Leak Detection and Location of Gas Pipelines Based on a Strong Tracking Filter

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Abtract: This paper presents an approach to leak detection and location of gas pipelines based on a strong tracking filter (STF). The STF has strong robustness against model uncertainties, which will deteriorate the performance of the extended Kalman filter. Hence, much faster and more accurate leak detection and location has been obtained. Computer simulation results demonstrate the effectiveness of the proposed approach.

Keywords: leak detection, location, pipelines, strong tracking filter

I. Introduction

In the past three decades, many developing countries have constructed large-scale pipeline networks in order to transport gases or liquids from the production to the consumption sites. Leaks of these pipelines can cause serious consequences, such as the considerable product losses, the environmental pollution if the materials conveyed are poisonous, and so on. Therefore, many methods and techniques for leak detection and location of pipelines have been proposed to prevent further losses and danger.

Volume balance is the simplest and most straightforward leak detection technique, which needs only flow meters and detects leaks according to the principle of mass conservation. However, according to the inherent flow dynamics and the superimposed noise, only relatively large leaks can be detected with this simple method (which are about >2% for liquid and >10% for gas pipelines) [1]. Furthermore, this method cannot locate the leaks.

Sonic and acoustic leak detection and location [2] are simple and accurate, especially the leak detection is almost instantaneous. Leaks produce a distinctive sound that can be used to identify and locate them by means of some devices such as stethoscopes, hydrophones and so on. For example, an interval between the times of arrival of the sounds to each device can be used to deduce the approximate location of the leak. In [3], the pressure wave behavior caused by leaks was analyzed in detail and some advices were presented to improve the accuracy of this method. In [4], the mechanism of the stress wave propagation along the pipeline caused by turbulent ejection from pipeline leakage was studied, and the characteristics of the propagation were collected to detect the leakage by using artificial neural network. Unfortunately, it could not be applied to small and slow leaks, because there is no signal large enough to be detected.

There are many other leak detection techniques, for example, remote field inspection, magnetic flux leakage method, and ultrasound inspection [2]. Remote field inspection is a through-wall, electromagnetic, nondestructive evaluation technology, which can be used to estimate the future life of a pipeline, but is very expensive and requires access to the inside of the pipeline. Magnetic flux leakage method can work only on cast iron and steel, because it needs an arrangement of magnets designed to put a steady direct-current magnetic field into the pipe wall so that the magnetic field travels in the same direction as the pipe axis. Ultrasound inspection is carried out by using a beam of coherent sound energy, with frequencies higher than people can hear. The sound wave travels into the object to be inspected and is reflected whenever there is a change in the density of the material. This method can detect not only leaks but also pits. Ultrasonic tools are commercially available for oil pipeline inspection, but this method can only inspect tuberculation-free pipe, because the tuberculation can easily reflect the sound.

The methods mentioned above are all model free, however, the methods based on models are promising for small and slow leaks. Billmann and Isermann [1] used nonlinear adaptive state observers for the pipeline dynamics and a special correlation technique for the leak detection and location. In [5][6], volume balance technique was greatly improved by mathematical modeling. Fukuda and Mitsuoka [7] and Wang et al. [8] formulated the pressure gradients by using the autoregressive (AR) model, then they used AIC and Kullback information to detect leaks, respectively. Chernick and Wincelberg [9] applied the autoregressive moving-average (ARMA) model with the " variate difference method" to the pressure, whose results were that 95% of the variation of the site pressure data was estimated to be process noise and 59% of the variation of the pressure data at the end of pipelines was due to process noise. Hence some improvement in leak detection capability could be achieved through use of the model. Berkherouf and Allidina [10] presented a kind of faulty model and used an extended Kalman filter to estimate the state variables, and then detected and located leaks in long pipelines. In [11], a thermal model was considered to locate the leak more accurately.

In this paper, a new model based approach to leak detection and location of gas pipelines by use of a strong tracking filter(STF) is provided. The STF, in fact, is a suboptimal fading extended Kalman filter (SFEKF) [12], which is more efficient than extended Kalman filter, especially when there are large modeling errors and noise. This method can locate leakage sites more accurately and much faster, thus is very useful for maintenance of long pipelines. Computer simulation results

Manuscript received: Aug. 8, 2000, Accepted: Feb. 20, 2001.
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※This work was supported by the National Natural Science Foundation and the National Education Ministry of China.

illustrate the effectiveness of the proposed approach.

This paper is organized as follows. Section 2 summarizes the mathematical models of pipelines. Section 3 presents the outline of strong tracking filter. In Section 4, leak detection and location method is introduced. Some simulation results are given to show the good performance of the proposed approach in Section 5, and finally, a short conclusion is made in Section 6.

II. Mathematical model of pipelines

A dynamic mathematical model of a pipeline was derived by theoretically modeling gas and liquid pipelines. Simplifying assumptions such as a constant diameter D, a turbulent flow and isothermal condition result in a common description for the gas and liquid flow dynamics. Since small leak detection for gas pipelines is more difficult than liquid pipelines, we will discuss the leak detection of gas pipeline only in this paper. It is pointed out that the results of this paper are easily extended to liquid pipelines. The one-dimensional isothermal model for gas pipelines is described by the following equations [10]:

$$\frac{\partial p}{\partial t}+\frac{c^2}{A}\frac{\partial q}{\partial x}=0 \tag{1}$$

$$\frac{\partial q}{\partial t}+A\frac{\partial p}{\partial x}+\frac{\lambda c^2}{2DA}\frac{q|q|}{p}=0 \tag{2}$$

where p [Nm-2] is pressure, q [kgs-1] is mass flow rate, x [m] is length coordinate, t [s] is time coordinate, c [m s-1] is isothermal speed of sound in gases, A [m2] is pipeline cross-section, D [m] is pipeline diameter, λ is the friction coefficient.

This pipeline model is a set of partial differential equations of hyperbolic type with nonlinear distributed parameters. The suitable boundary conditions [13] may be chosen as follows:

$$\begin{cases} p(0,t)=f_p(t) \\ q(L,t)=f_q(t) \end{cases} \tag{3}$$

where L [m] is the pipe length, and the initial conditions:

$$\begin{cases} p(x,0)=p_0(x) \\ q(x,0)=q_0(x) \end{cases} \tag{4}$$

If a leak q^k [kgs-1] occurs at $x = x^k$, Eqs. (1) and (2) are still valid for all $x\in[0,x^k)\cup(x^k,L]$. However, at $x = x^k$, the conservation of mass yields:

$$q(x^{k-},t)-q(x^{k+},t)=q^k \tag{5}$$

It is assumed that the leak introduces a negligible momentum in the x direction, so that Eq. (2) is unaffected for $x=x^k$.

The problem is to estimate the size q^k and the position x^k of the leak using available measurement data, generally pressure measurement data at discrete points along the pipeline. Then it is required to design a state estimator or filter for the nonlinear distributed parameter systems.

III. Outline of a modified strong tracking filter

In general, there are two problems in the extended Kalman filter. First, its robustness is not good for model uncertainties [14][15]. Second, the extended Kalman filter will lose its tracking ability for abrupt changes when systems reach their steady state, because the gain matrix $K(i+1)$ is too small at that time. Therefore, in order to overcome the modeling errors and other uncertainties, and track the abrupt changes efficiently, the strong tracking filter (STF), which is in fact a suboptimal fading extended Kalman filter (SFEKF), is presented in this paper.

Consider a class of discrete-time nonlinear systems of the form:

$$x(i+1)=f(u(i),x(i))+\Gamma(i)v(i) \tag{6}$$

$$y(i+1)=h(x(i+1))+e(i+1) \tag{7}$$

where state $x\in R^n$, input $u\in R^p$, output $y\in R^m$, nonlinear functions $f:R^p\times R^n\to R^n$, and $h:R^n\to R^m$ have continuous derivatives with respect to x, the process noise $v(i)\in R^q$ is a zero-mean, Gaussian white noise with covariance $Q(i)$, the measurement noise $e(i)\in R^m$ is also a zero-mean, Gaussian white noise with covariance $R(i)$, $\Gamma(i)\in R^{n\times q}$ is a known matrix with proper dimension, $v(i)$ and $e(i)$ are statistically independent.

This SFEKF is obtained by applying the orthogonality principle to the primary performance index of the extended Kalman filter[12]. Namely, we need to choose a time-variant gain matrix $K(i+1)$ to satisfy the two performance indexes: One is $E[\tilde{x}(i+1)\tilde{x}(i+1)^T]$ = min, and the other is $E[\gamma(i+1+j)\gamma^T(i+1)]$ =0, where $i=0, 1, 2,\cdots$, $j=1, 2,\cdots$, $\tilde{x}(i+1) = x(i+1)-\hat{x}(i+1|i+1)$, and $\hat{x}(i+1|i+1)$ is the estimated value of state variables and $\gamma(i+1+j)$ is the residual, whose definition is in Eq. (13). The basic idea is to introduce a suboptimal fading factor to modify the original covariance matrix of the state predictive errors in the extended Kalman filter; thus, we can use the orthogonality principle to regulate the suboptimal fading factor to make the filter track the practical systems in spite of modeling errors and other uncertainties. If the suboptimal fading factor is chosen not less than one, the effects of history data to present filtering values will be attenuated. As a result, the tracking rapidity of filters will be improved. In order to obtain the online algorithm, the second performance index, i.e., the orthogonality principle is often satisfied approximately.

According to the analysis and deduction in [16], a modified strong tracking filter (MSTF) is obtained as follows [16]:

$$\hat{x}(i+1|i+1)=\hat{x}(i+1|i)+K(i+1)\gamma(i+1) \tag{8}$$

$$\hat{x}(i+1|i)=f(u(i),\hat{x}(i|i)) \tag{9}$$

with

$$\begin{aligned} K(i+1)&=P(i+1|i)H^T(i+1) \\ &\cdot[H(i+1)P(i+1|i)H^T(i+1)+R(i)]^{-1} \end{aligned} \tag{10}$$

$$\begin{aligned} P(i+1|i)&=\Lambda(i+1)F(i)P(i|i) \\ &\cdot F^T(i)+\Gamma(i)Q(i)\Gamma^T(i) \end{aligned} \tag{11}$$

$$\begin{aligned} P(i+1|i+1)&=[I-K(i+1) \\ &\cdot H(i+1)]P(i+1|i) \end{aligned} \tag{12}$$

$$\gamma(i+1) = y(i+1) - h(\hat{x}(i+1\mid i)) \tag{13}$$

$$F(i) = \left.\frac{\partial f(u(i),x(i))}{\partial x}\right|_{x=\hat{x}(i\mid i)} \tag{14}$$

$$H(i+1) = \left.\frac{\partial h(x(i+1))}{\partial x}\right|_{x=\hat{x}(i+1\mid i)} \tag{15}$$

$$\Lambda(i+1) = diag[\lambda_1 \ \ \lambda_2 \ \cdots \lambda_n] \tag{16}$$

$$\lambda_j = \begin{cases} \alpha_j d(i+1); \ \alpha_j d(i+1) > 1, \\ 1 \ ; \ \alpha_j d(i+1) \le 1, \end{cases} \tag{17}$$

$$d(i+1) = \frac{tr[N(i+1)]}{\sum_{j=1}^{n} \alpha_j M_{jj}(i+1)} \tag{18}$$

$$\begin{aligned} N(i+1) &= V_0(i+1) - \beta R(i+1) \\ &-H(i+1)\Gamma(i)Q(i)\Gamma^T(i)H^T(i+1) \end{aligned} \tag{19}$$

$$\begin{aligned} M(i+1) &= F(i)P(i\mid i) \\ &\cdot F^T(i)H^T(i+1)H(i+1) \end{aligned} \tag{20}$$

$$\begin{aligned} V_0 &= E[\gamma(i+1)\gamma^T(i+1)] \\ &\approx \begin{cases} \gamma(1)\gamma^T(1) \ ; \ i=0, \\ \dfrac{\rho V_0(i) + \gamma(i+1)\gamma^T(i+1)}{1+\rho}; \ i \ge 1, \end{cases} \end{aligned} \tag{21}$$

where $\Lambda(i+1)$ is the suboptimal fading factor matrix; $\rho = 0.95$ in Eq.(21) is a forgetting factor; $\beta \ge 1$ in Eq.(19) is a preselected softening factor, which is introduced to make the state estimation much smoother; in Eq.(17) $\alpha_i \ge 1$, $i=1,2,\cdots n$, are predetermined coefficients. For details how to select these parameters, we refer the readers to [12]

IV. Leak detection and location method

We will use the MSTF to estimate the leakage q^k and its location x^k. Solving distributed parameter state estimation problems needs approximating it with finite variables. First, the method of characteristics is applied to transforming partial differentials into total ordinary differentials [10]. For $x \ne x^k$, Eqs. (1) and (2) can be linearly combined for some real, nonzero r,

$$\begin{aligned} &\left(\frac{\partial p}{\partial t} + rA\frac{\partial p}{\partial x}\right) + r\left(\frac{\partial q}{\partial t} + \frac{c^2}{rA}\frac{\partial q}{\partial x}\right) \\ &+ r\frac{\lambda c^2}{2DA}\frac{q\mid q\mid}{p} = 0 \end{aligned} \tag{26}$$

If r is chosen as $rA = \frac{c^2}{rA} = \frac{\partial x}{\partial t}$, which defines the characteristic functions in the (x,t) -plane, then

$$\frac{\partial p}{\partial t} + rA\frac{\partial p}{\partial x} = \frac{\partial p}{\partial t} + \frac{\partial x}{\partial t}\frac{\partial p}{\partial x} = \frac{dp}{dt} \tag{27}$$

$$\frac{\partial q}{\partial t} + \frac{c^2}{rA}\frac{\partial q}{\partial x} = \frac{\partial q}{\partial t} + \frac{\partial x}{\partial t}\frac{\partial q}{\partial x} = \frac{dq}{dt} \tag{28}$$

Hereby, along the characteristic functions, the partial differential equations become ordinary differential ones. Then Eq. (26) becomes Eqs. (29) and (30):

$$\begin{cases} \dfrac{dp}{dt} + \dfrac{c}{A}\dfrac{dq}{dt} + \dfrac{\lambda c^3}{2DA^2}\dfrac{q\mid q\mid}{p} = 0, \\ \dfrac{\partial x}{\partial t} = c. \end{cases} \tag{29}$$

$$\begin{cases} \dfrac{dp}{dt} - \dfrac{c}{A}\dfrac{dq}{dt} - \dfrac{\lambda c^3}{2DA^2}\dfrac{q\mid q\mid}{p} = 0, \\ \dfrac{\partial x}{\partial t} = -c. \end{cases} \tag{30}$$

Second, for the purpose of lumping Eqs. (29) and (30), the differential should be substituted for the difference, and a second order approximation is used for the integration of the nonlinear friction term.

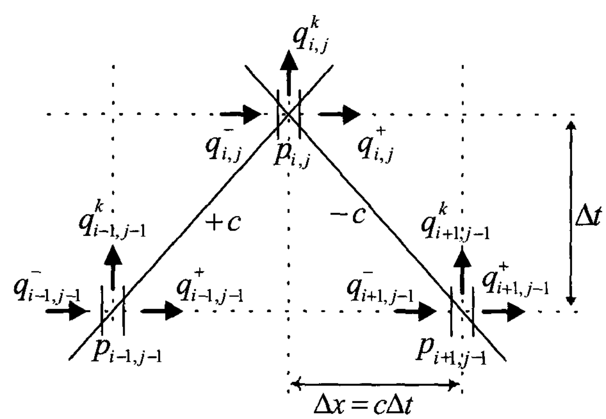

Fig. 1. Discretization scheme for the method of characteristics.

From the Fig. 1, the finite difference schemes of Eqs (29) and (30) are as follows:

$$\begin{aligned} &(p_{i,j} - p_{i-1,j-1}) + \frac{c}{A}(q^-_{i,j} - q^+_{i-1,j-1}) + \\ &\frac{\lambda c^3 \Delta t}{4DA^2}\left(\frac{q^-_{i,j}\mid q^-_{i,j}\mid}{p_{i,j}} + \frac{q^+_{i-1,j-1}\mid q^+_{i-1,j-1}\mid}{p_{i-1,j-1}}\right) = 0 \end{aligned} \tag{31}$$

$$\begin{aligned} &(p_{i,j} - p_{i+1,j-1}) - \frac{c}{A}(q^+_{i,j} - q^-_{i+1,j-1}) - \\ &\frac{\lambda c^3 \Delta t}{4DA^2}\left(\frac{q^+_{i,j}\mid q^+_{i,j}\mid}{p_{i,j}} + \frac{q^-_{i+1,j-1}\mid q^-_{i+1,j-1}\mid}{p_{i+1,j-1}}\right) = 0 \end{aligned} \tag{32}$$

$$q^-_{i,j} - q^+_{i,j} = q^k_{i,j} \tag{33}$$

$$q^k_{i,j} = q^k_{i,j-1} \tag{34}$$

where $p_{i,j} : p(x_i,t_j)$, $q^-_{i,j} : q(x^-_i,t_j)$, $q^+_{i,j} : q(x^+_i,t_j)$, $q^k_{i,j} : q^k(x_i,t_j)$, $x_i = (i-1)\Delta x$, $t_j = j\Delta t$ (Δx , Δt : mesh size, and there must be $\frac{\Delta x}{\Delta t} = c$), $p_{1,j} : f_p(t_j)$, $q_{N,j} : f_q(t_j)$ (N: last grid point), $q^k_{i,j}$: modeled leaks (The leak is assumed to be constant.).

In terms of [10], the relationships between the real leak ($q^k(j)$, $x^k(j)$) and the modeled leaks ($q^k_{i,j}$, x^k_i) are as follows:

$$q^k(j) = \sum_{i=2}^{N-1} q^k_{i,j} \qquad (35)$$

$$x^k(j) = \sum_{i=2}^{N-1} q^k_{i,j} x^k_i / q^k(j) \qquad (36)$$

The relationships are valid for a small leak q^k.

In order to apply the STF, we select the state variables as follows:

$$x(j) = [p_{2,j}, p_{3,j}, \cdots p_{N,j}, q^-_{1,j}, q^-_{2,j}, \cdots q^-_{N-1,j}, q^k_{2,j}, q^k_{3,j}, \cdots q^k_{N-1,j}]^T \qquad (37)$$

And Eqs. (31)- (34) can be written as the following:

$$g(x(j+1), x(j), u(j)) = 0 \qquad (38)$$

$$y(j) = Hx(j) \qquad (39)$$

where $u(j) = [f_p(j)\ \ f_q(j)]^T = [f_p(t_j)\ \ f_q(t_j)]^T$, and H is a matrix with elements to be 0 or 1, to provide the interesting measurements. Notice that there are 3 N -4 state variables and $g(\cdot)$ consists of 3 N -4 equations.

To get the estimated state variables, the STF will be utilized, in which the matrix $F(i)$ given by Eq. (14) is obtained by the following:

$$F(i) = \left.\frac{\partial f(u(i), x(i))}{\partial x}\right|_{x=\hat{x}(i,i)} = -\left(\frac{\partial g(x(i+1), x(i), u(i))}{\partial x(i+1)}\right)^{-1} \cdot \left.\frac{\partial g(x(i+1), x(i), u(i))}{\partial x(i)}\right|_{x=\hat{x}(i/i)} \qquad (40)$$

The final state estimates are applied to Eqs (35) and, (36) to estimate the leak and its location.

V. Simulation results

A pipeline simulator is used to model noisy gas flow in a pipeline having the specifications [10]: L =90km; D =0.785m; c =300m/s; λ =0.02. Zero-mean white Gaussian noise is added to the process equations and to the measurements to simulate a stochastic system. At time t =60 min a leak of 2% (4kg/s) at 50km from the upstream end of the pipe is suddenly introduced. Simulation results are presented in Fig.2. For comparison purpose we present also the simulation results of the extended Kalman filter in Fig.3.

Data used in the measurement simulator are as follows: Boundary conditions, Δx =10km, $p(0,t)$ =100bar=107 Pa, $q(L,t)$=200kg/s. Three pressure measurements at 30, 60 and 90 km are generated for the filter.

Parameters used in the filters are as follows: Δx = 30km, $x(j)$ = $[p_{2,j}, p_{3,j}, p_{4,j}, q^-_{1,j}, q^-_{2,j}, q^-_{3,j}, q^k_{2,j}, q^k_{3,j}]^T$. Therefore we have H as follows:

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$, boundary conditions are

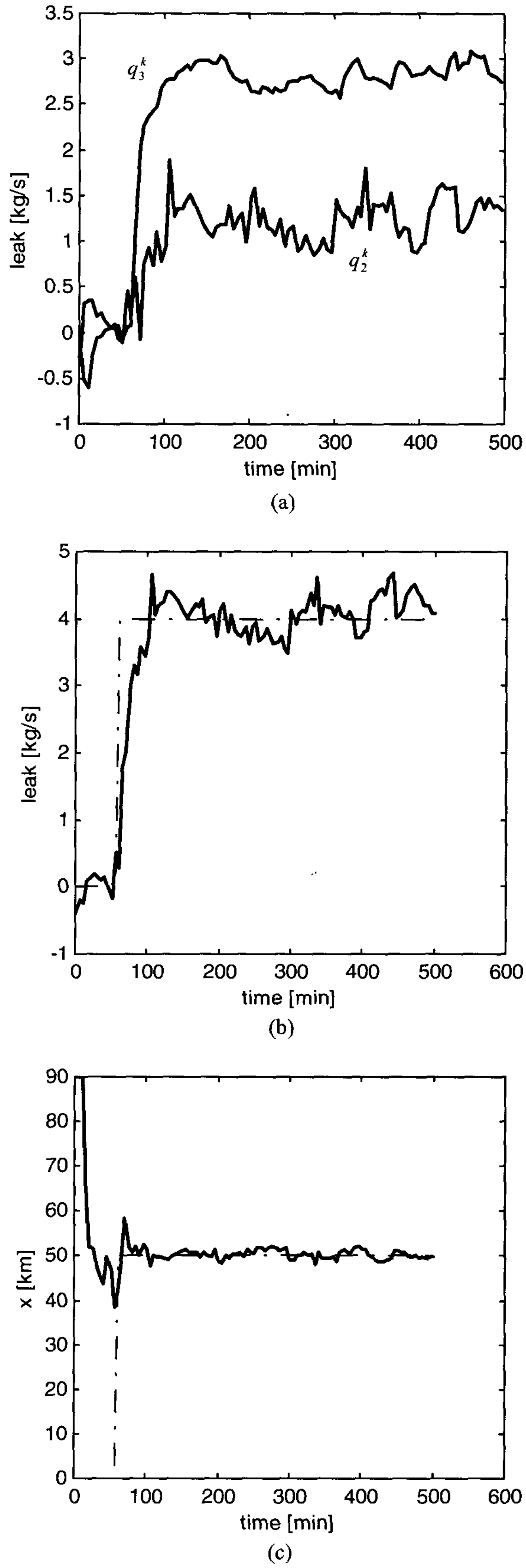

Fig. 2. The simulation results with MSTF: (a) The modeling leaks; (b) The estimated leak; (c) The estimated leak location by Eq. (36).

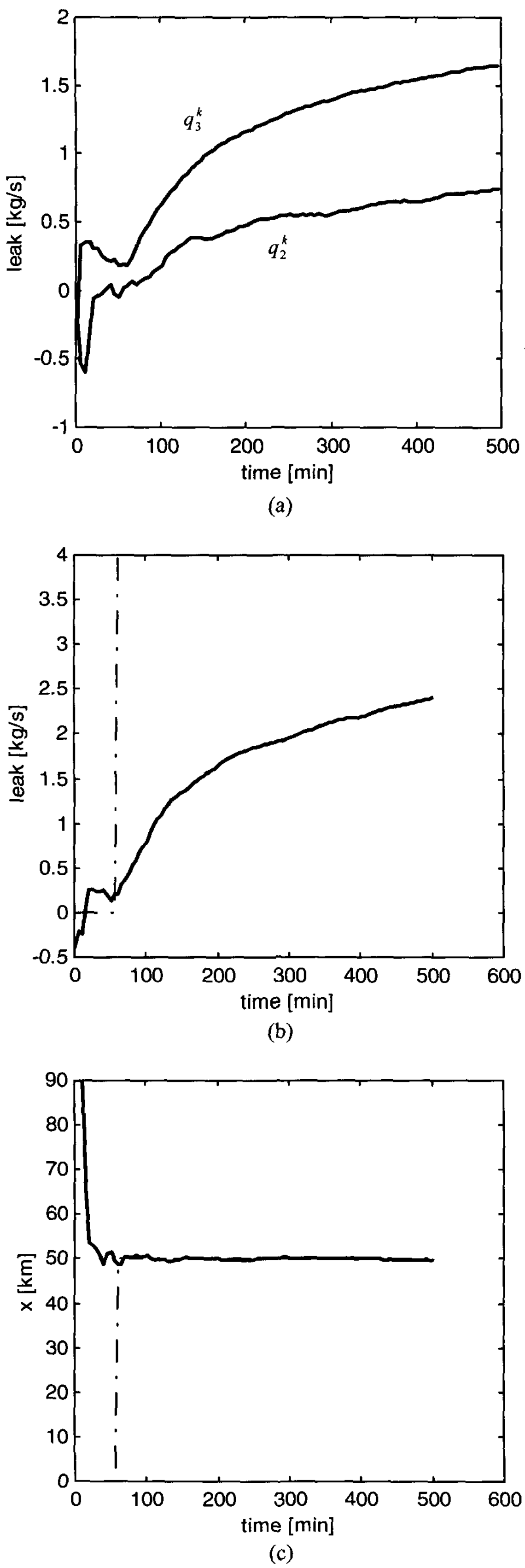

Fig.3. The simulation results with extended Kalman filter: (a) The model/ing leaks; (b) The estimated leak; (c) The estimated leak location by Eq. (36).

assumed known exactly. Initial conditions are $\hat{x}(0)$ = [94, 87.5, 80.5, 200, 200, 200, 0, 0]^T. Process and observation noise covariance matrices: $Q = \begin{bmatrix} \sigma_p^2 I_3 & 0 & 0 \\ 0 & \sigma_q^2 I_3 & 0 \\ 0 & 0 & \sigma_k^2 I_2 \end{bmatrix}$, σ_p^2 = 106 (Pa) 2, σ_q^2 = 0.01(kg/s) 2, σ_k^2 = 0.01(kg/s) 2, $R = \sigma_m^2 I_3$, σ_m^2 = 106 (Pa) .

From Figs. 2 and 3, it is obvious that the tracking ability of STF is much faster than that of the extended Kalman filter. The average estimated leak location using the STF is x = 50.2149 km, while the average estimated leak location using Kalman Filter is x = 51.0310 km, with relative errors being 0.24% and 1.15% , respectively.

In order to analyze the simulation results in detail, we first consider the modeling errors that occur in the pipeline model. In fact, there exist two kinds of errors in the model. One has been mentioned at the section 2, that is, simplification assumptions such as a constant diameter D , a turbulent flow and isothermal condition, which are trivial because we can add more equations and conditions to obtain more precise mathematical models if necessary; for example, the thermal equations are included in [11]. Another one is the approximation of finite difference schemes with lumped parameters to differential equations with nonlinear distributed parameters, which is more difficult to overcome than the former because these errors are inevitable and larger. Therefore, in the simulation, the more precise model (Δx =10km adopted) is used in simulator while Δx =30km in the filters. The second kind of modeling errors can be represented by these different choices in the simulator and the filters. Besides, initial conditions are also imprecise, which adds uncertainties to the model too.

Just as we discussed in the section 3, STF have suboptimal fading factors, which is crucial to improve the filtering performance. We have two ways to explain the superiority of STF. First, we should notice that every element of the suboptimal fading factor matrix $\Lambda(i+1)$ is more than or equal to one. Therefore, the present data acquire bigger weights while the history data are attenuated. Consequently, STF can track the present state more easily than the extended Kalman filter. Second, the suboptimal fading factors are determined by the orthogonality principle. Thus, no matter whether modeling errors exist, whether noise is fit for the statistic assumptions, and whether the initial conditions are imprecise, the orthogonality principle will regulate the suboptimal fading factors to force the filter to match the practical system states. Thereby, the STF can track the abrupt changes of system states efficiently. The simulation results verify exactly the above statements.

VI. Conclusions

For a pipeline, both detection promptness and location accuracy of the leakage are very important because the former can avoid further losses and the latter can save time to locate the leaks and repair them. Especially for a long pipeline, the minor relative error of location will lead to hundreds of meters in practice, which is hard for inspectors to find real leak location. In this paper, a problem of detecting and locating leaks in transmission pipelines has been discussed. The method used in this paper is based on MSTF for the nonlinear distributed parameter system representing the gas flow in a leaking pipeline. This nonlinear distributed parameter system is lumped by using the method of characteristics and the obtained nonlinear finite difference model is solved with the aid of an iterative numerical method. As a fault model, artificial leak states have been included. The MSTF is used as a state estimator in the leak detection and location, which not only is robust to modeling errors and other uncertainties, but also tracks the state of systems quickly. Therefore, we can get more accurate leak location and also get the leak information more quickly. Extensive computer simulations verify the superiority of MSTF to the extended Kalman filter.

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