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ITJ

ISSN 1812-5638

INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 11 (10): 1518-1522, 2012
ISSN 1812-5638 / DOI: 10.3923/itj.2012.1518.1522

Wavelet-based Kalman Filter for Traffic Flow Forecasting in Sensornets

[1]Yan-Chao Zhao, [1]Jian-Feng Wu, [2]Yan Zhang and [3]Bin Zhou
[1]Northeast Petroleum University, Daqing 163318, People's Republic of China
[2]Xinjiang Agricultural University, Urumqi 830052, People's Republic of China
[3]Xi'an University of Science and Technology, Xi'an 710054, People's Republic of China

Abstract: With the rapid development of Intelligent Transportation Systems (ITS), traffic controlling and traffic guidance have become a hot research issue. Better traffic controlling can reduce the cost and pollution efficiently. This study researches traffic flow forecasting in Sensornets. First, some observation nodes are proper set and the traffic flow data can be collected. Then wavelet is introduced to reduce the noise of the traffic flow data. Kalman filter is also introduced to forecast the next traffic flow and the result will be more advantageous for traffic controlling. The efficiency and the accuracy of the proposed model are shown in presented numerical examples.

Key words: Traffic flow, forecasting, wavelet-based, Kalman filter

INTRODUCTION

Sensornets have been applied in many fields (Akyildiz *et al*., 2002, 2007; Shan *et al*., 2011a) since the rapidly development (Wei *et al*., 2010a; Shan *et al*., 2010). The information collected by the nodes composes a discrete distribution and most applications will be processing on it, such as traffic controlling, navigation, environment monitoring and so on (Atluri and Zhu, 1998; Belytschko *et al*., 1996).

Recently, with the great increasing of economy, there are more and more vehicles running on the roads and it has caused some serious problems such as pollution, accidents, traffic jams and so on. Now the Intelligent Transportation System (ITS) has been a hot research issue. Traffic controlling and traffic guidance are the kernel parts in the system. Many researches about traffic controlling have been processed (Smith and Demetsky, 1997; Smith *et al*., 2002; Clark, 2003).

Traffic flow is a major factor for people understanding the traffic status and the forecasting of traffic flow is one of the most important problems. For avoiding traffic jams, costs and pollution, local authorities should adopt efficient measures to control traffic and it depends on understanding the evolution of traffic flow. A real-time, accurate and efficient forecasting can plays an activities role in traffic controlling. Then people and society will be benefited from it. With the help of traffic flow monitoring, people can get some information about traffic status. Precise representation of traffic flow evolution is beneficial to traffic controlling since it allows them to have more float time to take appropriate precautionary measures. However, these complex dynamics of the evolution are governed by various pertinent physical and biochemical factors (Nath and Patil, 2006).

For the complexity and uncertainty of the evolution, enormous computing cost and time will be consumed. Some intelligence algorithms such as Artificial neural networks (Chau and Cheng, 2002) have been applied for solving these problems but there are some drawbacks. More exactly, the training convergence speed is slow and it is easy to lead a local minimum (Rumelhart *et al*., 1994). Swarm intelligence is another technique that is developing quickly (Clerc and Kennedy, 2002; Kennedy and Eberhart, 1995). This technique has been applied in some problems and some satisfactory results have been obtained (Chau, 2004a, b). In some other numerical modeling, the physical problem is represented by highly coupled, non-linear Partial differential equations (PDEs) (Zhou *et al*., 2011; Feng *et al*., 2012).

Based on the previous researches about sensornets (Gao *et al*., 2010; Shan *et al*., 2011b), a wavelet-based model is introduced to forecast the traffic flow in this study. With the collection of previous traffic flow data, the evolution can be represented and the next traffic flow can be forecasted. It is helpful to take efficient measures for reducing jams, costs, pollution and so on. The accuracy and efficiency are shown in the numerical examples.

TRADITIONAL KALMAN FILTER FOR TRAFFIC FLOW FORECASTING

The distribution of observations and evolution of the traffic flow in a region will be considered. For precise

Corresponding Author: Yan-Chao Zhao, Northeast Petroleum University, Daqing 163318, People's Republic of China

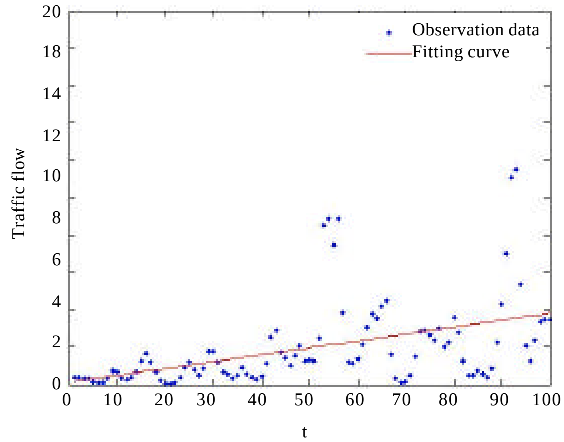


Fig. 1: Observation data with the traditional result

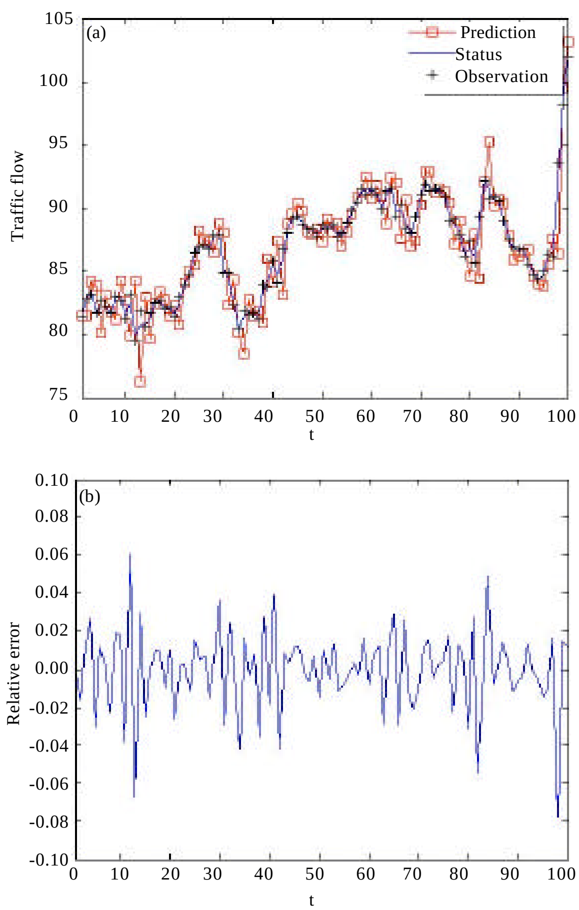


Fig. 2(a-b): Prediction for traffic flow by Kalman filter. (a) Prediction result and (b) Relative error

represent of the traffic flow evolution, some observation data collected in sensornets should be prepared first.

Using some mathematical methods such as polynomial function fitting, nonlinear fitting, least squares estimation, etc., a traffic flow curve can be get quickly and the estimation of future traffic status can also be obtained. Partial differential equations are often related with some complex behavior and many PDE-related models have been applied in presented researches, such as constructing potential field (Qiao *et al*., 2010; Wei *et al*., 2010b; Zhou *et al*., 2010a, b), image segmentation (Zhou and Mu, 2010) and so on. They can be also applied to represent the evolution.

However, the real evolution is complex and it is often driven by lots of factors. In fact these traditional methods can work well few times because the system is not fixed but dynamic. An example of observation data and the traditional result are show in Fig. 1.

As an efficient technique, Kalman filter has been applied in many researches (Julier and Uhlmann, 1997; Van der Merwe, 2003). The main formulas can be denoted by following:

$$\bar{X}(k+1|k) = A(k)\bar{X}(k) \tag{1}$$

$$K(k) = A(k)P(k)H^T(k)[H(k)P(k)H^T(k) + R(k)]^{-1} \tag{2}$$

$$\bar{X}(k+1) = \bar{X}(k+1|k) + K(k)[z(k) - H(k)\bar{X}(k+1|k)] \tag{3}$$

$$P(k+1) = A(k)[I - K(k)H(k)]P(k)A^T(k) + Q(k) \tag{4}$$

where, $\bar{X}(k)$ denotes status vector, z(k) denotes observation vector, H(k) denotes observation matrix, A(k+1, k) denotes transition matrix, R(k) denotes system error co-variance matrix, Q(k) denotes observation error co-variance matrix.

Equation 1 means the direct forecasting of real status and Eq. 2 denotes gain calculation. Correction of the forecasting result can be completed by Eq. 3 while Eq. 4 shows the recurrence computation of the system co-variance matrix. Set initial value of parameters. These equations can help to complete the forecasting process.

Figure 2 shows a forecasting result for a given observation data. As shown in the Fig. 2, the error seems a little big and it does less help to traffic controlling. In fact, the maximal relative error is 7.74% and the mean relative error is 1.64%. A part of the result is shown in Table 1.

However, many factors will affect the collected observation data in fact and the noise removal should be processed before the prediction. Wavelet transform and the inverse transform are often used to achieve this purpose. The main formulas are shown as following:

Table 1: A part of the result obtained by Kalman filter

t	1	11	21	31	41	51	61	71	81	91
Observation	81.470	83.080	82.950	84.860	84.110	88.280	91.120	91.860	85.640	86.730
Prediction	81.470	79.882	80.784	82.334	87.391	89.204	91.810	92.858	87.964	86.424
Relative error	0.000	-0.038	-0.026	-0.030	0.039	0.010	0.008	0.011	0.027	-0.004

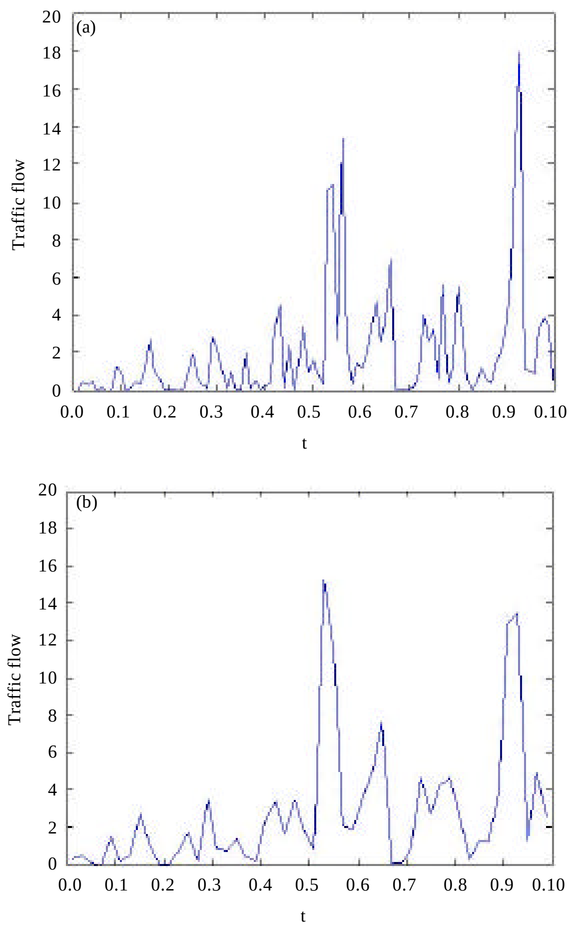


Fig. 3(a-b): Noise removal for the observation data by wavelet transform. (a) Original observation data and (b) Noise removal

$$(W_\Psi f)(b,a)=|a|^{-\frac{1}{2}}\int_{-\infty}^{+\infty} f(t)\overline{\Psi(\frac{t-b}{a})}dt \tag{5}$$

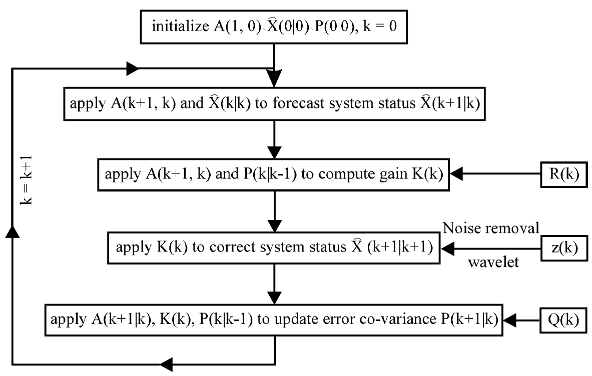
$$f(t)=\frac{1}{C_\Psi}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}[(W_\Psi f)(b,a)]\Psi_{a,b}(t)\frac{da}{a^2}db \tag{6}$$

Here f denotes original signal and $W_\Psi f$ denotes the wavelet transform. a and b mean the scale factor and shift factor.

With some given threshold, the low-frequency part (noise or other unimportant part) can be removed by the above two equations and a sample has been presented in Fig. 3.

WAVELET-BASED KALMAN FILTER FOR TRAFFIC FLOW FORECASTING

The wavelet will be combined with Kalman filter and the new model will be applied to forecast the traffic flow according to the observation data collected by sensors. The main formulas have been discussed in previous sections and here we give the model as show in following:



Here the system error co-variance R(k) and observation error co-variance Q(k) should be pre-decided.

NUMERICAL EXPERIMENTS

The proposed model will be used to forecast the traffic flow and the evolution can be obtained. Efficiency and applicability of proposed model are illustrated by following steps. First, the same collected observation data (Fig. 2) will be applied to verify the efficiency and accuracy of the model. The result is shown in Fig. 4.

From the results of our experiments, the prediction of proposed model is better than the one obtained by traditional method. In fact, the maximal relative error is 7.16% and the mean relative error is 1.39%. A part of the values has been given in Table 2.

It follows from the numerical results that the presented algorithm is successful in accuracy, convergence speed and insensitivity to initial observation stations.

Table 2: A part of the result obtained by wavelet-based Kalman filter

t	1	11	21	31	41	51	61	71	81	91
Observation	81.470	83.080	82.950	84.860	84.110	88.280	91.120	91.860	85.640	86.730
Prediction	81.470	80.456	81.177	83.658	86.729	88.683	91.535	92.462	86.873	86.208
Relative error	0.000	-0.032	-0.021	-0.014	0.031	0.005	0.005	0.007	0.014	-0.006

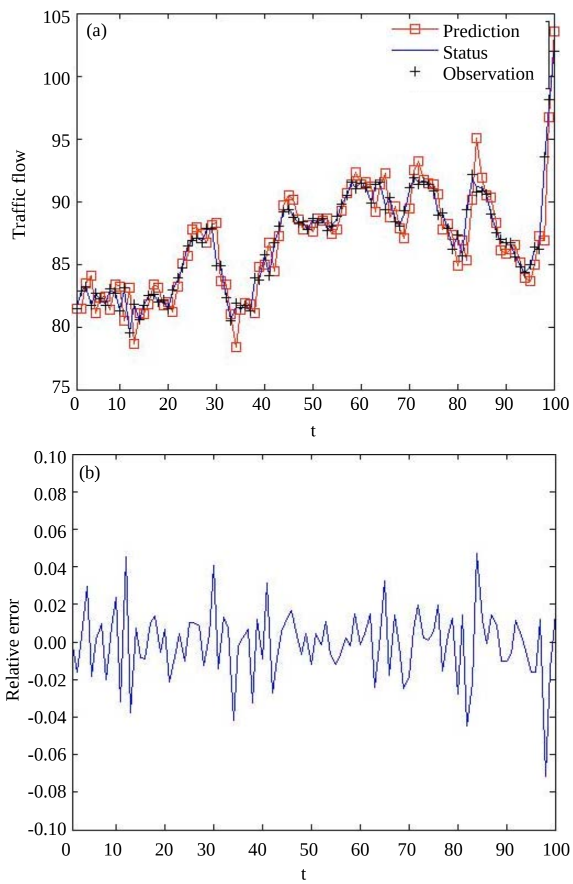


Fig. 4(a-b): Prediction for traffic flow by Wavelet-based Kalman filter. (a) Prediction result and (b) Relative error

CONCLUSIONS

This study proposed a wavelet-based Kalman filter model for the forecasting of traffic flow in sensornets. The observation data of the traffic flow can be collected by sensornets. The wavelet transform and Kalman filter were combined to achieve the prediction. The maximal of relative errors has been decreased from 7.74 to 7.16% while the mean of relative errors is decreased from 1.64 to 1.39%. The numerical result shows the efficiency and accuracy of proposed model.

ACKNOWLEDGMENTS

The authors would like to thank the editor and referees for their valuable comments and suggestions that help to improve this study. This study is supported in part by Science and Technology Research and Development Program of Qinhuangdao (Program No. 201101A229).

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