Journal of Process Control 53 (2017) 15–25

Contents lists available at ScienceDirect

Journal of Process Control

journal homepage: www.elsevier.com/locate/jprocont

Kalman filtering approach to multi-rate information fusion in the presence of irregular sampling rate and variable measurement delay☆

Alireza Fatehi [a,b], Biao Huang [a,*]

[a] The Department of Chemical and Materials Engineering, University of Alberta, Edmonton, Alberta, T6G 2 V4, Canada
[b] APAC Research Group, Industrial Control Center of Excellence, Faculty of Electrical Engineering, K.N. Toosi University of Technology, Tehran, 16317-14191, Iran

ARTICLE INFO

Article history:
Received 15 October 2015
Received in revised form 9 October 2016
Accepted 15 February 2017

Keywords:
Data fusion
Irregular sampling
Kalman filter
Measurement delay
Multi-rate measurement
Oil sands industry

ABSTRACT

State estimation for a system with irregular rate and delayed measurements is studied using fusion Kalman filter. Lab data in process plants is usually more accurate compared to other measurements. However, it is often slow rate and subject to variable delay and irregularity in sampling time. Fast rate state estimation can be conducted using fast rate measurement, while the slow rate lab data can be used to improve the accuracy of estimation whenever it is available. For this purpose, two Kalman filters are used to estimate the states based on each type of measurement. The estimates are fused in the next step by considering the correlation between them. An iterative algorithm to obtain the cross-covariance matrix between the estimation errors of the two Kalman filters is presented and employed in the fusion process. The improvement on the accuracy of estimation and comparison with other optimal fusion state estimation techniques are discussed through a simulation example, a pilot-scale experiment and an industrial case study.

1. Introduction

LAB analysis usually provides more accurate measurements for chemical process quality variables like composition of chemicals and so on. However, they are often infrequent (slow rate) with possible sampling irregularity. Besides, results from lab analysis may be available only after some variable time delay. Therefore, online instruments are usually incorporated to provide regular, fast rate and delay free measurements, which are normally not as accurate as lab data. The problem of fusing these two sets of data to provide a regular fast rate state estimate with maximum possible accuracy has attracted the attention of many researchers and practitioners.

State estimation in the presence of noise is well solved using Kalman filter (KF) by minimizing the mean square error of the estimated state [1]. This estimate can be used for various purposes including state feedback controller design [2,3], soft sensor development [4,5] and fault detection [6,7], to name a few. Multi sensor estimation can also be viewed as a filtering problem, so that Kalman filter can be used as means to fuse information of various sensors. Several methods have been proposed to fuse the information of measurements in order to improve the state estimation [8,9]. Willner [10] presents three different fusion methods. The parallel filter (PF) method simply considers the process as a multi-output system, and applies directly a multiple output KF for state estimation. This method is applicable when both sensor measurements are available at the same time. In sequential filter (SF), the estimate of states based on the KF using the first output is considered as the state prediction for the Kalman filter of the second output. In other words, the second output is used to improve the state estimate provided by the first output. The third method is called data compression or outputs fusion (OF), in which at first the outputs are fused using their noise covariance matrix, assuming the independency of the output noises. Then, this fused output is used as the measurement in a single output KF. This method requires similarity of the output measurements. In the track to track fusion (TTF) [11] the state

Abbreviations: ARSSE, average root sum of squared error; BFKF, back calculation fused Kalman filter; DP, differential pressure; DTTF, delayed track to track fusion; EIFKF, exclusive information fusion Kalman filter; FC, fusion center; FKFOE, fused Kalman filter with output extrapolation; FKF, Frequent Kalman filter; HRSG, heat recovery steam generator; IKF, infrequent Kalman filter; JFM, just frequent measurement; KF, Kalman filter; MDTTF, modified delayed track to track fusion; MDTTFR, Riccati equation based MDTTF; MTTF, modified track to track fusion; NTFKF, negative time estimation fused Kalman filter; OF, outputs fusion; PF, parallel filter; RMSE, root mean square error; SAGD, steam assisted gravity drainage; SF, sequential filter; TFP, track fusion prediction; TTF, track to track fusion.

☆ This work was supported by the Natural Sciences and Engineering Research Council of Canada (NSERC).

* Corresponding author.
E-mail addresses: afatehi@ualberta.ca, fatehi@kntu.ac.ir (A. Fatehi), biao.huang@ualberta.ca (B. Huang).

http://dx.doi.org/10.1016/j.jprocont.2017.02.010
0959-1524/

estimates of two individual single-output KFs are fused considering correlation between them. In this approach, each KF utilizes its own estimate at every sampling instant for the prediction step of the next sampling time. The main advantage of TTF is the independence of two estimators from each other. However, this results in sub-optimality of the estimation. Gao & Harris [12] proposed a variation of this method which they called modified TTF (MTTF). It is the same as TTF except that the fused state estimate is used for the prediction step of both individual KFs. The track fusion prediction (TFP) method, also presented by Gao & Harris [12], is the same as MTTF except that after the prediction steps, the predicted states of KFs are first fused and then used for state estimation in the update step of each individual KFs. Similar to MTTF, these two updated state estimates are fused to provide the final state estimate.

The above fusion methods are limited to delay free measurements with equal sampling rate among all sensors. In the presence of multi-rate sampling measurements, the estimation is based only on the fast rate measurement except in the samples at which the slow rate measurements are available, in which, the estimation comes out of fusion of both sensors [13]. In many applications like target tracking [14,15], network communication [16,17], vision-based robot movement or environment estimation [18] and including laboratory measurement for estimation in the process plants [4,19], the multi-rate sensor fusion considers time delays in some of the measurements. To deal with multi-rate time delay problem one can use delayed measurement to update the state estimate at the time when the sample is taken. Then, repeat the KF of frequent (fast rate) measurement for the rest of the samples up to the current time [20]. This method needs a historical data storage as well as large amount of re-computation by the fast rate Kalman filter when the infrequent (slow rate) data becomes available. Alexander [21] studied this problem by updating the filter covariance matrix when the delayed measurement is available. Larsen et al. [20] improved this method by using the concept of extrapolating the measurement output, in which they defined an extrapolated output at the time the lab data is available. This extrapolated output is tuned so that the estimation error using it and the current state estimate is the same as the estimation error at the time the lab sample is taken. The tuned extrapolated output is used in a Kalman filter to update the state estimate, while the gain of the Kalman filter is determined by minimizing the trace of the covariance matrix of the estimation. Penarrocha et al. [22] obtained the state estimate through negative time calculation. Out-of-sequence measurement (OOSM) method [14,23], uses the same concept by state retrodiction of the fast rate estimate to the time the delayed measurement is taken and then incorporate the delayed measurement through sequential filter state estimation. Guangyue et al. [18] fused the state estimate from delayed vision measurement with that of the fast rate sensors in motion estimation of robot end effector using some fusion approximation in the framework of MTTF. Guo and Huang [4] considered two sequential filters using the state and covariance matrix at the time the lab data is sampled to estimate the states at the time the lab data is ready. The effect of their mutual information was extracted from one of them and the residual was fused with the other state estimate. Delayed fusion estimation is also important when data are transmitted over network, where delay time of packet arrival is a random variable. So the fusion should also consider the probabilistic behavior of the communication delay. In [24], the output measurement is re-organized in order to introduce an output based on the innovation of the measurement signal when a delayed measurement is available. Shi et al. [25] used a data storage and recalculation of the state estimate when a delayed data was available. They studied the maximum data storage length to have efficient improvement in the state estimation. Zhu et al. [26] introduced an augmented state space model considering the current and delayed measurement and data availability indices as well as the original model states. Then Kalman filter was used to estimate the state of this model.

In this paper, we present the modified delayed TTF (MDTTF) as the extension of the MTTF method of [12] into the case of multi-rate output when one of the outputs is fast, regular and delay free and the other is slow, irregular and only available after varying delay. In contrast to the method presented in [4], the mutual information is not extracted explicitly from one of the estimates; instead, they are directly fused using optimal fusion method. As a result, its optimality is also guaranteed in the presence of noise. The proposed method is compared with alternative methods for the same problem through simulation and experimental case studies.

The remainder of the paper is organized as follows. The problem statement is explicitly presented in Section 2. In Section 3, the cross-covariance matrix of the state estimations is derived and an iterative Kalman filter fusion algorithm is presented to fuse the state estimates. In Section 4, the presented algorithm is compared to some other methods through simulation and experimental industrial case studies. Section 5 concludes the paper.

2. Problem statement

Consider a chemical process with two sets of sensors. The first set consists of ordinary sensors which provide delay free measurements at a regular yet fast sampling rate. The second set comprises of lab data. As illustrated in Fig. 1, a chemical material sample is taken from the process at some specific time instant s automatically or manually by operators, and sent to the laboratory for analysis. Usually, it takes a long time for the laboratory to analyze the material and provide the measurement at some sample time k_s. This lab data is usually more accurate compared to ordinary fast rate sensors. However, it is slow rate and available after some variable time delay depending upon the time taken for lab analysis. The time interval between two consecutive samples may also be irregular in case samples are collected manually by operators. The problem is to find a method to fuse the fast rate, regular, delay free but less accurate measurement with the slow rate, irregular, delayed but more accurate measurement to improve the state estimation through a Kalman filter.

Consider the following process:

$$x(t+1) = Ax(t) + Bu(t) + w(t) \quad (1)$$

$$y_f(t) = C_f x(t) + v_f(t) \quad (2)$$

$$y_i(k_s) = C_i x(s) + v_i(s) \quad (3)$$

where $x \in \Re^n$ is the state to be estimated, $u \in \Re^m$ is the input vector, $y_f \in \Re^{m_f}$ is the regular and frequent output and $y_i \in \Re^{m_i}$ is the irregular and infrequent measurements. The noises w, v_f and v_i are *i.i.d.* Gaussian with zero mean and covariance matrices Q, R_f & R_i, respectively. All matrices have conformable dimensions. The frequent output y_f is measured at every sampling instant and its

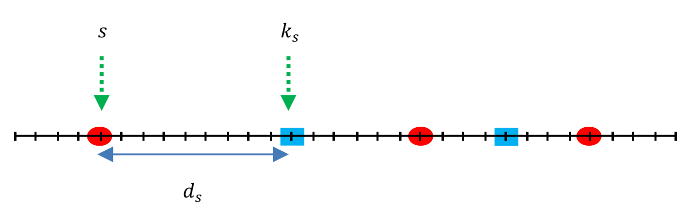

Fig. 1. Time distribution of the process sampling strategy. Black ticks are the fast rate sampling time, denoted by t in the formulations and the red dots denote the time a sample of material is taken for laboratory analysis. This slow rate sample time might be irregular. Blue squares show the time the lab measurement is available. This is the also the time at which the state estimates are fused. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)