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Kalman Filter-based Identification of Systems with Randomly Missing Measurements and Linear Constraints ⋆

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Abstract: The available information of linear constraint in linear dynamic systems, which is often unexplored in previous works, is taken advantage of to improve the accuracy of the parameter estimation, particularly in the presence of randomly missing measurements. Specifically, a Kalman filter-based identification for systems without constraint but with the randomly missing measurements is first introduced. Then the result is extended to systems with linear constraint under normal conditions. By doing so we show that the accuracy of the estimation is improved by taking the constraint into account, both theoretically and numerically.

Keywords: system identification, Kalman filter, constraint, randomly missing measurements.

1. INTRODUCTION

Dynamic models are often taken for granted in the development of any control methodologies. To obtain these models in reality, however, requires an essential step called "system identification" which tries to build the model from measured data. System identification has been the focus of the control community for more than half a century since its first introduction by Zadeh in 1956 , and it is now not surprising to see that system identification has been a very general topic, with different techniques proposed for different models to be identified: linear, nonlinear, hybrid, etc. Two main avenues can be seen in the development of system identification. One is the realization approach, i.e., the realization of linear state-space models from impulse responses, Ho and Kalman (1966), leading to so-called subspace methods, e.g. Larimore (1983), Van Overschee and DeMoor (1996). The other avenue is the prediction-error approach, more in line with statistical time-series analysis and econometrics. For more information on this approach please refer to Astrom and Bohlin (1965).

System identification requires the observed input-output data to do its job. However, this information is often unobservable or missing in the practical environment. For example, in networked control systems, the measurements often randomly miss due to the imperfect communication channels. In dual-rate systems, the output data is often missing due to the intersample output (Ding and Chen (2005)). Therefore, this poses a challenge of identifying the system with missing measured data.

To meet this challenge, a frequency domain solution is proposed in Pintelon and Schoukens (2000) which treats all missing measurements as parameters, potentially leading to a large amount of parameters to be identified. Yang Shi and Huazhen Fang (2010) show a Kalman filter-based identification for systems with randomly missing measurements in a network environment. Different from these existing methods, in this paper, we first model the input and output missing as two separate Bernoulli processes, then design a missing output estimation and finally develop a recursive algorithm for parameter estimation by modifying the Kalman filter-based algorithm. Compared with Yang Shi and Huazhen Fang, by using the information in the parameter estimation process, the accuracy of parameter estimation is improved (Mahata Kaushik (2004)).

The rest of the paper is organised as follows. The problem is formulated in Section 2, which also includes the output estimator and the recursive algorithm for parameter estimation by modifying the Kalman filter-based algorithm in [10]. In Section 3, we derive the constraint of the system and give the recursive algorithm for parameter estimation by modifying the constraint of Kalman filter-based algorithm. In Section 4, convergence properties of the proposed algorithms are analysed. In Section 5, an illustrative example is given to show the effectiveness of the method proposed. Section 6 concludes the paper.

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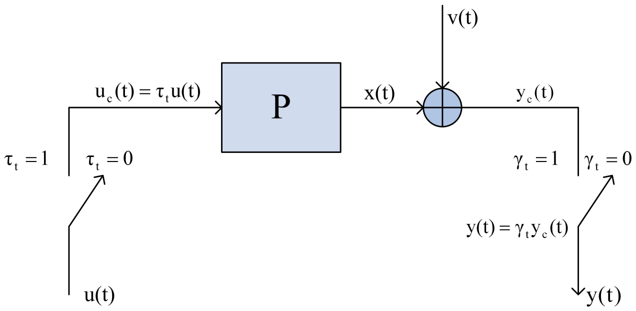

Fig. 1. the NCSs scenario

2. PROBLEM FORMULATION

Similar to [10], consider the following system as illustrated in Fig. 1,

$$x(t) = P_z u_c(t) = \frac{\beta(z)}{\alpha(z)} u_c(t) \tag{1}$$

$$y_c(t) = x(t) + v(t) \tag{2}$$

$$u_c(t) = \tau_t u(t) \tag{3}$$

$$y(t) = \gamma_t y_c(t) \tag{4}$$

where P_z is the discretization of the continuous plant P and is given as

$$P_z = \frac{\beta_0 + \beta_1 z^{-1} + \beta_2 z^{-2} + \cdots + \beta_n z^{-n_\beta}}{1 + \alpha_1 z^{-1} + \cdots + \alpha_n z^{-n_\alpha}} \tag{5}$$

The polynomial orders n_α and n_β are assumed to be known. Bernoulli random variables τ_t and γ_t are introduced to characterise the data missing pattern. The probability distributions of τ_t and γ_t are defined as:

$$P(\tau_t) = \begin{cases} \tau, & \tau_t = 1 \\ 1-\tau, & \tau_t = 0 \end{cases}$$

$$P(\gamma_t) = \begin{cases} \gamma_t, & \gamma_t = 1 \\ 1-\gamma_t, & \gamma_t = 0 \end{cases}$$

The output estimation for (1–4) is taken as follows,

$$z_t = y(t) + (1-\gamma_t)\hat{y}, \hat{y} = \varphi_t^T \hat{\theta}_t, y(t) = x_t + v_t \tag{6}$$

The Kalman filter-based identification algorithm in [10] is as follow,

$$\hat{\theta}_{t+1} = \hat{\theta}_t + K_{t+1}(z_t - \varphi_t^T \hat{y}) \tag{7}$$

$$K_{t+1} = \frac{P_t \varphi_t}{q_t + \varphi_t^T P_t \varphi_t} \tag{8}$$

$$P_{t+1} = P_t - \gamma_t \frac{P_t \varphi_t \varphi_t^T P_t}{q_t + \varphi_t^T P_t \varphi_t} \tag{9}$$

$$x_t = \varphi_t^T \hat{\theta}_{t+1} \tag{10}$$

where

$$\varphi_t^T = [-x_{t-1} \cdots - x_{t-n_\alpha} \tau_t u_t \cdots \tau_{t-n_\beta} u_{t-n_\beta}]^T$$

$$\hat{\theta}_t = [\hat{\alpha}_1 \hat{\alpha}_2 \cdots \hat{\alpha}_{n_\alpha} \ \hat{\beta}_0 \ \hat{\beta}_1 \ \cdots \ \hat{\beta}_{n_\beta}]$$

3. KALMAN FILTER-BASED WITH CONSTRAINT ALGORITHM

3.1 Derive the constraint with system

Assumed P is described as follow:

$$\begin{aligned} y^{(n)} &= a_{n-1} y^{(n-1)} + a_{n-2} y^{(n-2)} + \cdots + a_0 y \\ &+ b_0 u + b_1 u^{(1)} + \cdots + b_n u^{(n)} \end{aligned} \tag{11}$$

Discretize P with Δt, denoted W_z as (12), then

$$W_z = \frac{\beta_0 + \beta_1 z^{-1} + \beta_2 z^{-2} + \cdots + \beta_n z^{-n}}{1 - \alpha_1 z^{-1} - \cdots - \alpha_n z^{-n}} \tag{12}$$

Theorem 1. For $\Delta t \to 0$ and the parameter of a_0 and b_0 being nonzero and bounded, then

$$\sum_{i=1}^{n} \alpha_i + \sum_{j=0}^{n} \beta_j = 1 \tag{13}$$

Proof: Write (12) as follows,

$$\begin{aligned} y(k) &= \alpha_1 y(k-1) + \cdots + \alpha_n y(k-n) + \beta_0 u(k) \\ &+ \beta_1 u(k-1) + \cdots + \beta_n u(k-n) \end{aligned} \tag{14}$$

Discretize (11) with Δt, we obtain

$$\begin{cases} y^{(1)} = \dfrac{y(k+1) - y(k)}{\Delta t} \\ y^{(2)} = \dfrac{y(k+2) - 2y(k+1) + y(k)}{\Delta t^2} \\ y^{(3)} = \dfrac{y(k+3) - 3y(k+2) + 3y(k+1) - y(k)}{\Delta t^3} \\ \vdots \\ y^{(n)} = \dfrac{y(k+n) - \sum_{i=0}^{n-1} (-1)^{(i+1)} y(k+i) C_n^i}{\Delta t^n} \end{cases} \tag{15}$$

Then Table 1 can be obtained. It is seen that each degree in the numerator satisfies the Yang Hui's triangle and the sum of the coefficient of numerator each degree equal zero. Thus $\sum_{i=0}^{n-1} (-1)^{(i+1)} C_n^i = 1$.

Table 1. Yang Hui's triangle

degree	The coefficient
1	1 -1
2	1 -2 1
3	1 -3 3 -1
n	$1 \ (-1)^{n+1} C_n^{n-1} \ (-1)^n C_n^{n-2} \cdots - C_n^1 \ 1$

Considering (11) and (15) it follows

$$\begin{aligned} y(k) &= a_{n-1}(y(k-1) - \sum_{i=0}^{n-2} (-1)^{(i+1)} C_{n-1}^i \\ & y(k+i-n))\Delta t + a_{n-2}(y(k-2) - \sum_{i=0}^{n-3} \\ & (-1)^{(i+1)} C_{n-2}^i y(k+i-n))\Delta t^2 + \cdots + \\ & a_0 y(k-n)\Delta t^n + \sum_{i=0}^{n-1} (-1)^{(i+1)} C_{n-1}^i y(k \end{aligned}$$

$$+ i - n) + b_n(u(k) - \sum_{i=0}^{n-1}(-1)^{(i+1)}C_{n-1}^i$$
$$u(k+i-n)) + \cdots + b_0u(k-n)\Delta t^n \quad (16)$$

Since the sum of coefficient in (16) equals the sum of coefficient in (14), and the sum of each degree coefficient is zero, therefore,

$$\sum_{i=1}^{n}\alpha_i + \sum_{j=0}^{n}\beta_j = a_0\Delta t + b_0\Delta t + \sum_{i=0}^{n-1}(-1)^{(i+1)}C_{n-1}^i \quad (17)$$

Then for $\Delta t \to 0$ and a_0, b_0 in (11) being nonzero and bounded,

$$\sum_{i=1}^{n}\alpha_i + \sum_{j=0}^{n}\beta_j = \sum_{i=0}^{n-1}(-1)^{(i+1)}C_{n-1}^i = 1 \quad (18)$$

This completes the proof.

(18) can be written as follows,

$$D\theta = d, D = [11\cdots 11]_{2n+1}, d = 1 \quad (19)$$
$$\theta = [-\hat{\alpha}_1 - \hat{\alpha}_2 \cdots - \hat{\alpha}_n\ \hat{\beta}_0\ \hat{\beta}_1\ \cdots\ \hat{\beta}_n]$$

.

3.2 Kalman filter with constraint

Theorem 2. The Kalman filter estimation of θ with constraint in (19) is as follows,

$$\tilde{\theta}_t = \hat{\theta}_t - W^{-1}D^T(DW^{-1}D^T)^{-1}(D\hat{\theta}_t - d)$$

where $\hat{\theta}_t$ is the Kalman estimation of θ without constraint and W is a positive-definite weighting matrix.

Proof: The constrained Kalman filter is obtained by directly projecting the unconstrained state estimate $\hat{\theta}_t$ onto the constraint surface. That is, we solve the problem: $min_{\tilde{\theta}_t}(\tilde{\theta}_t - \hat{\theta}_t)^T W(\tilde{\theta}_t - \hat{\theta}_t), such\ that\ D\tilde{\theta}_t = d;$

The conclusion can be readily made by using the Lagrangian method, the details of which are omitted here.

Remark 1: For $W = I$, the result of constrained estimation is closer to the true state than the unconstrained estimate at each time step. $W = P_t^{-1}$ results in the minimum variance filter.

3.3 The algorithm

Suppose the system plant satisfies Theorem 1, the algorithm for the Kalman filter-based with linear constraint identification can be organized as follows,

$$\hat{\theta}_{t+1} = \hat{\theta}_t + K_{t+1}(z_t - \varphi_t^T\hat{y}) \quad (20)$$

$$K_{t+1} = \frac{P_t\varphi_t}{q_t + \varphi_t^T P_t\varphi_t} \quad (21)$$

$$P_{t+1} = P_t - \gamma_t\frac{P_t\varphi_t\varphi_t^T P_t}{q_t + \varphi_t^T P_t\varphi_t} \quad (22)$$

$$x_t = \varphi_t^T\hat{\theta}_{t+1} \quad (23)$$

$$\tilde{\theta}_{t+1} = \hat{\theta}_{t+1} - W^{-1}D^T(DW^{-1}D^T)^{-1}(D\hat{\theta}_{t+1} - d) \quad (24)$$

$$\hat{\theta}_t = [-\hat{\alpha}_1 - \hat{\alpha}_2 \cdots - \hat{\alpha}_n\ \hat{\beta}_0\ \hat{\beta}_1\ \cdots\ \hat{\beta}_n]$$

$$D = [11\cdots 11]_{2n+1}, d = 1$$

4. CONVERGENCE ANALYSIS

The convergence analysis of the parameter estimation in (7–10) and the output estimation in (6) had been well studied in [2–4] and [10]. Here we summarize certain related theorems.

Theorem 3. [10] For the system considered in (1–4) with the following assumptions,

(A1) $E(v(t)) = 0, E(v(t)^2) = q_t \le \infty, a.s.$

(A2) $\exists m_0, d_0, c_0 \in R^+$ and $t_0 \in N^+$,

(A3) $G_z = \frac{1}{\alpha(z)} - \frac{1}{2}$ is strictly positive real.

the square parameter estimation error $||\hat{\theta}_t - \theta||^2$, produced by the algorithm (7–10), satisfies:

(B1) $||\hat{\theta}_t - \theta||^2 = O[\frac{(\ln t)^c}{t}] \to 0, as..c > 1$

(B2) $||\hat{\theta}_t - \theta||^2 = O[\frac{(\ln t(\ln\ln t)^c)}{t}] \to 0, as..c > 1$

Theorem 4. Let $W = P_t^{-1}$ in (20–24), then $Cov(\theta - \tilde{\theta}_t) \le Cov(\theta - \hat{\theta}_t)$. Let $W = I$, then $||\tilde{\theta}_t - \theta||_2 \le ||\hat{\theta}_t - \theta||_2$.

Proof: Let $W = P_t^{-1}$,
then $\tilde{\theta}_t = \hat{\theta}_t - P_tD^T(DP_tD^T)^{-1}(D\hat{\theta}_t - d)$,

$$\begin{aligned}\theta - \tilde{\theta}_t &= (I - P_tD^T(DP_tD^T)^{-1}D)(\theta - \hat{\theta}_t)\\ &= (I - J)(\theta - \hat{\theta}_t)\end{aligned} \quad (25)$$

where $J = P_tD^T(DP_tD^T)^{-1}D$.

$$\begin{aligned}Cov(\theta - \tilde{\theta}_t) &= E([(I - J)(\theta - \hat{\theta}_t)][(I - J)(\theta - \hat{\theta}_t)]^T)\\ &= (I - J)Cov(\theta - \hat{\theta}_t)(I - J)^T\\ &= P_t - JP_t - P_tJ^T + JP_tJ^T\end{aligned} \quad (26)$$

Since $P_tJ^T = JP_tJ^T$, then $Cov(\theta - \tilde{\theta}_t) = P_t - JP_t \le P_t = Cov(\theta - \hat{\theta}_t)$;

Let $W = I$, since $D = [11\cdots 11]_{2n+1}$, then

$$\begin{aligned}J &= D^T(DD^T)^{-1}D\\ &= \frac{1}{2n+1}ones(2n+1)\end{aligned} \quad (27)$$

In equal (25), we get

$$\begin{aligned}||\tilde{\theta}_t - \theta||_2 &= ||(I - J)(\hat{\theta}_t - \theta)||_2\\ &\le ||(I - J)||_2||(\hat{\theta}_t - \theta)||_2\\ &\le ||\hat{\theta}_t - \theta||_2\end{aligned} \quad (28)$$

For the eigenvalues of $(I - J)^T(I - J)$ are all less than 1.

Remark 2: since $D = [11\cdots 1]_{2n+1}$, it thus holds that

$$\forall W = W^T \ge 0, Cov(\theta - \tilde{\theta}_t) \le Cov(\theta - \hat{\theta}_t)$$

.

Remark 3: Let $W = I$, we have $||\tilde{\theta}_t - \theta||_2 \le ||\hat{\theta}_t - \theta||_2$ only for D being full rank in (11).

Since $\tilde{\theta}_t$ of in the algorithm (20–24) is just by directly projecting the unconstrained state estimate $\hat{\theta}_t$ onto the constraint surface, then with the same assumptions of (A1), (A2) and (A3), $||\tilde{\theta}_t - \theta||^2$ produced by the algorithm (20–24), satisfies:

(C1) $||\tilde{\theta}_t - \theta||^2 = O[\frac{(\ln t)^c}{t}] \to 0, as..c > 1.$

(C2) $||\tilde{\theta}_t - \theta||^2 = O[\frac{\ln t(\ln \ln t)^c)}{t}] \to 0, as..c > 1.$

Remark 4. With **theorem 4**, let $W = I$ in the algorithm (20–24), then $||\tilde{\theta}_t - \theta||_2 \le ||\hat{\theta}_t - \theta||_2$; let $W = P_t^{-1}$, then $E(||\tilde{\theta}_t - \theta||^2) \le E(||\hat{\theta}_t - \theta||^2)$.

Theorem 5.[10] Suppose that the assumptions (A1)–(A3) hold, and the input is bounded. Then there exists a positive integer t_0 such that for any $t \ge t_0$, the output estimation error $z_t - y(t)$ satisfies:

(C3) $\sum_{i=t_0}^{t} (z_t - y(t))^2 = O[(\ln t)^{c+1}]$, as $c \ge 1$.

(C4) $\frac{1}{t} \sum_{i=t_0}^{t} (z_t - y(t))^2 = O[\frac{(\ln t)^{c+1}}{t}] \to 0$, as $c \ge 1$.

Remark 5. (C1)–(C2) reveal that the parameter estimation error of the algorithm (20)–(24) will converge to zero at the speed of $O[\frac{(\ln t)^c}{t}]$. **Theorem 5** reveals that the output estimation error of (6) will converge to zero in average sense at the speed of $O[\frac{(\ln t)^{c+1}}{t}]$.

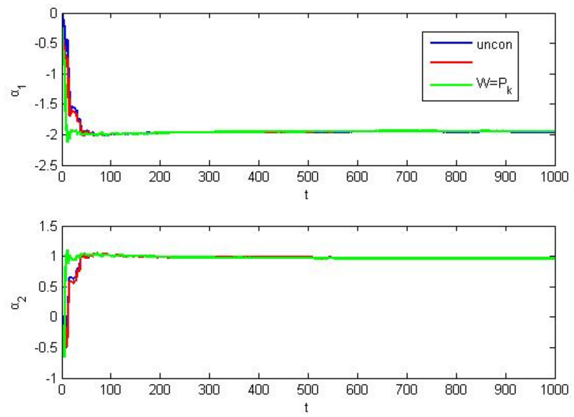

Fig. 2. the case 1 of α_1 and α_2

5. SIMULATION

Considered the plant P with the transfer function being $W(s) = \frac{5s-8}{s^2+s+8}$ in the system (1). Then take $\Delta t = 0.05$ will make $P_z = \frac{0.2332z^{-1} - 0.2527}{1 - 1.949z^{-1} + 0.9512z^{-2}}$. Denote $\delta_{par}(\%) = \frac{||\tilde{\theta}_t - \theta||_2}{||\theta||_2} \times 100\%$.

Case 1: Take $\tau = 0.8$ and $\gamma = 0.7$. In this case, about 20% of the input data and 30% of the output data are missing. The estimated parameters and corresponding estimation errors are shown in Fig. 2–Fig. 4. They consider three cases: one is the algorithm without constraint as in (7–10), one is for $W = I$ in algorithm (20–24), and the last is for $W = P_t^{-1}$ in (20–24).

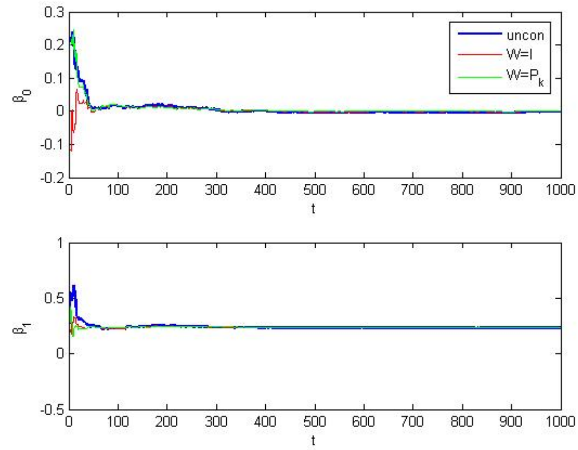

Fig. 3. the case 1 of β_0 and β_1

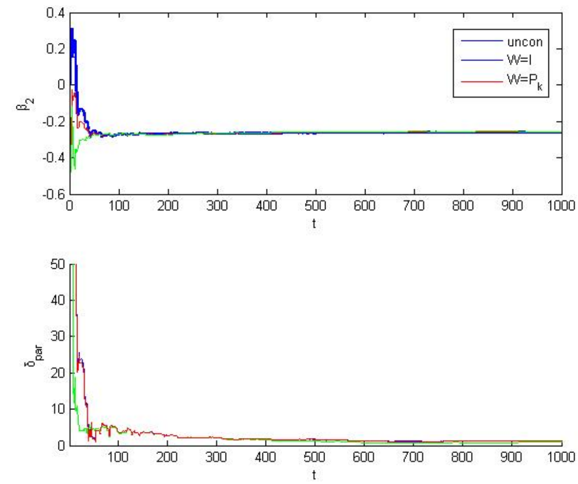

Fig. 4. the case 1 of β_2 and $\delta_{par}(\%)$

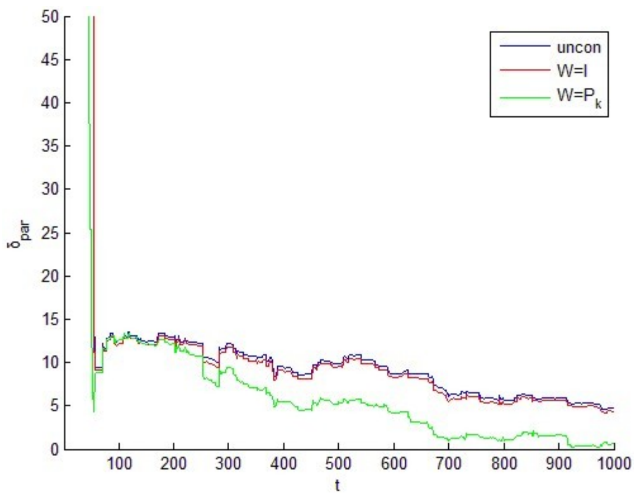

Fig. 5. the case 2 of $\delta_{par}(\%)$

Case 2: Take $\tau = 0.4$ and $\gamma = 0.3$. In this case, the missing data scenario is much worse than that in **case 1**. Estimations of five parameters are shown in Table 2–Table 4 with the errors in Fig. 5.

Table 2. Intermediate parameter and errors (Case 2 uncon)

t	10	100	500	1000	true
α_1	0	-1.7030	-1.7394	-1.8394	-1.9320
α_2	0	0.8574	0.8563	0.9123	0.9512
β_0	0	0.0163	0.0042	0.0068	0
β_1	0.1409	0.1642	0.2317	0.2393	0.2332
β_2	0	-0.1578	-0.2240	-0.2260	-0.2527
$\delta_{par}(\%)$	99.5166	12.5801	9.9333	4.7794	

Table 3. Intermediate parameter and errors (Case 2 $W = I$)

t	10	100	500	1000	true
α_1	-0.2282	-1.7319	-1.7652	-1.8581	-1.9320
α_2	-0.2282	0.8285	0.8305	0.8938	0.9512
β_0	-0.2282	-0.0452	-0.0215	-0.0118	0
β_1	-0.0873	0.1353	0.2060	0.2207	0.2332
β_2	-0.2282	-0.1867	-0.2498	-0.2447	-0.2527
$\delta_{par}(\%)$	96.7257	12.2251	9.5739	4.3783	

Table 4. Intermediate parameter and errors($W = P_t^{-1}$)

t	10	100	500	1000	true
α_1	-0.2837	-1.7202	-1.8401	-1.9377	-1.9320
α_2	-0.2837	0.8307	0.8760	0.9619	0.9512
β_0	-0.2837	-0.0443	-0.0060	-0.0017	0
β_1	0.1348	0.1259	0.2265	0.2321	0.2332
β_2	-0.2837	-0.1922	-0.2565	-0.2580	-0.2527
$\delta_{par}(\%)$	95.4530	12.6757	5.3724	0.6128	

Table 5. Intermediate parameter and errors comparison

Case 1 (t)	10	100	500	1000
$\delta_{par}([10])$	90.9390	3.6225	1.6950	1.3603
$\delta_{par}(W = I)$	86.0324	3.6154	1.6622	1.3381
$\delta_{par}(W = P_t^{-1})$	13.2035	3.3840	1.2758	0.8943
Case 2 (t)	10	100	500	1000
$\delta_{par}([10])$	99.5166	12.5801	9.9333	4.7794
$\delta_{par}(W = I)$	96.7257	12.2251	9.5739	4.3783
$\delta_{par}(W = P_t^{-1})$	95.4530	12.6757	5.3724	0.6128

Remark 6. We can see that the algorithm (20)–(24) of parameter estimation converges to the true value in the Simulation results of Fig. 2–Fig. 4 and Table 2–Table 4. What's more, in the Table 5, it shows the algorithm (20)–(24) improves the accuracy of parameter estimation clearly, and taking $W = I$ will make sure the result of constrained estimation is closer to the true state than the unconstrained estimate at each time step. However, taking $W = P_t^{-1}$ in the algorithm (20)–(24) may not ensure that the result is better than the unconstrained estimate at each time step, but the mathematical expectation of the result is better. These also proof the previous analysis of **Theorem 4**. In conclusion, the results show that algorithm (20–24) improve the accuracy of parameter estimation in both cases. In particular, the improved results are more evident with large amount of missing data by using (20–24) with $W = P_t^{-1}$.

6. CONCLUSIONS

A Kalman filter-based identification algorithm is proposed for systems with randomly missing measurements. This algorithm takes advantage of the linear constraints and improves the accuracy of parameter estimation compared with previous results. Simulation examples illustrate the effectiveness of the proposed approach. Further improvements may be make by, e.g., decreasing the Δt and using the soft constraint $D\theta \approx d$ instead of $D\theta = d$.

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Abstract: The available information of linear constraint in linear dynamic systems, which is often unexplored in previous works, is taken advantage of to improve the accuracy of the parameter estimation, particularly in the presence of randomly missing measurements. Specifically, a Kalman filter-based identification for systems without constraint but with the randomly missing measurements is first introduced. Then the result is extended to systems with linear constraint under normal conditions. By doing so we show that the accuracy of the estimation is improved by taking the constraint into account, both theoretically and numerically. Copyright © 2013 IFAC.
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