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Scheduling parallel Kalman filters with quantized deadlines[☆]

Shiyuan Lu[a,b], Zhiyun Lin[a,b,c], Ronghao Zheng[a,b,d,*], Gangfeng Yan[a,b]

[a] College of Electrical Engineering, Zhejiang University, 38 Zheda Road, Hangzhou 310027, PR China

[b] State Key Laboratory of Industrial Control Technology, Zhejiang University, 38 Zheda Road, Hangzhou 310027, PR China

[c] School of Electrical Engineering and Computer Science, University of Newcastle, Callaghan, NSW, 2308, Australia

[d] Zhejiang Province Marine Renewable Energy Electrical Equipment and System Technology Research Laboratory, Zhejiang University, 38 Zheda Road, Hangzhou 310027, PR China

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ABSTRACT

In this paper we explore the problem of scheduling parallel processes of Kalman filters to meet individual estimation error requirements. It is assumed that at each time-step measurements of only one process are received. We define real-time deadlines of transmissions and convert the problem into arranging sequence of tasks with corresponding deadlines. To reduce computations, cycles of transmissions are calculated and virtual processes are introduced into scheduling. A sliding window method is then designed to adjust the processes against real-time disturbances in applications. Compared with algorithms proposed in Lin and Wang (2013), the proposed algorithm is able to schedule a feasible sequence adaptively within a short scheduling window and requires little computation.

1. Introduction

Advances in micro-electro-mechanical system and wireless communication technology have boosted the applications of wireless sensor networks (WSNs). In WSNs, a large number of sensors are deployed in an area to collect environmental information, process data and transmit messages. Sensor scheduling problems are thence proposed to allocate sensor resources for certain optimization objectives, which have attracted wide attention.

Kalman filters are widely applied to sensor scheduling researches in recent years. Since sensor nodes are powered by batteries usually, the communications are always limited to expand network lifetime. Without loss of generality, it is assumed that at each time-step only one sensor is able to transmit data in many works. Gupta et al. [1] designed a sensor switching method to achieve the minimal estimate error covariance through a tree search method. Huber [2] proposed an optimal pruning method to reduce computational costs. Shi et al. [3] considered a periodic scheduling algorithm for two sensors which expands scheduling horizon to infinite. A bounded tree search approach was developed by Shi and Chen [4] for general cases with multiple sensors. Cabrera [5] analyzed the phenomenon of periodic switching between the high quality sensor with delay and the low quality sensor without delay. Orihuela et al. [6] discussed recent works and concluded that a periodic scheduling always exists in Kalman-based algorithm under some mild conditions. In all these works, the communication channels are assumed to be perfect and data drop-outs are not considered.

However, wireless communications are not always reliable in applications. Transmission errors and losses are likely to happen due to interferences. Sinopoli et al. [7] investigated Kalman filters with intermittent observations and derived the upper and lower bounds of estimation error covariance when the arrival rate of observations is above a critical value. Their assumptions, (a) observations are obtained either fully or lost and (b) packet losses obey Bernoulli distribution, are widely adopted in later works and so are in this paper. Shi et al. [8] viewed the problem as the computation of $\Pr(P_k \leq M)$. According to their work, given the upper bound M of error covariance P_k, the number of allowed consecutive drop-outs can be computed and the probability can thus be estimated. Assuming packet loss rate is inversely proportional to transmission energy, Ren et al. [9] developed a dynamic algorithm to minimize the average estimation error with two sensors of differed energy levels and Li et al. [10] equipped sensors with energy harvesters and enabled them to adjust energy levels. Properties of intermittent observations can also be applied

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* Corresponding author at: College of Electrical Engineering, Zhejiang University, 38 Zheda Road, Hangzhou 310027, PR China.

E-mail addresses: linz@zju.edu.cn (Z. Lin), rzheng@zju.edu.cn (R. Zheng).

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into scheduling. For example, Liu et al. [11] explored the covariance optimization with limited number of observations in periodic scheduling. Online algorithms with event triggered mechanism were proposed in [12,13]. In those works, sensor nodes will not transmit observations unless measurement innovations exceed certain thresholds. Instead of scheduling observation sequence of a single process, Lin and Wang [14] considered the idea of scheduling parallel Kalman filters. In that work, every process is corresponding to a sensor and transmissions of sensor measurement should be arranged so that all processes will not exceed their individual estimation error thresholds. Despite the advantage of enhancing system capacities with the parallel method, their computation is complex and the algorithm is not adaptive to interferences.

This paper is based on [14] and presents a fast scheduling algorithm which (a) simplifies the computation of process cycles, reduces the scheduling window size and avoids the numerous tree search operations, (b) is adaptive to packet losses and occasional changes in quality requirements. We follow the assumption that only one process has access to measurement data (observations) at each time-step. In addition, we assume that sensors are able to store consecutive measurements and send the data in a package if the measurement matrix is not full rank. Real-time deadline D_k^i for process s_i at time-step k is defined and estimated, which indicates the maximum update steps without data. When the system is linear and time-invariant, cycles of processes are computed according to [8]. Therefore, the problem is transformed into scheduling periodic tasks with interferences. A sliding window algorithm is designed for scheduling, and all process cycles are specialized to sharpen the window size. Virtual processes are introduced into scheduling so that the sequence without disturbances is determined. In the case of packet losses and system changes in applications, two methods are developed to switch the arranged transmissions of measurement. Compared with the tree pruning method, our algorithm requires considerable less computation to adjust the sequence in the forecast window. Simulations report significant performance improvement against drop-outs in our algorithm.

Notation: We use $b_i|b_j$ to denote that b_j is divisible by b_i. For a set of integers denoted by $D = \{d_1, d_2, \ldots, d_n\}$, the least common multiple of all integers in D is written as LCM$\{D\}$. $\lfloor\ \rfloor$ and $\lceil\ \rceil$ are the rounding symbols with $\lfloor 1.2 \rfloor = 1$ and $\lceil 1.2 \rceil = 2$, for example. For matrices A and B, $A \prec B$(or $A \preceq B$) means $B - A$ is positive definite (or positive semi-definite).

2. Problem formulation

This paper focuses on scheduling parallel Kalman filters to meet individual estimation performances of processes. Linear discrete time system is considered.

2.1. System and sensor models

Consider a system with n independent processes $s_1, s_2, \ldots, s_n$ evolving as follows:

$$\begin{aligned} x_k^i &= A^i x_{k-1}^i + w_{k-1}^i, \\ y_k^i &= C^i x_k^i + v_k^i, \end{aligned} \tag{1}$$

where, for each process s_i at time step k, $x_k^i \in \mathbb{R}^{p^i}$ is the process state to be estimated, $y_k^i \in \mathbb{R}^{q^i}$ is the measurement. $w_k^i \in \mathbb{R}^{p^i}$ is the process noise and $v_k^i \in \mathbb{R}^{q^i}$ is the measurement noise and both are assumed to be white Gaussian and zero mean with covariance matrix Q^i and R^i respectively. A^i and C^i are the system matrix and the measurement matrix, respectively. Moreover, we assume that the pair (A^i, C^i) is observable and $(A^i, \sqrt{Q^i})$ is controllable.

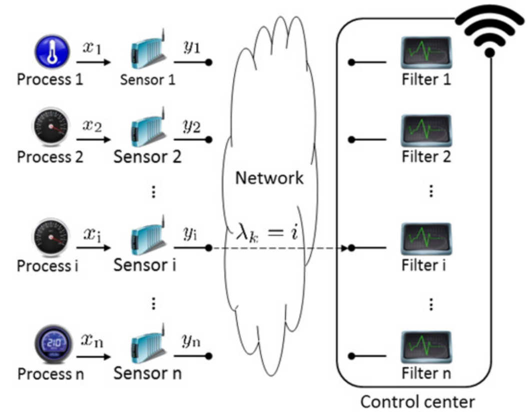

Fig. 1. System framework at time-step k.

2.2. Kalman filter

In this paper, the discrete Kalman filter is applied to estimate the process's state. Define $\hat{x}_{k|k-1}^i$ as the priori state estimate with prior knowledge and $\hat{x}_{k|k}^i$ as the posteriori state estimate with measurement y_k^i at step k. The priori estimation error covariance and the posteriori estimation error covariance are represented by $P_{k|k-1}^i$ and $P_{k|k}^i$, respectively. Thus, a standard Kalman filter can be described as follows:

$$\begin{cases} \hat{x}_{k|k-1}^i = A^i \hat{x}_{k-1|k-1}^i, \\ P_{k|k-1}^i = A^i P_{k-1|k-1}^i (A^i)^T + Q^i. \end{cases} \tag{2a}$$

$$\begin{cases} K_k^i = P_{k|k-1}^i (C^i)^T [C^i P_{k|k-1}^i (C^i)^T + R^i]^{-1}, \\ \hat{x}_{k|k}^i = \hat{x}_{k|k-1}^i + K_k^i (y_k^i - C^i \hat{x}_{k|k-1}^i), \\ P_{k|k}^i = (I - K_k^i C^i) P_{k|k-1}^i. \end{cases} \tag{2b}$$

Kalman filter can be considered having two parts [15]: the 'predict' part (2a), for which the estimate at current step is predicted according to the system model; and the 'correct' part (2b), for which the estimate at current step is updated using the measurement.

2.3. Estimation of parallel processes with a single channel

As shown in Fig. 1, it is assumed that at each time step, only one process's measurement can be sent to the control center to update the estimation. Each process is observed by a Kalman filter and its measurement data are collected by one corresponding sensor.

If measurement data of a process are received in the control center, its estimate and estimation error covariance will be updated by the standard Kalman filter (2). Otherwise, the center only performs the predict part (2a) for the process due to the absence of measurement. For clarity, we define the following functions:

$$\begin{aligned} &h_i(X) \triangleq A^i X (A^i)^T + Q^i, \\ &g_i(X) \triangleq X - X(C^i)^T [C^i X (C^i)^T + R^i]^{-1} C^i X, \\ &[g_i \circ h_i](X) \triangleq g_i(h_i(X)), \\ &[h_i]^j(X) \triangleq \underbrace{h_i \circ h_i \circ \cdots \circ h_i}_{j \text{ times}}(X) = \underbrace{h_i(h_i(\ldots h_i}_{j \text{ times}}(X))). \end{aligned}$$

Let $\lambda_k = i$ indicate that the measurement data of process s_i are received at time-step k. Let $\lambda_k = 0$ indicate that no measurement data is received. Distinguished from the standard Kalman filter, the estimation error covariance of each process s_i is thus updated as follows:

$$P_{k|k}^i = \begin{cases} h_i(P_{k-1|k-1}^i), & \lambda_k \neq i, \\ [g_i \circ h_i](P_{k-1|k-1}^i), & \lambda_k = i. \end{cases} \tag{3}$$