Gain Scheduling for Sampled-data State Estimation over Lossy Networks

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This paper proposes a design method for sampled-data state estimator over lossy networks. When a measurement signal loss is detected, the proposed estimator switches gains and continues to update the estimate based upon last received measurement. The gains are computed in advance by means of a common solution of linear matrix inequalities so that the estimation is suboptimal with respect to the mean square error in the steady state. The effectiveness of the proposed method is illustrated/evaluated via numerical simulations.

1. Introduction

State estimation has a long history of research since Kalman filtering[1]. Even today, it confronts a new challenge that emerges along with the advent of IoT technology[2]. In networked/remote control systems we often encounter situations where measured signals are lost from time to time, due to transmission error or temporal sensing failure; e.g., packet loss in narrow communication channels, eyesight drop-off due to occlusion, to name a few. Such failure usually recovers soon and it is enough to resend the signal in most cases. This might be fatal, however, in real-time applications like measurement and control.

Tadenuma et al.[3] have proposed, in a deterministic framework, a gain switching state observer to address this issue, under the assumption that i) the maximal length of successive signal loss is known at design time; and ii) the loss can be detected at the same time as it happens in operation. When the loss is detected, the observer switches gains and continues to update estimation based upon last received measurement. Stability of the error system is guaranteed by means of switched quadratic Lyapunov functions (SQLF)[4], which are derived by solving linear matrix inequalities (LMIs). This approach is furthermore applicable to the so-called round-robin scheduling architecture[3]. It is then generalized to feedback control systems design where actuator command signal may also be lost[5]. This setting appears natural since the feedback loop has both paths to/from the remote plant. We have to use, however, a special acknowledgment packet to detect actuator command signal loss, which requires additional architecture. We thus confine ourselves to the state estimation as above in the present paper. Such a problem may be found when, for example, an in-vehicle controller uses remote visual sensing with wireless communication[3].

The above works have mainly focused upon stability issues under gain switching, though we can introduce a decay rate in the LMIs. Yet it is more desirable in practice if we also guarantee some stochastic performance[6], further to stability. Naturally we are unable to design optimal estimator since it is unpredictable when and how long signals are lost. In this paper we aim at designing a gain switching state estimator that is suboptimal with respect to a mean square error. Instead of its minimization, we let it be less than a specified value, under any signal loss pattern satisfying the successive length condition. Whether or not such estimator exists depends on solvability of a certain set of LMIs.

State estimation over lossy networks has been extensively studied in literature; see [2,7–9] for recent works among others. Okano et al.[7] studied a Markovian lossy channel for observation. Okajima[8,9] proposed to use median to compensate outliers in observed signals, and gave an observer design method based on a robust invariant set. This approach is relevant to the present paper in that common solutions for LMIs play a key role in the design. To the present authors’ best knowledge, however, no research has been made so far on the suboptimal design in terms of

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mean square error in switching state estimation over lossy networks.

The remainder of this paper is organized as follows. After formulating our problem in 2, we give a solution in 3. In 4 two kinds of numerical simulation are carried out. The one is a simple example to illustrate our method and the other is to evaluate the method in a rather practical situation. In 5 we mention some discussions from SSS '20.

**Notations.** \( \mathbb{E}[X] \) denotes the expectation of random variable \( X \). \( \mathbb{R}, \mathbb{R}^+ \) and \( \mathbb{N} \) are the sets of all real numbers, all real nonnegative numbers, and all non-negative integers, respectively. Dirac's delta function is denoted by \( \delta(\cdot) \) and Kronecker delta is \( \delta_{i,j} = \begin{cases} 1, & (i=j) \\ 0, & (i \neq j) \end{cases} \).

The floor function of \( t \in \mathbb{R}^+ \) is defined by

\[
[t] = k \in \mathbb{N} \quad \text{if} \quad t \in [k,k+1).
\]

\( A^T, \text{tr}A, \) and \( \det A \) respectively mean the transpose, trace, and determinant of matrix \( A \). For brevity, we write \( A^{-1} := (A^T)^{-1} = (A^{-1})^T \) and \( A^j := (A^j)^T \) for \( j = 1, 2, \ldots \), with slight abuse. \( I_n \) stands for the \( n \)-th order identity.

**2. Problem Formulation**

Let a continuous-time linear state space model be

\[
\begin{align*}
\dot{x}(t) &= Ax(t) + Gw(t), \\
y(t) &= Cx(t) + Hv(t),
\end{align*}
\]

where \( t \in \mathbb{R}^+ \) is time, \( x \in \mathbb{R}^n \) is the state to be estimated, \( y \in \mathbb{R}^p \) is the measured signal, \( w \in \mathbb{R}^r \) and \( v \in \mathbb{R}^p \) are white Gaussian noises such that

\[
\begin{align*}
\mathbb{E}[w(t)] &= 0, \quad \mathbb{E}[v(t)] = 0, \\
\mathbb{E}
\begin{bmatrix}
w(t) \\
v(t)
\end{bmatrix}
\begin{bmatrix}
w(t') \\
v(t')
\end{bmatrix}^T
&= I_{r+p}\delta(t-t')
\end{align*}
\]

for any \( t,t' \in \mathbb{R}^+ \). We assume that \( A,C,G, \) and \( H \) are known matrices of appropriate sizes, the pair \((A,C)\) is observable, \( G \) has rank \( r \), and \( H \) is nonsingular. Let \( x(0) = 0 \) for simplicity.

If we can use continuous-time state estimator

\[
\hat{x}(t) = Ax(t) + L(y(t) - C\hat{x}(t)), \quad \hat{x}(0) = 0,
\]

then it is well known[1,6] that the Kalman filter is optimal in the sense that it minimizes

\[
\lim_{t \to \infty} \mathbb{E}[\|e(t)\|^2],
\]

where the estimation error is defined by

\[
e(t) = x(t) - \hat{x}(t).
\]

In this paper, on the contrary, we consider sampled-data measurement over a lossy channel, where \( y \) is not available continuously but we receive it through a lossy sampler \( S \) and a last received signal hold \( H \); see Fig. 1 for an image of signals through the lossy channel. To be more specific, let a given number \( \Delta > 0 \) be a basic period. We define

\[
(\mathcal{H}S\varepsilon)(t) = \varepsilon(t_k), \quad t \in [t_k, t_{k+1}), \quad k \in \mathbb{N}
\]

where

\[
t_0 = 0; \quad \text{and} \quad t_{k+1} - t_k = h_k \Delta, \quad h_k \in \{1, \ldots, n+1\}
\]

We assume that the time sequence \( \{t_k\}_{k \in \mathbb{N}} \) is unknown (i.e., signal loss is unpredictable) at design time but that we set an upper bound \( \bar{h} \in \mathbb{N} \) of successive signal loss length. The latter is a technical assumption to keep the number of LMI's finite (see 3), and might be a drawback in practice. We will evaluate performance degradation when this is violated via simulation (4).

In this setting we assume, instead of (2), that

\[
\begin{align*}
\mathbb{E}[w(t)] &= 0, \quad \mathbb{E}[v(\kappa \Delta)] = 0, \\
\mathbb{E}
\begin{bmatrix}
w(t) \\
v(t)
\end{bmatrix}
\begin{bmatrix}
w(t') \\
v(t')
\end{bmatrix}^T
&= I_{r+p}\delta(t-t')
\end{align*}
\]

for any \( t,t' \in \mathbb{R}^+ \) and \( \kappa, \kappa' \in \mathbb{N} \).

The signal arrival pattern (6) is unknown when designing the estimator, but we can detect signal arrival/loss in real time. If loss is detected, we may want to reuse a previously received signal with a different gain from (3). We address this issue by switching the gains successively. Namely we adopt

\[
\dot{x}(t) = A\tilde{x}(t) + L_{\sigma(t)}(y(t_k) - C\tilde{x}(t_k)), \quad \sigma(t) = [(t-t_k)/\Delta], \quad t \in [t_k, t_{k+1}).
\]

\( L_{\sigma(t)} \) depends on the number \( \sigma(t) \) of how many times the signal \( y \) is lost in succession before time \( t \) (Figs. 1 and 2). Hence the suffix \( \sigma(t) \) is a function of \( t \in \mathbb{R}^+ \) taking values in \( \{0, \ldots, \bar{h}\} \).

Stability of the above estimator is discussed in[3]. On the other hand, our problem in the present paper is to find suboptimal gains \( L_0, \ldots, L_{\bar{h}} \) such that, for given \( \gamma > 0 \), the estimation error in (5) satisfies the performance
unpredictable when we can receive the next signal is availabe/unavailable at a current time, but it is
We should note that, we can judge if the measurement for any arrival pattern (6).

Fig. 2 Block diagram of the proposed state estimator with signals at time \( t \in \mathbb{R} \)

\[
\begin{align*}
  & t := 0, h := 0, \hat{x} := 0, y := 0 \\
  & k := k + 1 \\
  & \text{Update } \hat{e} \\
  & t_k := t, h := 0 \\
  & \hat{C} := y - C\hat{x} \\
  & h := h + 1 \\
  & \text{Reuse previous } \hat{e} \\
  & \hat{x} := e^{A\Delta}x + L_h \hat{C}x \\
  & \text{no} \\
  & \text{yes} \\
  & \text{Receive new } y? \\
\end{align*}
\]

Fig. 3 Flowchart of switching gains

\[
limsup_{k \to \infty} \mathbb{E}[\|e(t_k)\|^2] < \gamma^2 \tag{9}
\]

for any arrival pattern (6).

Fig. 3 indicates how our state estimation proceeds. We should note that, we can judge if the measurement is available/unavailable at a current time, but it is unpredictable when we can receive the next signal successfully. In other words, at time \( t \in (t_k, t_{k+1}) \) in (6), \( t_k \) and \( t \) are available while \( t_{k+1} \) is not. We need to schedule gains \( L_0, \ldots, L_\bar{h} \) in this situation.

3. Main Results

We first define matrices

\[
A = e^{At}, \quad \Gamma = \int_0^\Delta e^{At}d\tau, \tag{10}
\]

\[
Q_h = \int_0^{h\Delta} e^{At}G(e^{At}G)^T d\tau, \quad R = HH^T \tag{11}
\]

and, for the gains \( L_0, \ldots, L_\bar{h} \) to be designed,

\[
L_h = \int_0^{h\Delta} e^{A(h\Delta - \tau)}L_{(\tau/\Delta)}d\tau \tag{12}
\]

for \( h \in \{1, \ldots, \bar{h} + 1\} \).

Now suppose that we are given a signal arrival pattern (6). Then by (1) and (8) we have

\[
\dot{e}(t) = Ae(t) + Gw(t) - L_h(t)(C\hat{e}(t) + Hv(t)) \quad \text{for } t \in [t_k, t_{k+1}),
\]

which is solved as

\[
\dot{e}(t) = e^{At-h_k}e(t_k) + \int_{t_k}^t e^{A(t-\tau)}Gw(\tau)d\tau - \int_{t_k}^t e^{A(t-\tau)}L_{0}(C\hat{e}(t) + Hv(t)) \tag{13}
\]

in the same interval.

We are able to show the following lemma.

**Lemma 1.** The error covariance matrix \( X_k = \mathbb{E}[e(t_k)e^T(t_k)] \), \( k \in \mathbb{N} \) satisfies recurrence formula

\[
(\mathcal{A}_h - L_h C)X_k(\mathcal{A}_h - L_h C)^T - X_{k+1}
+ Q_h + L_h R L_h^T = 0, \quad k = 0, 1, \ldots. \tag{15}
\]

To prove Lemma 1, we first show the following.

**Claim 1.** By taking \( t \uparrow t_{k+1} \) in (13) we obtain recurrence formula

\[
\dot{e}(t_{k+1}) = (\mathcal{A}_h - L_h C)\dot{e}(t_k)
+ \int_{t_k}^{t_{k+1}} e^{A(t_{k+1} - \tau)}Gw(\tau)d\tau - L_h H v(t_k). \tag{16}
\]

**Proof of Claim 1.** Substitute \( t = t_{k+1} \) in the right-hand side of (13). Then the first term becomes \( \mathcal{A}_h \dot{e}(t_k) \). To compute the second term, we divide the integral interval as

\[
\int_{t_k}^{t_{k+1}} e^{A(t_{k+1} - \tau)}L_{0}(C\hat{e}(t) + Hv(t))d\tau
= \sum_{j=0}^{h-1} \int_{t_k+j\Delta}^{t_k+(j+1)\Delta} e^{A(t_{k+1} - \tau)}L_{j}d\tau. \tag{17}
\]

By putting \( \tau' = t_{k+1} + (j+1)\Delta - \tau \),

\[
\begin{align*}
& \int_{t_k+j\Delta}^{t_k+(j+1)\Delta} e^{A(t_{k+1} - \tau')}d\tau' \\
= & \int_0^{\Delta} e^{A(t_{k+1}-t_{k} -(j+1)\Delta + \tau')}d(-\tau') \\
= & \int_0^{\Delta} e^{A\hat{h}_k-\hat{h}_k-1 \hat{h}_k}d(-\tau') \quad \text{by (6)} \\
= & \Gamma(\mathcal{A}_{\hat{h}_k-\hat{h}_k-1}L_0 + \ldots + A\mathcal{L}_{\hat{h}_k-\hat{h}_k-1} + \mathcal{L}_{\hat{h}_k-\hat{h}_k-1})L_{\hat{h}_k} \quad \text{by (10)},
\end{align*}
\]

for \( j = 0, \ldots, \hat{h}_k - 1 \). Then the right-hand side of (17) is

\[
\Gamma(\mathcal{A}_{\hat{h}_k-\hat{h}_k-1}L_0 + \ldots + A\mathcal{L}_{\hat{h}_k-\hat{h}_k-1} + \mathcal{L}_{\hat{h}_k-\hat{h}_k-1})L_{\hat{h}_k}
\]

This shows (16), as expected.

**Proof of Lemma 1.** By using (16) and (2) we compute
Lemma 2. Let $X>0$ be such that

$$
(A^b - \mathcal{L}_h C) X (A^b - \mathcal{L}_h C)^T + Q_h + L_h R L_h^T < 0 \quad \text{for } h = 1, \ldots, \bar{r} + 1.
$$

(18)

For any signal arrival pattern (6), define the error covariance matrix $X_k$ by (14). Then

$$
X_k < X \quad \text{for all } k \in \mathbb{N}
$$

and hence

$$
\limsup_{k \to \infty} \mathbb{E} [||e(t_k)||^2] < \text{tr}X.
$$

(19)

Proof of Lemma 2. We subtract (15) from (18)

and obtain

$$
F_k (X - X_k) F_k^T - (X - X_{k+1}) < 0, \quad k \in \mathbb{N},
$$

where

$$
F_k = A^{b_k} - \mathcal{L}_h C.
$$

Hence we have

$$
X - X_{k+1} \succ F_k (X - X_k) F_k^T \succ \cdots \succ F_k \cdots F_k X F_k^T \cdots F_k^T \succ 0.
$$

Here we have used $X_0 = \mathbb{E} [e(0) e(0)^T] = 0$.

The above matrix inequality means that $X \succ X_k$ for any $k \in \mathbb{N}$. By properties of the trace, we obtain

$$
\text{tr}X > \text{tr}X_k = \mathbb{E} [||e(t_k)||^2].
$$

Hence (19) holds by the above bound.

Now we are ready to give our main result.

Theorem. Assume that LMIs

$$
\begin{pmatrix}
-X Y A^b - K_h C & Q_h^{1/2} - K_h H \\
* & -Y \\
* & * & -I_n \\
* & * & * & -I_p
\end{pmatrix} < 0,
\tag{20}
$$

have solutions $W, Y, K_1, \ldots, K_{\bar{r}+1}$. Then the switching state estimator (8) with the gains

$$
\begin{align*}
L_0 &= \Gamma^{-1} Y^{-1} K_1, \\
L_{h-1} &= \Gamma^{-1} Y^{-1} K_h - A^{b-1} L_0 - \cdots - A L_{h-2}, \quad h = 2, \ldots, \bar{r} + 1
\end{align*}
$$

(22)

satisfies the performance (9) for any signal arrival pattern (6).

Proof. By (22) we have

$$
Y^{-1} K_h = \Gamma (A^{b_h-1} L_0 + \cdots + L_{h-1}) = \mathcal{L}_h,
$$

for $h = 1, \ldots, \bar{r}$. Put $X = Y^{-1}$. Then (20) becomes

$$
\begin{pmatrix}
X^{-1} - X^{-1} (A^b - \mathcal{L}_h C)^T & X^{-1} Q_h^{1/2} - X^{-1} \mathcal{L}_h H \\
* & -X^{-1} \\
* & * & -I_n \\
* & * & * & -I_p
\end{pmatrix} < 0.
$$

Then by Schur complement we have

$$
X^{-1} (A^b - \mathcal{L}_h C) X (A^b - \mathcal{L}_h C)^T X^{-1} - X^{-1} + X^{-1} (Q_h + \mathcal{L}_h R \mathcal{L}_h^T) X^{-1} < 0.
$$

Pre- and postmultiplying this matrix inequality both by $X$, we obtain (18). By (21) we have $\text{tr}X < \gamma^2$. Hence (9) is satisfied by Lemma 2.

4. Numerical Simulation

Numerical simulation has been carried out to illustrate/evaluate the proposed method. Let us put

$$
A = \begin{pmatrix} 0 & -0.01 \\ 1 & -0.1 \end{pmatrix}, \quad G = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad C = (0 \ 1), \quad H = 0.1
$$

(23)

in the continuous-time noise model (1) and $\Delta = 0.1$ as a basic sampling period.

4.1 Illustration with a Simplest Case

We first consider a simple lossy sampling with $\bar{r} = 2$. In this case, LMIs (20) and (21) are solved for $\gamma = 0.8$, which is almost as small as possible (in fact, the LMIs are unsolvable for $\gamma = 0.7$). Then switching gains $L_0, L_1, L_2$ are computed by the proposed method.

By Theorem 1, the proposed state estimator satisfies the mean square error condition (9) for any signal loss pattern as far as the length of successive loss is less than or equal to $\bar{r} = 2$. To illustrate this, we take a specific loss pattern that repeats RLRLL (with R, L denoting received and lost, respectively) for simulation; see Table 1 for the resulting receiving times.

Fig. 4 shows the loss pattern and time evolution of the state variables and their estimations by the proposed and conventional methods (Kalman filtering designed by algebraic Riccati solution). It appears that the proposed method (dashed) successfully follows the true values (solid) in spite of the signal loss.
Table 1 Receiving times by signal loss pattern of 4.1

| $t_k$ | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 |
|------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $t_i$ | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | 29 | 30 | 31 | 32 | 33 | 34 | 35 | 36 | 37 | 38 | 39 | 40 | 41 | 42 | 43 | 44 | 45 | 46 | 47 | 48 | 49 | 50 |

Fig. 4 Sample paths of the state variables and their estimations

Fig. 5 Mean square errors by a thousand realizations for the both methods and their theoretical bounds

Kalman filter without switching (long dashed) naturally fails to follow the true values while Kalman filter with switching (i.e., we take zero gain at the time of signal loss; dotted) gives similar estimation to the proposed method. This feature is further verified by Fig. 5 which indicates the mean square errors of the estimations by a thousand realizations together with its theoretical bounds.

4.2 Evaluation by more complex cases

We next put $\bar{h} = 4$ in the noise model (23). Then we can solve LMIs (20) and (21) for $\gamma = 0.96$, which is close to the smallest value. In fact, they are unsolvable for $\gamma = 0.95$.

If the number of successive loss is less than or equal to $\bar{h} = 4$, then the mean square error condition (9) is theoretically guaranteed by the Theorem. This has been verified by simulation of a thousand realizations, as in 4.1, but we omit to show its figure.

In this subsection, we test a more practical situation. In order to simulate lossy sampling we adopt what is called simplified Gilbert model which is often used in tc command to emulate lossy networks; see Fig. 6. Note that this model does not necessarily satisfy the assumption of the Theorem. In fact, as in the following simulation results, the number of successive loss sometimes exceeds $\bar{h}$. For such cases we reuse $L_\pi$ in the proposed method for convenience; i.e., we put $L_h = L_\pi$ if $h \geq \bar{h}$.

Fig. 6 Simplified Gilbert model

We first put the transition probabilities $p = 0.6$ (from “receive” to “loss”) and $r = 0.4$ (from “loss” to “receive”). Fig. 7 shows a realization of signal loss pattern and sample paths. Fig. 8 shows another realization. Fig. 9 shows the mean square error by 1000 realizations in this case. The result shows that the error bound by the proposed method is satisfied in spite that the loss sometimes exceeds the bound.

This is, however, not guaranteed for all conditions. Figs. 10 and 11 show that the error bound is not satisfied for the case of $p = 0.6$ and $r = 0.2$, namely when the loss happens more often. In these conditions the proposed method gives better performance than the switched Kalman filter but this is not theoretically guaranteed, either.

5. Discussion

Some precious comments arised when a preliminary version of this study was presented in SSS ’20 (as referred in the footnote of the top page). Below are the authors’ replies to them.

Comment: Do the LMIs become difficult to solve as the number of them becomes larger?

Reply: Yes. As shown in 4., the LMIs are sometimes difficult to solve when $\bar{h}$ is large or $\gamma$ is small.

Comment: In practice it seems difficult to find appropriate $\bar{h}$.

Reply: Yes. However, as shown in 4.2, even if the successive loss sometimes exceeds the bound $\bar{h}$, the performance remains acceptable. Furthermore, the authors consider that a hybrid design is feasible. This idea will be presented elsewhere.

Comment: The problem appears to be solvable also by means of time-varying Kalman filtering, since the loss at time $t$ may be regarded as the case of $C(t) = 0$. 

– 13 –
Reply: Yes, the proposed method includes a switching Kalman filter as a special case by letting $\gamma \to \min$ numerically, as shown in the examples above. In Theorem 1, we can incorporate other specifications than the mean square error by adding further LMIs. But it is left as our future work to further inspect relations of the proposed method and Kalman filtering, the latter of which is a tribute of long history of research.

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