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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): 1508-1512, 2012
ISSN 1812-5638 / DOI: 10.3923/itj.2012.1508.1512

Dynamic Analysis of Kalman Filter for Traffic Flow Forecasting in Sensornets

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Abstract: Intelligent Transportation System (ITS) plays an important role in traffic controlling and traffic guidance which can greatly reduce the cost and pollution. In some senses, efficient traffic controlling is supported by accurate forecasting of the traffic flow and Kalman filter is one of the most used techniques. This study researches some dynamic behaviors of the Kalman filter in traffic flow forecasting. First, some observation nodes are proper set and the traffic flow data can be collected. Then Kalman filter is introduced to forecast the future traffic flow. Finally, the relation between dynamic parameters and forecasting result is analyzed. Several experiments are introduced to verify the conclusion.

Key words: Traffic flow, forecasting, dynamic analysis, Kalman filter

INTRODUCTION

Sensornets have been applied in many applicable scenarios (Akyildiz *et al*., 2002, 2007; Tubaishat and Madria, 2003; Shan *et al*., 2011a) and some observation data can be collected for advanced applications. Most applications will be processing on it, such as traffic controlling, navigation, environment monitoring, and so on (Arici and Altunbasak, 2004; Chong and Kumar, 2003; Wei *et al*., 2010a; Shan *et al*., 2010).

More and more vehicles run on the roads with the great development of economy and the caused problems such as pollution, accidents, traffic jams, etc, become more and more serious. Intelligent Transportation System (ITS) can relieve these and it has been a hot issue in the past few years. Traffic controlling and traffic guidance are the most important parts in the system. Lots of researches about traffic controlling have been processed (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. Based on the observation data of traffic flow, people can forecast the future traffic flow and some efficient measures can be carried out for avoiding traffic jams, costs and pollution. A real-time, accurate forecasting can plays an activities role in traffic controlling and everyone will be benefited from it. In other words, precise representation of traffic flow evolution is advantageous for traffic controlling. However, the complex dynamics of the evolution are decided by various physical and biochemical factors (Nath and Patil, 2006). Enormous computing cost and time will be required for the representation.

Artificial neural networks (Chau and Cheng, 2002) have been applied in traffic controlling and there are still some drawbacks such as slow training convergence speed and easy entrapment in a local minimum (Dia, 2001). Swarm intelligence is another technique that is developing quickly (Clerc and Kennedy, 2002). This technique has been applied in many problems and some satisfactory results have been presented (Chau, 2004a, b). In some other numerical modeling, the physical problem is represented by highly coupled, non-linear PDEs (Zhou *et al*., 2011; Feng *et al*., 2012).

According to the previous researches about sensornets (Gao *et al*., 2010; Shan *et al*., 2011b), Kalman filter is introduced to forecast the traffic flow and the dynamic behaviors are also analyzed. Some observation data collected by sensors are used to get some dynamic characters. Then different characters are applied in Kalman filter for the prediction. The relation between the characters and the prediction results is presented at last. The efficiency of our conclusion is verified by some experiments.

TRADITIONAL TRENDS ANALYSIS AND KALMAN FILTER FORECASTING FOR TRAFFIC FLOW

The distribution of observations and evolution of the traffic flow in a region will be considered. For precise represent of the traffic flow evolution, some observation data collected in sensornets should be prepared first.

Some traditional mathematical methods such as polynomial function fitting, nonlinear fitting, least squares estimation, etc., can be used for trends analysis and they have been applied in many fields. Assume that the observation data is denoted by (t_i, x_i), i = 1, 2, ..., n, then a related optimization problem can be presented as:

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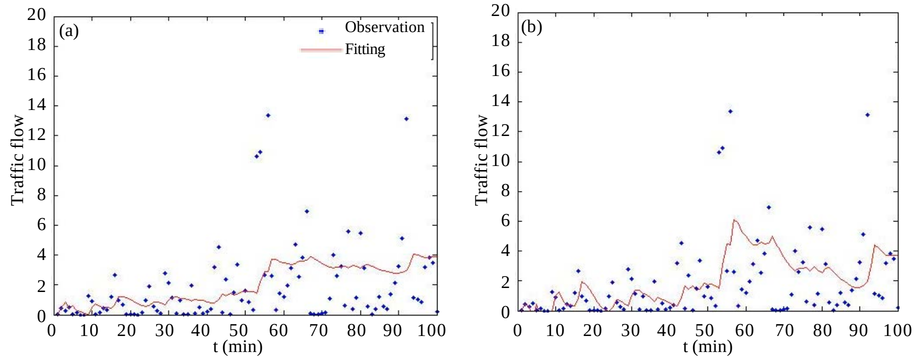

Fig. 1(a-b): Observation data with the traditional result (a) Linear fitting step by step and (b) Quadratic fitting step by step

$$\min \ E(C) = \sum_{i=1}^{n}\left[f(C, t_i) - x_i\right]^2 \tag{1}$$

where, C means the parameter and energy E(C) denotes the square error. Various formulas of f can be considered for different applications. What's more, the energy can be linked to other metrics similar with square error. These methods work well when the system is fixed.

However, the real traffic flow system is driven by lots of factors and it is often dynamic. So, the result of trends analysis by them provides few help to next work. As shown in Fig. 1, two traditional results are presented.

Partial differential equations are often related with the complex behaviors and they have been applied in many presented researches, such as constructing potential field (Qiao *et al*., 2010; Wei *et al*., 2010b; Zhou *et al*., 2010a), image segmentation (Zhou *et al*., 2010b; Zhou and Mu, 2010) and so on. They can be also applied to forecast the traffic flow.

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

$$\hat{X}(k+1|k) = A(k)\hat{X}(k) \tag{2}$$

$$K(k) = A(k)P(k)H^T(k)[H(k)P(k)H^T(k) + R(k)]^{-1} \tag{3}$$

$$\hat{X}(k+1) = \hat{X}(k+1|k) + K(k)[Z(k) - H(k)\hat{X}(k+1|k)] \tag{4}$$

$$P(k+1) = A(k)[I - K(k)H(k)]P(k)A^T(k) + Q(k) \tag{5}$$

where, $\hat{X}(k)$ 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 2 means the direct forecasting of real status and Eq. 3 denotes gain calculation. Correction of the forecasting result can be completed by Eq. 4 while Eq. 5 shows the recurrence computation of the system co-variance matrix. Set initial value of parameters. These equations can help to complete the forecasting process. The algorithm can be illustrated by Fig. 2.

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

DYNAMIC ANALYSIS OF KALMAN FILTER FOR TRAFFIC FLOW FORECASTING

Some dynamic behaviors of Kalman filter will be analyzed for traffic flow forecasting. The original observation data collected by sensors is only about traffic flow. However, some information about the forces of evolution system is necessary for the processing of Kalman filter. Here, the traffic flow will be looked as a special 'shift' s. Then the velocity and the acceleration will be considered.

Several formulas about the computation of velocity and acceleration can be given as follows:

$$\min \ E(v) = \sum_{j=1}^{i} c_j\left(\int_{I_j} v\,dt - \Delta s_j\right)^2 \tag{6}$$

$$\min \ E(a) = \sum_{j=1}^{i} d_j\left(\int_{I_j} a\,dt - \Delta v_j\right)^2 \tag{7}$$

where, v and a denote velocity and acceleration while c_j and d_j means the weight, I_j denotes the closed set $[t_{j-1}, t_j]$. The computation of v and a will be decided by some assumptions. For example, when v is assumed to be a constant, then it can be calculated by:

$$v = \left(\sum_{j=1}^{i} c_j \Delta s_j\right) / \Delta t$$

When a linear expression v = kt+b is satisfied, it can be determined by this linear system:

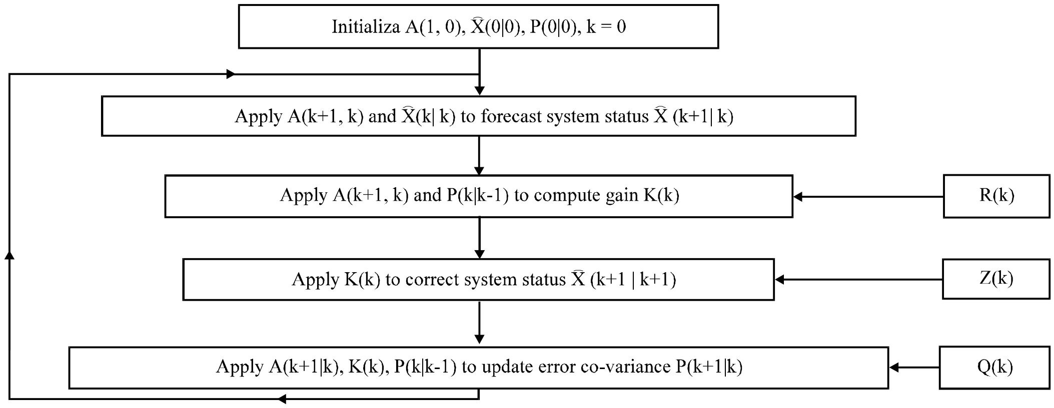

Fig. 2: An algorithm for Kalman filter

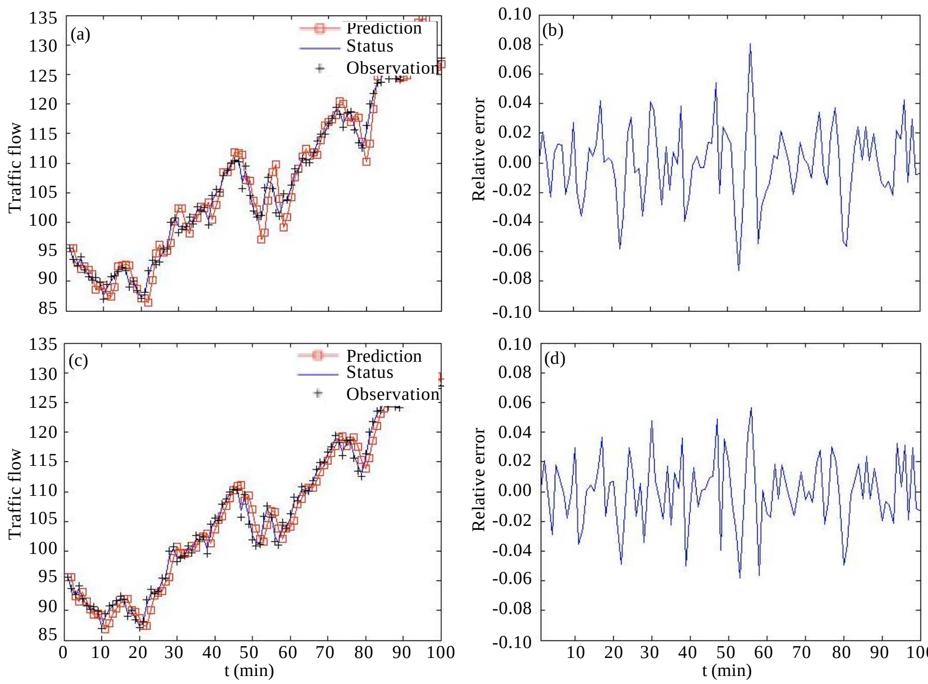

Fig. 3(a-d): Results with constant velocity, (a) Prediction result and (b) Relative error with increasing weight and (c) Prediction result and (d) Relative error with decreasing weight

$$\begin{pmatrix} \Delta t\sum_{j=1}^{i} c_j t_{j-1/2}^{2} & \Delta t\sum_{j=1}^{i} c_j t_{j-1/2} \\ \Delta t\sum_{j=1}^{i} c_j t_{j-1/2} & \Delta t \end{pmatrix} \begin{pmatrix} k \\ b \end{pmatrix} = \begin{pmatrix} \sum_{j=1}^{i} c_j t_{j-1/2}\Delta s_j \\ \sum_{j=1}^{i} c_j \Delta s_j \end{pmatrix} \tag{8}$$

where, $t_{j-1/2} = (t_{j-1}+t_j)/2$. Similar results can be obtained from the discussion about the acceleration a.

It can be known from Eq. 8 that the velocity v is related with the weight distribution $(c_1, c_2, \ldots, c_{i-1})$. After set the observation vector $Z = (s, v, a)^T$, the forecasting of traffic flow can be achieved by the algorithm as shown in Fig. 2.

NUMERICAL EXPERIMENTS

The proposed model will be used to forecast the traffic flow. First, the collected observation data will be applied to compute the velocity with different assumptions. Then the forecasting can be achieved. As velocity v is constant, the results are shown in Fig. 3.

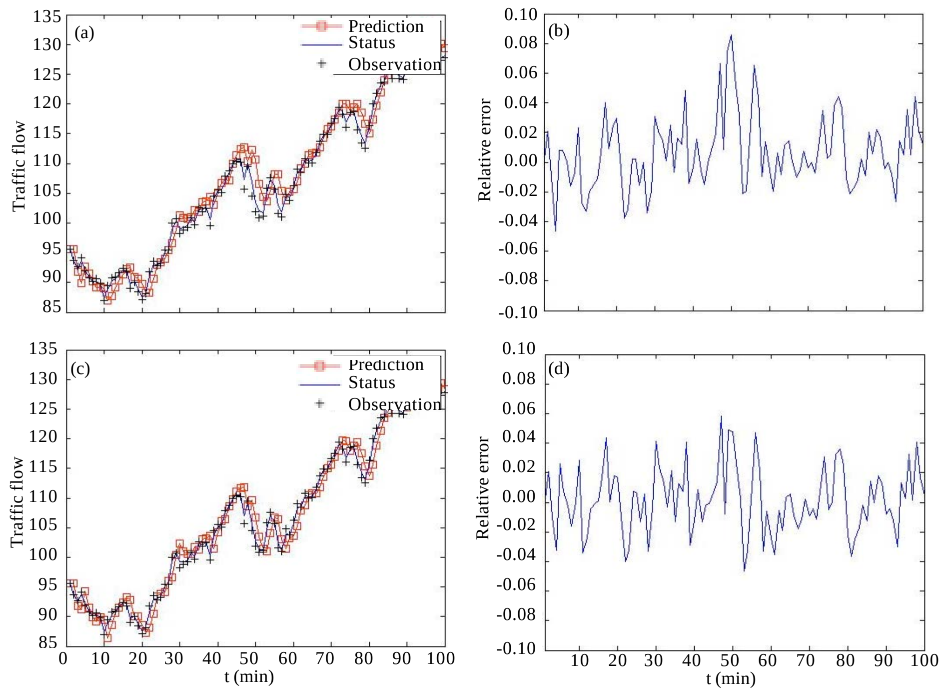

Fig. 4(a-d): Results with linear velocity, (a) Prediction result and (b) Relative error with increasing weight and (c) Prediction result with decreasing weight and (d) Relative error with decreasing weight

It can be known from the results that the maximal relative error is 8.06% and the average relative error is 1.97% as the weight is linear decreasing. If the weight is linear increasing, the two values can be reduced to 5.27% and 1.71%.

As velocity v is linear, the results are shown in Fig. 4.

It can be known from the results that the maximal relative error is 10.28% and the average relative error is 1.87% as the weight is linear decreasing. If the weight is linear increasing, the two values can be reduced to 5.83% and 1.73%.

CONCLUSIONS

Kalman filter is introduced to forecast traffic flow in this study and some dynamic analysis is processed. Velocity and acceleration are introduced to compose the observation vector in proposed algorithm. After setting proper assumptions on these dynamic parameters and the weight distribution, the forecasting can be achieved. Several experiments with different velocity characters and different weight distributions are presented. The results show that the predictions are related with assumptions of these dynamic parameters and some weight distributions. Exactly, an increasing weight distribution is advantageous than a decreasing one while there is no significant difference between constant velocity and linear velocity.

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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