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Saturated Power Control Scheme for Kalman Filtering via Wireless Sensor Networks*

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ABSTRACT

We investigate the Kalman filtering problem via wireless sensor networks over fading channels. When part or all of the observation measurements are lost in a random fashion, we obtain the conclusion that the packet dropout probabilities depend upon the time-varying channel gains and the transmission power levels used by the sensors. We develop a saturated power controller which trades off sensor energy expenditure versus state estimation accuracy. The latter is measured by the expected value of the future covariance matrices provided by the associated time-varying Kalman filter. We study the statistical convergence properties of the error covariance matrix and pointed out the existence of the admissible packet arrival probability bound.

Keywords: Power Control; Kalman Filtering; Fading Channel; Packet Dropout

1. Introduction

Recently, the rapid evolution of wireless sensor networks, see e.g., [1-4] has made wireless sensors (WSs) cheap and reliable enough to be brought into commercial use. WSs offers several advantages for industrial control systems, such as flexibility, low cost, and fast deployment. Furthermore, WSs and actuators can be placed where wires cannot go, or where power sockets are unavailable. The use of wireless communications for state estimation and closed loop control, however, also brings new challenges in system design.

A drawback of using wireless channels is that they are subject to fading and interference, which frequently leads to packet errors [5-8]. Interestingly, the time-variability of the fading channel can be compensated for by adjusting the power levels [9-13]. Since energy is severely limited in most WS applications, power control design involves trading energy consumption for accuracy [14-18]. Thus, an important challenge is to design suitable power control schemes [19].

Kalman filters are widespread in estimation and control applications, and the effect of random measurement losses on filter stability has received considerable attention in the literature. In particular, Sinopoli *et al.* [20] studied a single link estimation setup for linear time-invariant (LTI) plants where the packet dropout processes are independent and identically distributed (i.i.d.). In this modeling paradigm, it was assumed that the packet dropout probability remains unchanged from one transmission to the next, and all the sensor measurements need to be encoded in a single packet and the sensors should be collocated. The result was extended to deal with the general case of multi-channel Kalman filtering problem [21]. The existence of the critical arrival rate of the observation was proved and both the upper and the lower bound were computed. Plarre and Bullo [22] examines a state estimation architecture with two channels affected by i.i.d. packet dropouts. The case of Kalman filtering with a single link was investigated in Huang and Dey [23-25], where the packet dropouts are described by a time homogeneous two-state Markov chain. Zhang [26] considered a multi-rate distributed estimation problem for wireless sensor networks with packet dropout, the output measurements of the adjacent nodes' are utilized to generate the state estimation and then fused. In [27], sufficient conditions are established which ensure the convergence of the Kalman filter co-variance matrix. The conditions obtained are used to formulate stabilizing optimal power allocation laws which minimize the total power used by each sensor.

Inspired by the previous work [27], saturated power

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controllers are designed which provide a time-varying successful probability by inverting the channel gain. We can prove that there exists a critical value such that the expectation of the estimation error covariance is always bounded if the arrival probability of an observation at time is greater than the value. We call the critical value as the admissible packet arrival rate and the computational procedure is presented to design the power controller gain according to the value.

Notation: We write $\Pr(\Omega|\Delta)$ for the conditional probability of Ω given Δ, and $\Pr(\Omega)$ for the unconditional probability. A random vector v, which is Gaussian distributed with mean value m and covariance matrix $\Gamma > 0$ is denoted by $v \sim N(m, \Gamma)$.

2. Problem Formulation

Consider an uncontrolled LTI n-dimensional systems:

$$x_{k+1} = Ax_k + w_k \tag{1}$$

where the initial system state is Gaussian distributed with mean x_0 and covariance P_0. The driving noise process $w_k, k \in N$ is i.i.d., where each $w_k \sim N(0, Q)$.

To remotely estimate the system state sequence $x = x_k (k \in N)$, a network of L sensors is used. Each sensor $l (\in \{1, 2, \cdots, L\})$ provides a nosiy measurement signal, say $y_l = y_{l,k} (k \in N)$:

$$y_{l,k} = C_l x_k + v_{l,k} \tag{2}$$

where $v_l = v_{l,k} (k \in N)$ is an i.i.d. process with each $v_{l,k} \sim N(0, R_l)$

The L values in (2) are transmitted through the wireless links to the single gateway. The received signals are then used to remotely estimate the state of system (1). In the following scenario, we assume that $L = 2$ for the sake of convenience, *i.e.*, there are two measurement outputs encoded separately and sent over different wireless channels at each time step:

$$y_k = \begin{bmatrix} y_{1,k} \\ v_{2.k} \end{bmatrix} = \begin{bmatrix} C_1 \\ C_1 \end{bmatrix} x_k + \begin{bmatrix} v_{1,k} \\ v_{2,k} \end{bmatrix}$$

with $R = \operatorname{cov}(v_{1,k}, v_{2,k}) = \begin{bmatrix} R_1, 0 \\ 0, R_2 \end{bmatrix}$.

2.1. Channel with Rayleigh Fading

In the present work, we will adopt a block-fading channel gain model, which is a common information theoretic model for fading wireless channels where the channel power gains remain invariant over a block [21]. Furthermore, we assume the single measurement $y_l(k)$ to be a packet, thus, the block length equals the packet transmission time. The associated channel gain processes are denoted by $h_l = h_{l,k}$ (“$k \in N$”), which are exponentially distributed with cdf

$$F_{h_{l,k}(h)} = \begin{cases} 1 - e^{-\lambda_l h_l} & \text{if } h_l \geq 0 \\ 0 & \text{if } h_l < 0 \end{cases} \tag{3}$$

where, $\lambda_l > 0$.

Suppose that the binary phase shift keying transmission over the i.i.d. block fading additive white Gaussian noise channels is used [26]. Each sensor measurement consists of a packet containing b bits. Since the bit errors are independent within a packet, the success probabilities can be written as, see [6],

$$f_l(hu) = \left(\int_0^{\sqrt{hu}} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} \mathrm{d}t \right)^b \tag{4}$$

After approximate calculation, we have the following theorem.

Theorem 1

$$f_l(hu) \doteq \left(1 - e^{\frac{2}{\pi}hu} \right)^{\frac{b}{2}} \tag{5}$$

Proof: For a random variable $X \sim N(0,1)$, its cdf can be represented by

$$\Phi_X(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} \mathrm{d}t$$

It is easy to see

$$\begin{aligned} \left[\Phi(a) - \Phi(-a) \right]^2 &= \frac{1}{2\pi} \int_{-a}^{a} \int_{-a}^{a} e^{-\frac{x^2+y^2}{2}} dxdy \\ &= \frac{1}{2\pi} \int_0^{2\pi} \int_0^R e^{-\frac{\rho^2}{2}} \rho d\rho d\theta \\ &= 1 - e^{-\frac{1}{2}R^2} \end{aligned}$$

The second equality is obtained if we approximate square with round, *i.e.*,

$$\pi R^2 = 4a^2$$

and obtain

$$\Phi(a) = \frac{1}{2}(1 \pm \sqrt{1 - e^{-\frac{2}{\pi}a^2}})$$

which yields (5). This ends the proof of Theorem 1.

Since the l links between sensors and gateway are wireless, transmission errors are likely to occur. Faulty packets will be discarded when estimating the system state. We will model transmission effects by introducing the l binary stochastic arrival processes $\gamma_l = \gamma_{l,k} (k \in N)$, where:

$$\gamma_{l,k} = \begin{cases} 1 \text{ if } y_{l,k} \text{ arrives error-free at time } k \\ 0 \text{ if } y_{l,k} \text{ arrives error-free at time } k \end{cases}$$

The success probabilities of $\gamma_{l,k}$ are determined by the propagation environment and transmission power. In the present work, the saturated power controller is used

$$u_{l,k}=\begin{cases}K_l/h_{l,k} & \text{if } h_{l,k}\ge K_l/u_l^{\max}\\ u_l^{\max} & \text{if } h_{l,k}<K_l/u_l^{\max}\end{cases} \tag{6}$$

where $u_l^{\max}$ is the peak power level, and K_l is the power controller gain for the l channel. Moreover,

$$\Pr\left(\gamma_{l,k}=1\middle|h_{l,k}=h,u_{l,k}=u\right)=f_l\left(hu\right) \tag{7}$$

For further reference, we also define the overall arrival process of all *l* links, say $\gamma_l=\gamma_l\left(k\right)_{k\in N}$ via

$$\gamma\left(k\right)=\left[\gamma_1\left(k\right)',r_2\left(k\right)'\right]' \tag{8}$$

We will assume that the data transmission incorporates error detection coding. Hence, the gateway knows the packets received from the sensors contain errors or not. Thus, at any time *k*, the past and present realizations of the overall transmission process are available at the gateway. For state estimation purposes, the system amounts to sampling (1)-(2) only at the successful transmission instants of each sensor link. Indeed, the conditional probability distribution of the system state at any time *k*, given the correctly received sensor measurements up to time *k*, is Gaussian.

Let $\gamma_0^k=\left\{\gamma\left(0\right),\gamma\left(1\right),\cdots,\gamma\left(k\right)\right\},y_0^k=\left\{y_0,y_1,\cdots,y_k\right\}$, we define

$$\hat{x}_{k|k}=E\left[x_k\middle|y_0^k,\gamma_0^k\right]$$
$$P_{k|k}=E\left[\left(x_k-\hat{x}_{k|k}\right)\left(x_k-\hat{x}_{k|k}\right)'\middle|y_0^k,\gamma_0^k\right]$$
$$\hat{x}_{k+1|k}=E\left[x_{k+1}\middle|y_0^k,\gamma_0^k\right]$$
$$P_{k+1|k}=E\left[\left(x_{k+1}-\hat{x}_{k+1|k}\right)\left(x_{k+1}-\hat{x}_{k+1|k}\right)'\middle|y_0^k,\gamma_0^k\right]$$

The time update of the Kalman filter is independent of the observation process and thus stays the same as in the classical Kalman filter:

$$\begin{aligned}\hat{x}_{k+1|k}&=A\hat{x}_{k|k}\\ P_{k+1|k}&=AP_{k|k}A'+Q\end{aligned} \tag{9}$$

The measurement update is now stochastic since the received measurements depend on the random variables $\gamma_{1,k}$ and $\gamma_{2,k}$.

Let $P_k=P_{k|k-1}$, a general form of the error covariance matrix is given by

$$\begin{aligned}P_{k+1}=&AP_kA'+Q-\gamma_{1,k}\gamma_{2,k}AP_kC'\left(CP_kC'+R\right)^{-1}CP_kA'\\ &-\gamma_{1,k}\left(1-\gamma_{2,k}\right)AP_kC_1'\left(C_1P_kC_1'+R_1\right)^{-1}C_1P_kA'\\ &-\left(1+\gamma_{1,k}\right)\gamma_{2,k}AP_kC_2'\left(C_2P_kC_2'+R_2\right)^{-1}C_2P_kA'\end{aligned} \tag{10}$$

In the next section, we will focus on the statistical properties of the error estimation covariance P_k.

3. Convergence Conditions

First, we define the modified algevraic Riccati equation for the Kalman filter with random packet dropout as follows,

$$\begin{aligned}g_{\lambda_1\lambda_2}\left(X\right)=&AXA'+Q-\lambda_1\lambda_2AXC'\left(CXC'+R\right)^{-1}CXA'\\ &-\lambda_1\left(1-\lambda_2\right)AXC_1'\left(C_1XC_1'+R_1\right)^{-1}C_1XA'\\ &-\left(1+\lambda_1\right)\lambda_2AXC_2'\left(C_2XC_2'+R_2\right)^{-1}C_2XA'\end{aligned} \tag{11}$$

Some useful properties of the function $g_{\lambda_1\lambda_2}\left(X\right)$ are presented and the proof can be found in [21].

Lemma 1 [21] $g_{\lambda_1\lambda_2}\left(X\right)$ is concanve and nondecreasing function in *X*.

Lemma 2 [21] For fixed $0<\lambda_1<1$, $g_{\lambda_1\lambda_2}\left(X\right)$ is decreasing in λ_2, vice versa for λ_1.

Lemma 3 [21] $Eg_{\lambda_1\lambda_2}\left(X\right)\le g_{\lambda_1\lambda_2}\left(EX\right)$.

Lemma 4 [21] Suppose $\exists$ matrices $\bar{K},\bar{K}_1,\bar{K}_2$ and $\bar{P}>0$ such that $\bar{P}\ge\varphi\left(\bar{K},\bar{K}_1,\bar{K}_2,\bar{P}\right)$, then

a) $\forall P_0\ge 0$, the iteration $\bar{P}_{k+1}=g_{\lambda_1\lambda_2}\left(\bar{P}_k\right)$ converges and

$$\lim\text{it}_{k\to\infty}g_{\lambda_1\lambda_2}^k\left(\bar{P}_0\right)=\bar{P} \tag{12}$$

independent of initial condition P_0.

b) $\bar{P}$ is the unique positive semidefinite solution of $\bar{P}_{k+1}=g_{\lambda_1\lambda_2}\left(\bar{P}_k\right)$

Lemma 5 [21] Assuming $\left(A,Q\right)$ is controllable and $\left(A,C\right)$ observable. Fix $0\le\lambda_1\le 1$. If $g_{\lambda_1\lambda_2}\left(P_k\right)$ is unstable for $\lambda_2=0$, whereas stable for $\lambda_2=1$, then $\exists\lambda_{2c}\le 1$ such that

$$\lim\text{it}_{k\to\infty}E\left[P_k\right]=+\infty\ \text{ for }\lambda_2\le\lambda_{2c} \tag{13}$$

Furthermore, there exists a positive semidefinite matrix $M_{P_0}>0$ as a function of the initial condition $P_0>0$, such that

$$E\left[P_k\right]\le M_{P_0},\forall t\ \text{ for }\lambda_{2c}\le\lambda_2\le 1 \tag{14}$$

The vice visa for fixed λ_2.

The following theorem gives the power controller gain region for the above critical value $\lambda_{ic}\left(i=1,2\right)$.

Theorem 2 Assuming $\left(A,Q\right)$ is controllable and $\left(A,C\right)$ observable. Fix $0\le\lambda_1\le 1$. If $g_{\lambda_1\lambda_2}\left(P_k\right)$ is unstable which meets (13), then the corresponding power controller gain satisfies

$$K_l>\frac{\pi}{2}\ln\left(1-\sqrt[\frac{b}{2}]{\lambda_{2c}}\right) \tag{15}$$

for λ_{2c} mentioned above.

Proof: The proof is established based on Theorem 1 and Lemma 5. When $\lambda < \lambda_{2c}$, Equation (5) has an equivalent form

$$h_l u_l > \frac{\pi}{2}\ln\left(1-\sqrt[\frac{b}{2}]{\lambda_{2c}}\right)$$

when $K_l < h_l u_l^{\max}$, we can easily obtain

$$K_l = h_l u_l > \frac{\pi}{2}\ln\left(1-\sqrt[\frac{b}{2}]{\lambda_{2c}}\right)$$

when $K_l > h_l u_l^{\max}$, we obtain $u_l = u_l^{\max}$ from (6), which yields

$$K_l > h_l u_l^{\max} > h_l u_l$$

this ends the proof of Theorem 2.

The distributed protocol mentioned above is sketched below:

Procedure:

Step 1) For given $0 < \lambda_1 < 1$, we use bisection method to find λ_{2c}. For $\forall \varepsilon > 0$, search the $[0,1]$ interval to find some λ_2^1, such that $\left|g_{\lambda_1\lambda_2}(P_{k+1}) - g_{\lambda_1\lambda_2}(P_k)\right| < \varepsilon$.

Step 2) For the same $\varepsilon > 0$ and $0 < \lambda_1 < 1$, search the $[\lambda_2^1, 1]$ interval to find some λ_2^2, such that $\left|g_{\lambda_1\lambda_2}(P_{k+1}) - g_{\lambda_1\lambda_2}(P_k)\right| < \varepsilon$. Use this method, we can find the greatest lower bound of the critical value λ_{2c}.

Step 3) Design the power controller gain according to the above admissive upper bound obtained in Step 2).

Remark 1 It follows from the reasoning above that one can improve the transmission reliability and the state estimation accuracy for a given wireless propagation environment simply by increasing the power controller gain used by the transmitter. However, it is of fundamental importance to save energy in wireless sensor networks. There is the tradeoff between the stability of Kalman filter and a energy resource.

4. Conclusions

An energy efficient power control scheme for state estimation via wireless sensor networks operating over fading channels was presented. The time variability of the fading channels frequently leads to transmission errors with subsequent random packet drops. State estimation in the face of intermittent observations was then performed by a time-varying Kalman filter. In our scheme, the transmission power of the radio amplifier of each of the wireless sensors was controlled by the gateway. For that purpose, we proposed a saturated power controller.

The results in this paper can also be generalized to the case where the observation data is contained in more than two packets. In the generalization, the Kalman filter updating upon one or more packet losses can be computed in the same manner since we can always divide the observation into two parts: the received and the lost. The statistical properties of the error covariance matrix iteration stay the same with appropriate extensions. In our future work, we would like to study the convergence properties of the Kalman filtering problem.

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