Aerospace Science and Technology 39 (2014) 465–471

Contents lists available at ScienceDirect

Aerospace Science and Technology

www.elsevier.com/locate/aescte

Multirate multisensor data fusion for linear systems using Kalman filters and a neural network

Sajjad Safari [a], Faridoon Shabani [a], Dan Simon [b,*]

[a] School of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran
[b] School of Electrical and Computer Engineering, Cleveland State University, Cleveland, USA

ARTICLE INFO

Article history:
Received 11 November 2013
Received in revised form 11 February 2014
Accepted 11 June 2014
Available online 1 July 2014

Keywords:
State estimation
Data fusion
Multirate
Multisensor
Neural network
Kalman filter

ABSTRACT

In this paper the data fusion problem for asynchronous, multirate, multisensor linear systems is studied. The linear system is observed by multiple sensor systems, each having a different sampling rate. Under the assumption that the state space model is known at the scale of the highest time resolution sensor system, and that there is a known mathematical relationship between the sampling rates, a comprehensive state space model that includes all sensor systems is presented. The state vector is estimated with a neural network that fuses the outputs of multiple Kalman filters, one filter for each sensor system. The state estimate is shown to perform better than other data fusion approaches due to the new neural network based sensor fusion approach.

1. Introduction

State estimation is the process of inferring the state of a system from indirect and uncertain observations [1]. Using multiple sensor systems instead of one single sensor system increases the performance of estimation due to the use of complementary information and increased reliability [24]. Data fusion is a process in which data from different sensor systems, observing the same system, are combined to obtain better estimation accuracy [8]. For example, in image processing, one scene may be captured by different cameras with different sampling rates [18]. In earlier data fusion work, the sensor systems observing the process had equal sampling rates, which led to fairly simple data fusion problem with limited applicability [13]. In reality, different sensor systems often use different sampling rates, and the sampling rates are often asynchronous [21].

Various methods have been presented to fuse data from multiple sensor systems. Among them, Carlson presents a method based on Kalman filtering to fuse data from sensor systems having the same sampling rate [3,4]. Kazerooni et al. developed a federated ensemble Kalman filter algorithm [12]. Other popular state estimators, such as particle filters [14] and H-infinity filters [10], have been used. Soft computing methods, such as fuzzy logic [17], genetic algorithms [15], and neural networks [6], have also been used. Wavelet methods have been developed to fuse data from different sensor systems with different sampling rates [5,23]. All of these works have some limitations on the sampling times of the sensor systems and on the relationship between the different sampling rates.

Yan et al.'s algorithm is applicable to systems in which the sensor system sample rates are asynchronous with any known integer sampling rate ratio [22]. In their work the limitation on the sampling rate ratio is relaxed relative to previous research; that is, the ratio between sampling rate ratios is assumed only to be a positive integer. The system model is known only at the finest sampling rate, and they extend the federated Kalman filter [3] to fuse data from the multiple sensor systems.

This paper uses Yan et al.'s method [22] to transform the multirate multisensor system into a single-rate multisensor model. The states of the new system are estimated with a standard Kalman filter, one filter for each sensor system. Then, instead of using a classical method such as a federated Kalman filter, a neural network fuses the estimated state vectors from each Kalman filter. The results are shown to be more accurate than the method of [22]. The results of this paper use the same sampling rate assumptions as in [22]; therefore, the improved results in this paper are due to the neural network based sensor fusion that is proposed here.

This paper is organized as follows. In Section 2, multirate system modeling is reviewed. In Section 3, data fusion and state estimation using the new combination of Kalman filters and a neural

* Corresponding author.
E-mail addresses: s.safari@gmail.com (S. Safari), shabani@shirazu.ac.ir (F. Shabani), d.j.simon@csuohio.edu (D. Simon).

http://dx.doi.org/10.1016/j.ast.2014.06.005
1270-9638/

network is presented. Section 4 presents simulation results, and Section 5 provides a conclusion.

2. Modeling a multirate system

A linear dynamic system with N sensor systems is described as follows [22]:

$$x(N,k+1) = A(N,k)x(N,k) + w(N,k) \tag{1}$$

$$z(i,k) = C(i,k)x(i,k) + v(i,k), \quad i = 1, 2, \ldots, N \tag{2}$$

The state space model is valid at the highest sensor system sampling rate, which is denoted by N. Vector $x(N,k) \in R^{n\times 1}$ is the state variable at the k-th time step at time scale N, which is the same time scale as the highest time resolution sensor system. The system matrix $A(N,k) \in R^{n\times n}$. Vector $x(i,k) \in R^{n\times 1}$ is the state variable at the k-th time step at time scale i, and is generally different than $x(j,k)$ for $j \neq i$ because time scales i and j are different. Note that we do not have a system model for $x(i,k)$ for $i < N$. There are N sensor systems, with the i-th sensor system output at the k-th time step of the i-th time scale denoted by $z(i,k)$, and with $C(i,k) \in R^{q_i \times n}$. The system and measurement noises are independent, white, and zero-mean:

$$E\left\{w(N,k)w^T(N,l)\right\} = Q(N)\delta_{kl} \tag{3}$$

$$E\left\{v(i,k)v^T(j,l)\right\} = R(i)\delta_{ij}\delta_{kl} \tag{4}$$

Sensor system N has the highest sampling rate, and it is the only sensor system that uses uniform sampling. The other sensor systems have lower, and possibly non-uniform, sampling rates. The i-th sensor system sample rate is denoted S_i. The sampling rates of the sensor systems satisfy the following limitation:

$$S_i = S_{i+1}/n_i, \quad i \in [1, N-1] \tag{5}$$

where each n_i is a known positive integer. The n_i parameters are system-specific parameters that depend on the sensor system configuration. The determination of the n_i parameters are part of the system modeling problem, just as the determination of the model parameters in (1)–(4) are part of the system modeling problem.

This relationship given by (5) implies that the highest sensor system frequency is a fixed integer multiple of each of the other sensor system frequencies. There are many factors that affect sample rates in multisensor systems, and the assumption of (5) is restrictive. However, (5) is a reasonable model for many multisensor systems because data from multisensor systems are often fused in a central processor. The central processor often has a fixed rate at which it retrieves data from the multiple sensor systems. Therefore, (5) is often enforced by the architecture of the multisensor system. This is the case in many systems, including navigation systems [7], industrial systems [2], and transportation systems [11], and many others.

The initial state $x(N,0)$ is random with known mean x_0 and known covariance P_0, and is independent of the system and measurement noises.

An example of a multirate multisensor system is shown in Fig. 1. In this figure, there are three sensor systems ($N = 3$). The dynamic system is modeled at the rate S_3, which is the rate of the highest-rate sensor system, or the third sensor system. The second sensor system has sample rate $S_2 = S_3/2$. The first sensor system has sample rate $S_1 = S_2/3$.

The problem in this section is to find an approximate system model that applies to all sensor systems, under the assumption that the system presented in (1) is applicable only for the highest sampling rate N. In another words, our goal is to reformulate the multirate multisensor system as a single-rate multisensor system.

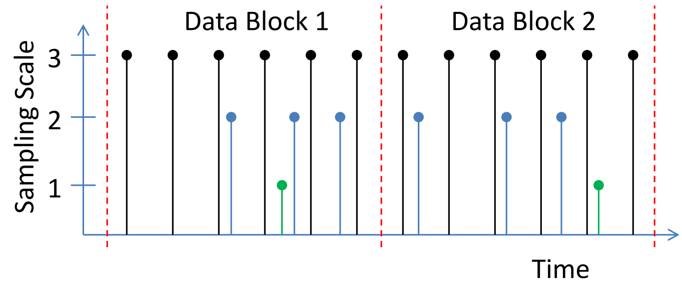

Fig. 1. Example of a multirate, multisensor system. The highest sample rate is sampling scale 3, which is uniform and includes 6 samples per data block. The two lower sample rates are asynchronous, but are constrained to be related to the highest sample rate by a known integer. This figure is adapted from [22].

Then, in the next section, we will deal with the multisensor data fusion problem by using one sampling rate for all sensors, which will be more tractable than the original problem. Based on [22] we approximate the state at time scale k as an average of the state at the highest time scale. That is,

$$x(i,k) \approx \frac{1}{\tilde{M}_i}\sum_{m=0}^{\tilde{M}_i-1} x(N, k\tilde{M}_i - m)$$

$$\tilde{M}_i = \prod_{j=1}^{N-1} n_j \tag{6}$$

for $i \in [1,\ N-1]$. An example will be given later in this section. This approximation gives the following state space model, which applies to all sensor system sampling rates:

$$X_N(k+1) = A_N(k)X_N(k) + W_N(k) \tag{7}$$

$$Z_i(k) = C_i(k)X_N(k) + V_i(k) \tag{8}$$

for $i \in [1, N-1]$, where

$$X_N(k) = \begin{bmatrix} x(N,(k-1)M+1) \\ x(N,(k-1)M+2) \\ \vdots \\ x(N,kM) \end{bmatrix} \tag{9}$$

$$A_N(k) = \begin{bmatrix} 0 & 0 & \cdots & A(N,kM) \\ 0 & 0 & \cdots & A(N,kM+1)A(N,kM) \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \prod_{l=M-1}^{0} A(N,kM+l) \end{bmatrix} \tag{10}$$

$$Z_i(k) = \begin{bmatrix} z(i,(k-1)M_i+1) \\ z(i,(k-1)M_i+2) \\ \vdots \\ z(i,kM_i) \end{bmatrix} \tag{11}$$

$$C_i(k) = \frac{1}{\tilde{M}_i}\operatorname{diag}\left\{C\left(i,(k-1)M_i+1\right)I_{\tilde{M}_i} \quad C\left(i,(k-1)M_i+2\right)I_{\tilde{M}_i} \quad \ldots \quad C(i,kM_i)I_{\tilde{M}_i}\right\} \tag{12}$$

$$M_i = \prod_{j=0}^{i-1} n_j$$

$$M = M_N$$

$$\tilde{M}_N = 1$$

$$n_0 = 1 \tag{13}$$