Geospatial Monitoring of Air Pollution (GMAP) which is a powerful and cost-effective method to study the air quality on urban traffic road. The GMAP vehicle is a zero-emissions electric car, equipped with an air monitoring instrument, a high-resolution GPS, and mini-type meteorological station. An on-board supply is also employed to keep all instruments working while parked (engine off). Sampling using fast-response air monitoring instruments while driving, the GMAP vehicle can rapidly gather air pollution data and draw out a high temporal- and spatial-resolution map of street atmospheric pollution concentration [16]. The GMAP vehicle enable the mobile measurement on every road but not in real-time especially in a mega-city. So they are often be used to investigate the impact of roadside structures (e.g., buildings, noise walls, vegetation) on the dispersion of air pollution from a source with multiple repeats of the driving route accomplished within one day [17], [18].

Inspired by these two methods, a fusion approach to map street atmospheric pollution concentration is proposed in this paper. On one hand, the indirect prediction method using some main parameters to map street atmospheric pollution concentration in real-time within a short period is easy to realize and accurate, but the results will deteriorate over time. On the other hand, direct measurement method using the GMAP vehicle to gather pollution data is accurate for long-term measurement but not in real-time. Realizing that the two methods have the complementary characteristics, a linear model is established and then a fusion approach called weighting filter derived from the concept of Kalman filter. Moreover, a self-tuning regulator is introduced to adjust the parameters of filter for the changing noise statistical characteristics over time which mainly caused by season switch. The performances of asymptotic stability and asymptotic optimality are both mathematically proven. Finally a simulation test is conducted to verify this approach.

The rest of the paper is organized as follows. Section 2 presents the mathematical modelling procedure integrating the dispersion models. Section 3 details the design of weighting filter and its performance. Section 4 shows the simulation results to reveal the effectiveness of the proposed approach. The paper is concluded in Section 5.

II. Mathematical Modeling and Problem Statement

The traffic emission dispersion model which is able to reveal the dispersion and transformation principals of pollution in urban atmospheric environment can be used to simulate and predict pollution temporal- and spatial-distribution. However, these models based on the solutions of basic flow and dispersion equations are still too complex for many practical applications. Alternative are models that are basically parameterised semi-empirical models making use of a priori assumption about the flow and dispersion conditions. It indicates that the street atmospheric pollution is almost totally a traffic-generated pollution and the street atmospheric pollution concentration will trend to the high-level's after a sufficient air exchanging at the situation without traffic emission. According to these points, we have

$$x(t) = x(t-1) + \tau u(t-1) + \mu + w(t-1) \tag{1}$$

where $x(t)$ represents for street (the inner box) atmospheric pollution concentration, μ for the average high-level (the external box) atmospheric pollution concentration, $u(t)$ for the "new" concentration by traffic emission, $w(t)$ for Gaussian white noise. The equation indicates the changing principle of inner-external concentration difference over time. Considering the seasons switch can lead a variation of parameters especially the μ, a Gaussian white noise $w(t)$ is introduced to improve the accuracy of the model.

It is mentioned that the GMAP vehicle is employed to correct the estimation, rearranging (1) and modeling the GMAP vehicles' measurements yield the two stochastic difference equations as follows.

$$\begin{aligned} x(t) &= x(t-1) + \tau u(t-1) + \mu + w(t-1) \\ y(t) &= x(t) + v(t) \end{aligned} \tag{2}$$

where $y(t)$ for the GMAP vehicles' measurement, $w(t) \sim \mathcal{N}(0, p(t))$ and $v(t) \sim \mathcal{N}(0, q(t))$ for two independent Gaussian white noises. The time step t is usually be set as *an hour* to realize hourly mapping of street atmospheric polluton concentration.

The conventional method to solve the problem is to employ the model-based Kalman filter, which is theoretically possible but computationally complex. What is more, the time-varying noise variances p_t and q_t, are usually assumed to be constant in practice to facilitate the analysis. The assumption gives rise to a decrease on the computational complexity at the cost of the decrease of the filtering accuracy. Hence, we proposed a fusion algorithm considering all the problems existing in this case. For the reason that the concept is derived from Kalman filtering, the fusion algorithm has the similar form with Kalman filtering. The filter design and performance analysis

will be based on the two mathematical models ignoring the physics characteristics.

III. Self-Tuning Weighting Filter Design

To develop a cost-efficient filtering method that is computationally simple and theoretically optimal, the weighting filter is proposed. Moreover, considering the time-variant property of noise statistical characteristics, a self-tuning regulator is introduced to adjust the weight adaptively and improve the filtering accuracy.

A. Weighting Filter

The Kalman filter is a frequently-used technique to solve the multi-sensor-fusion problem. The filter estimates the process states and then obtains feedback in the form of measurement, dividing the equations for the Kalman filter into two groups: predictor equation and corrector equation. The former is responsible for projecting forward the current state and error covariance estimate to obtain the a priori estimates for the next time step. The latter is responsible for the feedback, that is, incorporating a new measurement into the *a priori* estimation to obtain an improved *a posteriori* estimation. The process is repeated with the previous *a posteriori* estimation used to predict the new *a priori* estimation. Hence, the Kalman filter performs as a time-variant recursive filter, where the filtering gain $K(t)$ is time-variant, leading to more computational complexity. The weighting filter is thus proposed to make the technique feasible in practice.

Theorem 1: The weighting filter for system shown in (2) is of the following form

$$\begin{aligned}&\hat{x}(t|t)\\&=\alpha[\hat{x}(t-1|t-1)+\tau u(t-1)+\mu]+(1-\alpha)y(t)\end{aligned}\tag{3}$$

where $\hat{x}(t|t)$ is the estimation at time step t and $\alpha = \frac{2\sigma_v^2}{\sigma_w^2+2\sigma_v^2+\sqrt{\sigma_w^4+4\sigma_w^2\sigma_v^2}}$ is the weighting coefficient. It is asymptotically optimal and stable.

Proof: Under the assumption that $\sigma_w^2(t) = \sigma_w^2$ and $\sigma_v^2(t) = \sigma_v^2$, the estimation of Kalman filter at time step t is obtained as

$$\begin{aligned}\hat{x}(t|t)&=\tfrac{\sigma_v^2}{P(t|t-1)+\sigma_v^2}\hat{x}(t|t-1)+\tfrac{P(t|t-1)}{P(t|t-1)+\sigma_v^2}y(t)\\\hat{x}(t|t-1)&=\hat{x}(t-1|t-1)+\tau u(t-1)+\mu\end{aligned}\tag{4}$$

where $\hat{x}(t|t)$ is the optimal estimate at time step t, and $\hat{x}(t|t-1)$ the a *priori* estimation at time step $t-1$. Solving Riccati Equation for the noise variance $P(t|t-1)$ yields

$$P(t|t-1)=\frac{P(t-1|t-2)\sigma_w^2}{P(t-1|t-2)+\sigma_w^2}+\sigma_v^2\tag{5}$$

where $P(1|0)$ can be selected as a extreme large number, say 10^5, since the device is static initially, weighting more to the accelerometer.

From (5), the filter is time-variant and $P(t|t-1)$ should be updated every time step, thus causing great computational complexity. To solve the problem, the convergence of (5) will be discussed first.

Under the assumption that $P(t-1|t-2) > 0$, it is easy to see that $P(t|t-1) > 0$. With the initial value $P(1|0) = 10^5 > 0$, the inequation $P(t|t-1|) > 0$ holds for every $t > 0$ using mathematical induction. This completes the proof on boundedness.

$$\begin{aligned}&P(t|t-1)-P(t-1|t-2)\\&=\frac{\sigma_w^4[P(t-1|t-2)-P(t-2|t-3)]}{[P(t-1|t-2)+\sigma_w^2][P(t-2|t-3)+\sigma_w^2]}\end{aligned}\tag{6}$$

By (6) it is obtained that $P(t|t-1)-P(t-1|t-2)$ and $P(t-1|t-2)-P(t-2|t-3)$ are of the same sign, consequently the $P(t|t-1)$ is monotonic for every $t > 0$. In fact, the $P(t|t-1)$ is monotonically declining for $P(1|0) > P(2|1)$. In conclusion that the $P(t|t-1) \to P$ at $t \to \infty$. Its value is shown as

$$P=\frac{\sigma_w^2+\sqrt{\sigma_w^4+4\sigma_w^2\sigma_v^2}}{2}\tag{7}$$

So (4) can be transformed into (3). The weighting filter is asymptotically optimal since the Kalman filter is optimal and the difference between them converges to 0 as t approaches infinity.

The filter is the weighted sum of gyroscope and accelerometer with fixed weighting coefficient, called the time-invariant weighting filter. Notice that the estimation is affected by the selection of initial value $\hat{x}(0|0)$ due to the recursiveness of the filter. To deal with this problem, consider two different initial value $\hat{x}^{(1)}(0|0)$ and $\hat{x}^{(2)}(0|0)$ that result in two estimates $\hat{x}^{(1)}(t|t)$ and $\hat{x}^{(2)}(t|t)$ at time step t, respectively. It holds that

$$\begin{aligned}\hat{x}^{(1)}(t|t)&=\alpha[\hat{x}^{(1)}(0|0)+\tau u(t-1)+\mu]+(1-\alpha)y(t)\\\hat{x}^{(1)}(t|t)&=\alpha[\hat{x}^{(2)}(0|0)+\tau u(t-1)+\mu]+(1-\alpha)y(t)\end{aligned}\tag{8}$$

The difference of the two estimates at time step t is

$$\delta(t)=\hat{x}^{(1)}(t|t)-\hat{x}^{(2)}(t|t)=\alpha\delta(t-1)=\alpha^t\delta(0)\tag{9}$$

where $\delta(0)=\hat{x}^{(1)}(0|0)-\hat{x}^{(2)}(0|0)$. since $0<\alpha<1$, it holds that $\delta(t)\to 0$ at $t\to\infty$. The filter, hence, is asymptotically stable as the initial value $\hat{x}(0|0)$ can be selected arbitrarily. ■

B. Self-Tuning Regulator

The filtering accuracy will be unacceptable due in large part to the fact that the weighting coefficient should be changed with noise statistical characteristics changing. Hence, it is necessary to design a regulator to adjust the weighting coefficient adaptively. Substituting α by $\hat{\alpha}(t)$, the estimate for α, the self-tuning weighting filter is obtained as

$$\begin{aligned}&\tilde{x}(t|t)\\&=\hat{\alpha}(t)[\tilde{x}(t-1|t-1)+\tau u(t-1)+\mu]+(1-\hat{\alpha}(t))y(t)\end{aligned}\tag{10}$$

Cancelling the $x(t)$ in (2), it is obtained that

$$\begin{aligned}&y(t)-y(t-1)\\&=\tau u(t-1)+\mu+w(t-1)+v(t)-v(t-1)\end{aligned}\tag{11}$$

Rearranging (12) yields

$$\begin{aligned} & z(t) \\ &= y(t) - y(t-1) - \tau u(t-1) + \mu \\ &= w(t-1) + v(t) - v(t-1) \end{aligned} \tag{12}$$

where $z(t)$ is the sum of two independent moving average process $w(t-1)$ and $v(t) - v(t-1)$, thus $z(t)$ being another moving average process whose order is the same as that of the component process of higher order.

Calculating correlation function of the random process on both sides in (12) yields

$$\begin{aligned} R_0 &= \mathrm{E}[z(t)z(t)] = \sigma_w^2 + 2\sigma_v^2 \\ R_1 &= \mathrm{E}[z(t)z(t-1)] = -\sigma_v^2 \end{aligned} \tag{13}$$

where E represents for expectation. Defining the estimate for R_0 and R_1 at time step t as

$$\begin{aligned} \hat{R}_0(t) &= \tfrac{1}{t}\sum_{i=1}^{t} z^2(i) \\ \hat{R}_1(t) &= \tfrac{1}{t}\sum_{i=1}^{t} z(i)z(i-1) \end{aligned} \tag{14}$$

Considering the variation of noise statistical characteristics, the estimation of $\hat{R}_0(t)$ and $\hat{R}_1(t)$ must forget the older data gradually, and thus

$$\begin{aligned} \hat{R}_0(t) &= \tfrac{1}{t}\sum_{i=1}^{t} \lambda^{t-i} z^2(i) \\ \hat{R}_1(t) &= \tfrac{1}{t}\sum_{i=1}^{t} \lambda^{t-i} z(i)z(i-1) \end{aligned} \tag{15}$$

where $0 < \lambda < 1$ is referred to as the forgetting factor with the forgetting rate growing with the positive number λ getting smaller. λ should be selected as a larger number for slowly changing noises. To facilitate the implementation, the recursive form of (15) is studied as follows

$$\begin{aligned} & \hat{R}_0(t) \\ &= \tfrac{1}{t}\sum_{i=1}^{t} \lambda^{t-i} z^2(i) \\ &= \tfrac{1}{t}[\lambda \sum_{i=1}^{t-1} \lambda^{t-1-i} z^2(i) + z^2(t)] \\ &= \tfrac{t-1}{t}\tfrac{1}{t-1}[\lambda \sum_{i=1}^{t-1} \lambda^{t-1-i} z^2(i) + z^2(t)] \\ &= (1 - \tfrac{1}{t})\lambda \hat{R}_0(t-1) + \tfrac{1}{t} z^2(t) \\ &= \lambda \hat{R}_0(t-1) + \tfrac{1}{t}[z^2(t) - \lambda \hat{R}_0(t-1)] \end{aligned} \tag{16}$$

with initial value $\hat{R}_0(1) = z^2(1)$. The similar method shown in (16) yields

$$\begin{aligned} & \hat{R}_1(t) \\ &= \lambda \hat{R}_1(t-1) + \tfrac{1}{t}[z(t)z(t-1) - \lambda \hat{R}_1(t-1)] \end{aligned} \tag{17}$$

with initial value $\hat{R}_1(1) = z^2(1)$. According to the ergodicity of stationary stochastic process,

$$\begin{aligned} \hat{R}_0(t) &\to R_0, \quad t \to \infty, \quad \text{w.p.1} \\ \hat{R}_1(t) &\to R_1, \quad t \to \infty, \quad \text{w.p.1} \end{aligned} \tag{18}$$

where w.p.1 is the abbreviation of with possibility one. So the estimations for $\hat{\sigma}_w^2$ and $\hat{\sigma}_v^2$ are obtained.

$$\begin{aligned} \hat{\sigma}_w^2 &= \hat{R}_0(t) + 2\hat{R}_1(t) \\ \hat{\sigma}_v^2 &= -\hat{R}_1(t) \end{aligned} \tag{19}$$

By (18) it is induced that

$$\begin{aligned} \hat{\sigma}_w^2 &\to \sigma_w^2, \quad t \to \infty, \quad \text{w.p.1} \\ \hat{\sigma}_v^2 &\to \sigma_v^2, \quad t \to \infty, \quad \text{w.p.1} \end{aligned} \tag{20}$$

Consequently

$$\hat{\alpha}(t) \to \alpha, \quad t \to \infty, \quad \text{w.p.1} \tag{21}$$

C. Asymptotic Optimality Analysis

The conventional adaptive filter, composed of a state estimator and noise statistical characteristics estimator that are cross-coupling, is industrially efficient without theoretical guarantee of asymptotical optimality. The self-tuning weighting filter proposed in the paper is asymptotically optimal.

Theorem 2: The self-tuning weighting filter shown in (10) is asymptotical optimal.

Proof: Define $\phi(t) = \tilde{x}(t|t) - \hat{x}(t|t)$, the deference of optimal estimates between the self-tuning weighting filter shown in (10) and the time-invariant weighting filter shown in (7), and we obtain

$$\begin{aligned} & \phi(t) \\ &= \tilde{x}(t|t) - \hat{x}(t|t) \\ &= \hat{\alpha}(t)[\tilde{x}(t-1|t-1) - \hat{x}(t-1|t-1)] + \theta(t) \\ &= \hat{\alpha}(t)\phi(t-1) + \theta(t) \\ & \theta(t) = -[\alpha - \hat{\alpha}(t)][y(t) - \hat{x}(t|t) - \tau u(t-1) - \mu] \end{aligned} \tag{22}$$

Applying (2), the $\theta(t)$ in (22) can be transformed into

$$\begin{aligned} & \theta(t) \\ &= -[\alpha - \hat{\alpha}(t)][x(t-1) - \hat{x}(t-1|t-1) + w(t-1) + v(t)] \end{aligned} \tag{23}$$

Let $\varphi(t) = x(t) - \hat{x}(t|t)$, and $\theta(t)$ can be simplified as

$$\theta(t) = -[\alpha - \hat{\alpha}(t)][\varphi(t-1) + w(t-1) + v(t)] \tag{24}$$

Applying (2) and (7) yields

$$\begin{aligned} & \varphi(t) = x(t) - \hat{x}(t|t) \\ &= \alpha[x(t-1) - \hat{x}(t-1|t-1)] + \vartheta(t) \\ &= \alpha\varphi(t-1) + \vartheta(t) \\ & \vartheta(t) = \alpha w(t-1) - (1-\alpha)v(t) \end{aligned} \tag{25}$$

Noticing that process noise $w(t)$ and measurement noise $v(t)$ are both uniformly bounded with possibility one,

$$\begin{aligned} |w(t)| &\le c_w, \quad c_w > 0, \quad \forall t > 0, \quad \text{w.p.1} \\ |v(t)| &\le c_v, \quad c_v > 0, \quad \forall t > 0, \quad \text{w.p.1} \end{aligned} \tag{26}$$

where $|\cdot|$ represents absolution. Consequently $\vartheta(t)$ is uniformly bounded with possibility one,

$$|\vartheta(t)| \le c_\vartheta, \quad c_\vartheta > 0, \quad \forall t > 0, \quad \text{w.p.1} \tag{27}$$

Iterating the $\varphi(t)$ in (25) yields

$$\begin{aligned} & \varphi(t) = \alpha\varphi(t-1) + \vartheta(t) \\ &= \alpha^t \varphi(0) + \sum_{i=0}^{t-1} \alpha^i \vartheta(t-i) \end{aligned} \tag{28}$$

Taking the absolute value on both sides of (28) yields

$$\begin{aligned}&|\varphi(t)|\\&\leq \alpha^t|\varphi(0)|+\sum_{i=0}^{t-1}\alpha^i|\vartheta(t-i)|\\&\leq \alpha^t|\varphi(0)|+c_\vartheta\sum_{i=0}^{t-1}\alpha^i\\&<|\varphi(0)|+\tfrac{c_\vartheta}{1-\alpha}\end{aligned}\tag{29}$$

for $t>0$. This indicates that $\varphi(t)$ is uniformly bounded with possibility one. Furthermore it is obtained that

$$\theta(t)\to 0,\quad t\to\infty,\quad \text{w.p.1}\tag{30}$$

Let $\hat{\alpha}(t)=\alpha+\Delta\alpha(t)$, and then $\Delta\hat{\alpha}(t)\to 0$ at $t\to\infty$ with possibility one. Thus there exists $t_0>0$ that $|\Delta\hat{\alpha}(t)|<\epsilon_0$ where $\epsilon_0<1-\alpha$ for all $t>t_0$. Define $0<\epsilon_m=\epsilon_0+\alpha<1$. For all $t>t_0$

$$|\hat{\alpha}(t)|\leq|\alpha|+|\Delta\hat{\alpha}(t)|<\epsilon_0+\alpha=\epsilon_m<1\tag{31}$$

Define $\hat{\alpha}(t,i)=\hat{\alpha}(t)\hat{\alpha}(t-1)\cdots\hat{\alpha}(i+1)$ with $|\hat{\alpha}(t,i)|<\epsilon_m^{t-i}$ for all $t>i$ and $\hat{\alpha}(t,t)=1$, the iteration of (22) is

$$\begin{aligned}&\phi(t)\\&=\tilde{x}(t|t)-\hat{x}(t|t)\\&=\hat{\alpha}(t)\phi(t-1)+\theta(t)\\&=\hat{\alpha}(t,0)\hat{\alpha}(0)+\sum_{i=1}^{t}\hat{\alpha}(t,i)\theta(i)\end{aligned}\tag{32}$$

By (30) it is obtained that $|\theta(t)|\leq c_\theta$ for $t>0$ where c_θ is a positive constant. Taking the absolute value on both sides of (32) yields

$$\begin{aligned}&|\phi(t)|\\&\leq|\hat{\alpha}(t,0)||\phi(0)|+\sum_{i=1}^{t}|\hat{\alpha}(t,i)||\theta(i)|\\&\leq\epsilon_m^t|\phi(0)|+c_\theta\sum_{i=1}^{t}\epsilon_m^{t-i}\\&<|\phi(0)|+\tfrac{c_\theta}{1-\epsilon_m}\end{aligned}\tag{33}$$

which shows that $\phi(t)$ is uniformly bounded with possibility one.

Let $\hat{\alpha}(t)=\alpha+\Delta\hat{\alpha}(t)$, and then $\hat{\alpha}(t)\to 0$ at $t\to\infty$ with possibility one. $\phi(t)$ shown in (22) can be rewritten as

$$\begin{aligned}&\phi(t)\\&=\hat{\alpha}(t)\phi(t-1)+\theta(t)\\&=[\alpha+\Delta\hat{\alpha}(t)]\phi(t-1)+\theta(t)\\&=\alpha\phi(t-1)+\zeta(t)\\&\zeta(t)=\theta(t)+\Delta\hat{\alpha}(t)\phi(t-1)\end{aligned}\tag{34}$$

According to (30) and the uniform boundedness of $\phi(t)$, it is obtained that

$$\zeta(t)\to 0,\quad t\to\infty,\quad \text{w.p.1}\tag{35}$$

and consequently $|\zeta(t)|\leq c_\zeta$ where c_ζ is a positive constant.

Iterating (35) yields

$$\phi(t)=\alpha^t\phi(0)+\sum_{i=0}^{t-1}\alpha^i\zeta(t-i)\tag{36}$$

Noticing that $0<\alpha<1$, there exist t_α and t_ζ that $\alpha_\alpha^t<\varepsilon$ for $t>t_\alpha$ and $|\zeta(t)|<\varepsilon$ for $t>t_\zeta$ where ε is a arbitrarily small positive constant. Taking the absolute value on both sides of (36) yields

$$\begin{aligned}&|\phi(t)|\\&\leq\alpha^t|\phi(0)|+\sum_{i=0}^{t-1}\alpha^i|\zeta(t-i)|\\&=\alpha^t|\phi(0)|+\sum_{i=0}^{t_\zeta}\alpha^i|\zeta(t-i)|+\sum_{i=t_\zeta+1}^{t-1}\alpha^i|\zeta(t-i)|\\&<\varepsilon|\phi(0)|+\varepsilon\sum_{i=0}^{t_\zeta}\alpha^i+c_\zeta\sum_{i=t_\zeta+1}^{t-1}\alpha^i\\&=\varepsilon|\phi(0)|+\tfrac{\varepsilon(1-\alpha^{t\alpha+1})}{1-\alpha}+\tfrac{c_\zeta\alpha^{t\alpha+1}(1-\alpha^{t-t\alpha-1})}{1-\alpha}\\&<\varepsilon(|\phi(0)|+\tfrac{1+c_\zeta}{1-\alpha})\end{aligned}\tag{37}$$

for all $t>t_\alpha+t_\zeta$. since ε is independent with $|\phi(0)|+\frac{1+c_\zeta}{1-\alpha}$ and can be arbitrarily small, $|\phi|$ can then be arbitrarily small,

$$\phi(t)\to 0,\quad t\to\infty,\quad \text{w.p.1}\tag{38}$$

which completes the proof. ■

IV. Simulation Results

This paper only proposed the imagine of a novel approach to map street atmospheric pollution concentration, so no real-world application can be exhibited. But the self-tuning weighting filter can be verified by a simulation test. The parameters are set as follows: noise variance $p=100$ for the first half period and $p=484$ for the second half period, noise variance $q=225$ for the whole test. Results are shown in Fig. 1, Fig. 2 and Fig. 3.

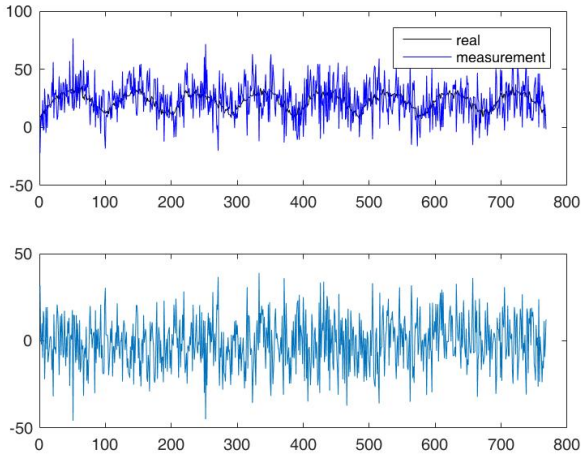


Fig. 1. Measurement results and error.

As the figures shown, we can find that the measurement will bring great uncertainty which the real value was almost be covered by the noise. When the Kalman filter is employed, the error is decreased to the great extent and the weight will converge to 0.5195. However, the error over second half period is unacceptable for the variance of noise statistics, thus the weight should be assigned less to the measurement. With the aid of self-tuning regulator, the noise variance can be estimated

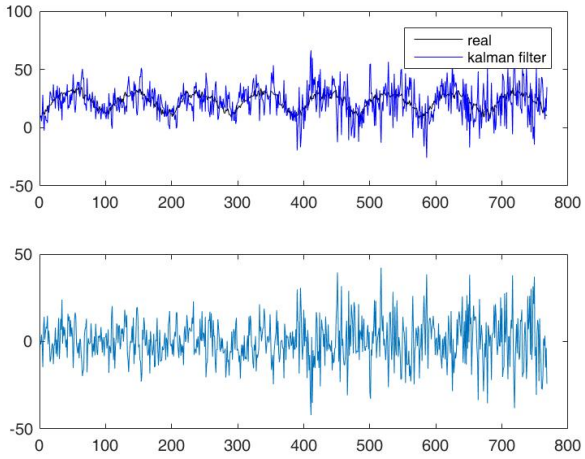


Fig. 2. Kalman filter-based estimation and error.

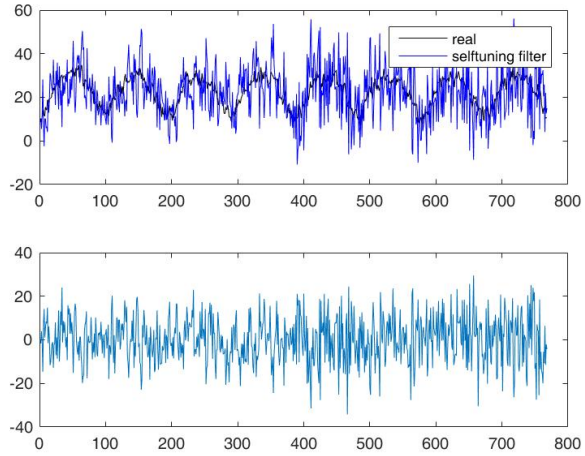


Fig. 3. Selftuning filter-based estimation and error.

and then adjust the weight to be 0.2568, and the results shows its effectiveness than the traditional Kalman filter.

V. Conclusions

The urban atmospheric pollution has become a noteworthy problem for its huge damage to residents. The strategy-makers can make more effective control strategies with the real-time mapping of street atmospheric pollution concentration which provide useful knowledge to decrease urban atmospheric pollution and improve urban atmospheric environment. The indirect prediction method uses existing data such as traffic condition, meteorology and street structure to predict the pollution concentration for every road is available currently in that the pollution concentration is related mainly by these factors. In fact, direct measuring the street atmospheric pollution concentration is relatively accurate but locating every road a sensor will bring a huge cost. So this paper came up with an idea to employ the mobile measurement, a GMAP vehicle equipped with pollution detector, to gather pollution data.

Hence, to enable the fusion approach we proposed, an filtering technique called weighting filter is developed based on the concept of Kalman filter. The estimation for street atmospheric pollution concentration is processing every time step, and the estimation is correct with available measurements. This filter is not better than a traditional Kalman filter but practicable in this program as a compromising approach. Considering the changing noises statistical characteristics over time which mainly caused by season switch, a self-tuning regulator is introduced which can estimate the noise variance automatically and recalculate the filter's parameters. The simulation test is conducted in the end which shows that the error variance of estimation is bounded, and the upper bound will be reduced with a higher frequency measurement. Moreover, there are still some problems remaining in this approach. The modeling in Section 2 is a parameterised semi-empirical model making use of a priori assumptions about the flow and dispersion conditions. Whether the assumptions is available or not will be a leading factor influencing the model's accuracy. In the further work, we expect to realize this method in mapping the street atmospheric pollution concentration and develop some control strategies to reduce the urban atmospheric pollution.

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1. Fusion approach for real-time mapping street atmospheric pollution concentration

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Abstract: The real-time mapping of street atmospheric pollution concentration does play an important role because its knowledge is crucial for strategy-makers to make more effective control strategies to decrease urban atmospheric pollution and improving urban atmospheric environment. Combining the conventional methods (e.g. the dispersion model prediction and neural network prediction) and mobile measurement technology (e.g. the GMAP vehicle) which their characteristics are complementary, a linear model is proposed and then a fusion approach called weighting filter derived from the concept of Kalman filter. Moreover, a self-tuning regulator is introduced to adjust the parameters of filter for the changing noise statistical characteristics over time which mainly caused by season switch. The performances of asymptotic stability and asymptotic optimality are both mathematically proven. Finally a simulation test is conducted to verify this approach. © 2016 IEEE.
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