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Covariance Intersection Fusion State Estimator for Descriptor and Non Descriptor Systems

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Abstract. Covariance intersection fusion state estimator is presented in this paper. The algorithm deals with descriptor and non descriptor discrete time time-invariant stochastic linear system, which is described by state space model. On the observability of the system under the assumption, the state of the system is a linear combination of input white noise, observation white noise and observation signal. Further non-recursive state estimators algorithm is presented, which can be computed by the white noise estimators and measurement predictor. In order to improve the accuracy of the state estimator, this paper presents information fusion algorithm is covariance intersection fusion, in the sense of linear minimum variance. The fusion estimation avoid calculating the cross-covariances of local estimate. The algorithm analyzes the relationship between the accuracy and the computation of the four fusion algorithm. A simulation example for non descriptor system with 3 sensors shows its correctness and effectiveness.

Keywords: Covariance intersection fusion, descriptor and non descriptor systems, state estimator

1 Introduction

At present, the research and development of multisensor information fusion technology have been attached great importance. In last decades, the application field of information fusion technology has increased widely [1]~[3]. The distributed fusion estimation needs to calculate the cross-covariances of local estimate[4]~[6]. However, in many theoretical and application problems, the cross-covariances are unknown, or it is very difficult to compute the cross-covariances, or can't calculate the cross-covariances. In order to overcome the disadvantages and limitations, Jeffrey K. Uhlman proposed the covariance intersection information fusion method[7]~[10].In this paper, distributed fusion Wiener deconvolution

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estimator is weighted by matrix, diagonal matrices, scalars, covariance intersection fusion for linear stochastic multichannel ARMA signal.

Descriptor system is a kind of power system, and it has a wider than normal system form. In the literature it is also named as singular systems, descriptor systems, semi-state systems, generalized state-space systems, differential-algebraic systems, implicit systems and degenerate systems etc.[11]. Descriptor systems occur naturally in robotics, economic, electronic and chemical systems, which are more common than conventional systems to describe the actual systems. The estimation problems for descriptor systems are fundamental to control and synthesis problems for them[12].

In this paper, covariance intersection fusion state estimator for descriptor and non descriptor systems is presented. The algorithm is using the modern time series analysis method and white noise estimator under the linear minimum variance sense. This paper presents information fusion algorithm is covariance intersection fusion. Compared with the single sensor case, the accuracy of the fused filter is greatly improved. A simulation example for non descriptor system with 3 sensors shows its correctness and effectiveness.

The main structure of this paper is as follows: Problem formulation is given in Section 2. ARMA innovation model is introduced in Section 3. In Section 4 non-recursive local optimal state estimator is presented. Distributed information fusion optimal state estimator for descriptor and non descriptor system is given in Section 5. A simulation example with 2-sensor is given in section 6. In Section 7 the conclusions of this paper are given.

2 Problem formulation

Consider the multi sensor descriptor and non descriptor discrete time time-invariant stochastic linear system

$$\boldsymbol{M}\boldsymbol{x}(t+1) = \Psi(t) + \Upsilon \boldsymbol{w}(t) \tag{1}$$

$$\boldsymbol{y}_j(t) = \Pi_j \boldsymbol{x}(t) + \boldsymbol{v}_j(t) \quad j = 1,\cdots,K \tag{2}$$

where t is the discrete time and k is the number of the sensor, $k \ge 2$. And $x(t) \in R^n$ is the state of the *j*th sensor, the scalar $y_j(t) \in R^{mj}$ is the measurement (output) of the *j*th sensor subsystem, $v_j(t) \in R^{mj}$ is the measurement noise of the *j*th sensor subsystem, $w(t) \in R^r$ is the input noise, $\boldsymbol{M}, \Psi, \Upsilon, \Pi$ is the known constant matrix.

Assumption 1 $\boldsymbol{M}$ is singular matrix ($\det \boldsymbol{M} = 0$) or $\boldsymbol{M} = \boldsymbol{I}_n$ (unit matrix).

Assumption 2 The system is regular.

Assumption 3 $w(t) \in R^r$ and $v_i(t) \in R^{mi}, i = 1,\cdots,L$ are independence white noises with zero mean and covariance are Q_w and Q_{vi} individually.

$$\mathrm{E}\left\{\begin{bmatrix} w(t) \\ v_j(t) \end{bmatrix}\begin{bmatrix} w^{\mathrm{T}}(k) & v_i^{\mathrm{T}}(k) \end{bmatrix}\right\} = \begin{bmatrix} Q_w & S_i \\ S_j^{\mathrm{T}} & Q_{v_{ji}} \end{bmatrix}\delta_{tk} \tag{3}$$

where E is the mathematical expectation, $\delta_{tt} = 1, \delta_{tk} = 0 (t \ne k)$.

Assumption 4 The system is completely observable, that is, for the arbitrary complex z have

$$\mathrm{rank}\begin{bmatrix} z\boldsymbol{M}-\Psi \\ \Pi_j \end{bmatrix}=n\,,\quad \mathrm{rank}\begin{bmatrix} \boldsymbol{M} \\ \Pi_j \end{bmatrix}=n \tag{4}$$

State estimation problem for descriptor and non descriptor system is based on the measurement $(\boldsymbol{y}_i(t+N),\ \boldsymbol{y}_i(t+N-1),\cdots)$, to obtain non-recursive state estimators $\hat{\boldsymbol{x}}_j(t\,|\,t+N),\ j=1,2\cdots K$. For $N=0,\ N>0$ or $N<0$, we named it as state filtering, smoothing or predictor. Further distributed optimal information fusion non-recursive state estimation $\hat{\boldsymbol{x}}_0(t\,|\,t+N)$ is obtained, it consists of weighted local state estimators.

3 ARMA innovation model

Lemma 1 For the system (1) and (2) under the Assumption 1-2, and having the left prime decomposition:

$$\Pi_j(\boldsymbol{M} - q^{-1}\Psi)^{-1}\Upsilon q^{-1}=\boldsymbol{A}^{-1}(q^{-1})\boldsymbol{B}^{-1}(q^{-1})q^{\tau} \tag{5}$$

where $\boldsymbol{A}(q^{-1})$ and $\boldsymbol{B}^{-1}(q^{-1})$ is polynomial matrix of the unit delay operator q^{-1}, and it has the type as $X(q^{-1})=X_0+X_1q^{-1}+\cdots+X_{n_x}q^{-n_x}$. X_i is the coefficient matrix, and n_x is the order, and q is the unit forward operator. $\boldsymbol{A}_0=I_m$, and $B_0\neq 0$. Where τ is the integer, $\tau=0$, $\tau>0$ or $\tau<0$.

From (1) and (2) having

$$y_i(t)=\Pi_j(\mathrm{M}-q^{-1}\Psi)^{-1}\Upsilon q^{-1}w(t)+v(t) \tag{6}$$

Substitutting (5) into (6), having

$$A^{(j)}(q^{-1})y_j(t)=B^{(j)}(q^{-1})q^{\tau}w(t)+A^{(j)}(q^{-1})v_j(t) \tag{7}$$

Because of left coprime factorization, and having the ARMA innovation model

$$A^{(j)}(q^{-1})y_j(t)=D^{(j)}(q^{-1})\varepsilon_j(t) \tag{8}$$

where $D^{(j)}(q^{-1})$ is stable, $D_0^{(j)}=I_m$, and innovation $\varepsilon_j(t)$ is white noises with zero mean and covariance are $Q_{\varepsilon j}$, and having

$$D^{(j)}(q^{-1})\varepsilon_j(t)=B^{(j)}(q^{-1})w(t)+A^{(j)}(q^{-1})v_j(t) \tag{9}$$

$D^{(j)}(q^{-1})$ and $Q_{\varepsilon j}$ can be computed by Gevers-Wouters[13].

4 Non-recursive local optimal state estimator

Lemma 2 For the system (1) and (2) under the Assumption 1-3, the following formula is established:

$$\mathrm{E}[w(t)\varepsilon_j^{\mathrm{T}}(i)]=Q_wF_{i-t+\max(\tau,0)}^{\mathrm{T}(j)}+S_jG_{i-t+\max(\tau,0)}^{\mathrm{T}(j)} \tag{10}$$

$$\mathrm{E}[v_j(t)\varepsilon_j^{\mathrm{T}}(i)]=Q_{vi}G_{i-t+\max(\tau,0)}^{\mathrm{T}(j)}+S_j^{\mathrm{T}}F_{i-t+\max(\tau,0)}^{\mathrm{T}(j)} \tag{11}$$

The coefficient $F_i^{(j)}$ and $G_i^{(j)}$ can be recursive calculated as

$$F_i^{(j)} = -D_1^{(j)} F_{i-1}^{(j)} - \cdots - D_{n_d}^{(j)} F_{j-n_d}^{(j)} + \bar{B}_i^{(j)} \tag{12}$$

$$G_i^{(j)} = -D_1^{(j)} G_{i-1}^{(j)} - \cdots - D_{n_d}^{(j)} G_{j-n_d}^{(j)} + \bar{A}_i^{(j)} \tag{13}$$

where letting $F_i^{(j)} = 0 (i < 0)$, $\bar{B}_i^{(j)} = 0 (i > n_{\bar{b}})$, $G_i^{(j)} = 0 (i < 0)$, $\bar{A}_i^{(j)} = 0 (i > n_{\bar{a}})$.

$$\bar{B}^{(j)}(q^{-1}) = B^{(j)}(q^{-1}) q^{\min(\tau,0)}, \quad \bar{A}^{(j)}(q^{-1}) = A^{(j)}(q^{-1}) q^{\min(\tau,0)} \tag{14}$$

Lemma 3 For the system (1) and (2) under the Assumption 1-3, the asymptotically stability local optimal white estimator is as follows[13]

When $N \geq -\max(\tau, 0)$, we have

$$\hat{w}(t \mid t+N) = \sum_{i=-\max(\tau \vee 0)}^{N} [Q_w F_{i+\max(\tau \vee 0)}^{(j)\mathrm{T}} + S_j G_{i+\max(\tau \vee 0)}^{(j)\mathrm{T}}] Q_\varepsilon^{(j)-1} \varepsilon_j(t+i) \tag{15}$$

$$\hat{v}_j(t \mid t+N) = \sum_{i=-\max(\tau \vee 0)}^{N} [Q_{vj} G_{i+\max(\tau \vee 0)}^{(j)\mathrm{T}} + S_j^{\mathrm{T}} F_{i+\max(\tau \vee 0)}^{(j)\mathrm{T}}] Q_\varepsilon^{(j)-1} \varepsilon_j(t+i) \tag{16}$$

When $N < -\max(\tau, 0)$, we have

$$\hat{w}(t \mid t+N) = 0, \quad \hat{v}(t \mid t+N) = 0 \tag{17}$$

Lemma 4 The measurement $y_j(t+i)$ has the recursive predictor[13]

$$A^{(j)}(\tilde{q}^{-1}) \hat{y}_j(t+N \mid t) = D^{(j)}(q^{-1}) \varepsilon_j(t+j), \quad N = 1, \cdots, i \tag{18}$$

where letting $\varepsilon_j(t+j) = 0 (j > 0)$, and $\hat{y}_j(i \mid N) = y(i) (i \leq j)$.

$$A^{(j)}(\tilde{q}^{-1}) \hat{y}_j(t+N \mid t) = y_j(t+N \mid t) + A_1^{(j)} y_j(t+N-1 \mid t) + \cdots + A_{n_a}^{(j)} y_j(t+N-n_a \mid t) \tag{19}$$

And innovation $\varepsilon_i(t)$ can be calculated by

$$\varepsilon_j(t) = A^{(j)}(q^{-1}) y(t) - D_1^{(j)} \varepsilon_j(t-1) - \cdots - D_{n_d}^{(j)} \varepsilon_j(t-n_d), \quad t = n_d, n_d+1, \cdots \tag{20}$$

Theorem 1 For the system (1) and (2) under the Assumption 1-4, asymptotically stability state estimator is as follows

$$\hat{x}(t \mid t+N) = \sum_{i=0}^{\beta-2} \Omega_i^{(j1)} \Pi w(t+i \mid t+N) + \sum_{i=0}^{\beta-1} \Omega_i^{(j2)} [y_j(t+i \mid t+N) - v_j(t+i \mid t+N)] \tag{21}$$

Defining $\Omega_i^{(j)}$ as

$$\Omega_j^{+} = (\Omega_j^{\mathrm{T}} \Omega_j)^{-1} \Omega_j^{\mathrm{T}} = \begin{bmatrix} \Omega_0^{(j1)} & \cdots & \Omega_{\beta-2}^{(j1)} & \Omega_0^{(j2)} & \cdots & \Omega_{\beta-1}^{(j2)} \\ \vdots & & \vdots & \vdots & & \vdots \\ \vdots & & \vdots & \vdots & & \vdots \end{bmatrix} \tag{22}$$

Proof: Form (1), (2) and (22)

$$x(t) = \sum_{i=0}^{\beta-2} \Omega_i^{(j1)} \Pi w(t+i) + \sum_{i=0}^{\beta-1} \Omega_i^{(j2)} [y_j(t+i) - v_j(t+i)] \tag{23}$$

Taking on (23) projective operation, and (21) is obtained. Due to white noise estimators and measurement predictor is asymptotically stable and asymptotically optimal about innovation initial value. So (21) also has the same properties. The proof is completed.

Theorem 2 For the system (1) and (2) under the Assumption 1-4, estimation error $\tilde{x}(t \mid t+N) = x(t) - \hat{x}(t \mid t+N)$ has the following expressions

$$\tilde{x}_j(t \mid t+N) = \sum_{i=0}^{\beta_j-2} \Omega_i^{(j)w} w_j(t+i) - \sum_{i=0}^{\beta_j-1} \Omega_i^{(j)v} v_j(t+i) + \sum_{i=0}^{n_0} \Omega_i^{(j)c} \varepsilon_j(t+i), \quad N \geq 0 \tag{24}$$

Where defining $n_0 = \max(\beta_j - 1, N)$, $\Omega_j^{(i)c}$ is obtained by the merger of similar coefficient matrix.

$$\tilde{\boldsymbol{x}}_j(t|t+N) = \sum_{i=0}^{\beta_j - 2} \Omega_i^{(j)w} \boldsymbol{w}_j(t+i) - \sum_{i=0}^{\beta_j - 1} \Omega_i^{(j)v} \boldsymbol{v}_j(t+i) + \sum_{i=0}^{n_1} \Omega_i^{(j)y} \ {}_j(t+N+1+i), \ N < 0 \quad (25)$$

Where defining $n_1 = (\beta_i - 2 - N)$, $\Omega_i^{(j)y}$ is obtained by the merger of similar coefficient matrix. (24) and (25) can be expressed as a unified form

$$\tilde{\boldsymbol{x}}_j(t|t+N) = \sum_{i=0}^{n_0} [\Omega_i^{(j)w} \boldsymbol{w}_j(t+i) - \Omega_i^{(j)v} \boldsymbol{v}_j(t+i) + \Omega_i^{(j)c} \ {}_j(t+i)], \ N \geq 0 \quad (26)$$

$$\tilde{\boldsymbol{x}}_i(t|t+N) = \sum_{j=0}^{n_1} [\Omega_j^{(i)w} \boldsymbol{w}_i(t+j) - \Omega_j^{(i)v} \boldsymbol{v}_i(t+j) + \Omega_j^{(i)y} \ {}_i(t+N+1+j)], \ N < 0 \quad (27)$$

And letting $\Omega_i^{(j)w} = 0(i > \beta_j - 2)$, $\Omega_i^{(j)v} = 0(i > \beta_j - 1)$.

Proof: (23) minus (21), then mergers similar items, (26)and (27) are obtained. The proof is completed.

Theorem 3 For the system (1) and (2) under the Assumption 1-4, estimation error covariance $P_j(N) = \mathrm{E}[\tilde{\boldsymbol{x}}_j(t|t+N)\tilde{\boldsymbol{x}}_j^{\mathrm{T}}(t|t+N)]$ is given as

$$P_j(N) = \sum_{r=0}^{n_0}\sum_{s=0}^{n_0} \begin{bmatrix} \Omega_r^{(j)w} & -\Omega_r^{(j)v} & \Omega_r^{(j)c} \end{bmatrix} \begin{bmatrix} Q_{\bar{w}_{ij}}\delta_{rs} & \bar{S}_j\delta_{rs} & \Lambda_{s-r}^{(j)\bar{w}_j} \\ \bar{S}_j^{\mathrm{T}}\delta_{rs} & Q_{v_j}\delta_{rs} & \Lambda_{s-r}^{(j)v_j} \\ \Lambda_{r-s}^{(j)\bar{w}_j\mathrm{T}} & \Lambda_{r-s}^{(j)v_j\mathrm{T}} & Q_{\varepsilon j}\delta_{rs} \end{bmatrix} \begin{bmatrix} \Omega_s^{(j)w\mathrm{T}} \\ -\Omega_s^{(j)v\mathrm{T}} \\ \Omega_s^{(j)c\mathrm{T}} \end{bmatrix}, \ N \geq 0 \quad (28)$$

$$P_j(N) = \sum_{r=0}^{n_1}\sum_{s=0}^{n_1} \begin{bmatrix} \Omega_r^{(j)w} & -\Omega_r^{(j)v} & \Omega_r^{(j)y} \end{bmatrix} \begin{bmatrix} Q_{\bar{w}_{ij}}\delta_{rs} & \bar{S}_j\delta_{rs} & \Lambda_{N+1+s-r}^{(j)\bar{w}_j} \\ \bar{S}_j^{\mathrm{T}}\delta_{rs} & Q_{v_j}\delta_{rs} & \Lambda_{N+1+s-r}^{(j)v_j} \\ \Lambda_{N+1+r-s}^{(j)\bar{w}_j\mathrm{T}} & \Lambda_{N+1+r-s}^{(j)v_j\mathrm{T}} & Q_{\varepsilon j}\delta_{rs} \end{bmatrix} \begin{bmatrix} \Omega_s^{(j)w\mathrm{T}} \\ -\Omega_s^{(j)v\mathrm{T}} \\ \Omega_s^{(j)y\mathrm{T}} \end{bmatrix}, \ N < 0 \quad (29)$$

Proof: (26) and (27)have the simplified expression

$$\tilde{\alpha}_j(t|t+N) = \sum_{r=0}^{n_0} \begin{bmatrix} \Omega_r^{(j)w} & -\Omega_r^{(j)v} & \Omega_r^{(j)c} \end{bmatrix} \begin{bmatrix} w(t+r) \\ v_j(t+r) \\ \varepsilon_j(t+r) \end{bmatrix}, \ N \geq 0 \quad (30)$$

$$\tilde{\alpha}_j(t|t+N) = \sum_{r=0}^{n_1} \begin{bmatrix} \Omega_r^{(j)w} & -\Omega_r^{(j)v} & \Omega_r^{(j)y} \end{bmatrix} \begin{bmatrix} w(t+r) \\ v_j(t+r) \\ \varepsilon_j(t+N+1+r) \end{bmatrix}, \ N < 0 \quad (31)$$

Thus by (3), (15) and (16) with the Assumption 1, (28)～(29)is obtained. The proof is completed.

5 Distributed information fusion optimal state estimator

Lemma 5 For the system (1) and (2), under the same conditions, when the variance of P_1 and P_2 are known, but the cross covariance P_{12} is unknown, using the covariance intersection (CI) fusion method, this paper proposes a suboptimal fusion Kalman estimators is as follows:

$$\hat{\boldsymbol{x}}_{CI}(t \mid t+N) = \boldsymbol{P}_{CI}[\omega \boldsymbol{P}_1^{-1}\boldsymbol{x}_1(t \mid t+N) + (1-\omega)\boldsymbol{P}_2^{-1}\boldsymbol{x}_2(t \mid t+N)] \tag{32}$$

where $\omega \in [0,1]$ and minimizes the performance index

$$J = \min_{\omega} \mathrm{tr}\boldsymbol{P}_{CI} \tag{33}$$

and $\boldsymbol{P}_{CI}$ is defined as

$$\boldsymbol{P}_{CI} = [\omega \boldsymbol{P}_1^{-1} + (1-\omega)\boldsymbol{P}_2^{-1}]^{-1} \tag{34}$$

For the non-linear optimization problems (34), the optimal weights ω can be obtained by 0.618 method or the Fabonacci method[14].

6 Simulation example

Consider the system (1) and (2), where $\mathrm{T}=1$ is the sampled period, $\Psi = \begin{bmatrix} 1 & \mathrm{T} & 0.5\times\mathrm{T}^2 \\ 0 & 1 & \mathrm{T} \\ 0 & 0 & 1 \end{bmatrix}$, $\Upsilon = \begin{bmatrix} \mathrm{T}^3/6 & \mathrm{T}^2/2 & \mathrm{T} \end{bmatrix}^{\mathrm{T}}$, $H_1 = H_2 = H_3 = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}$, $F_1 = 0.5$, $F_2 = 0.3$. And $\xi_j(t)$ is white noises with zero mean, $\sigma_{\xi 1}^2 = 0.1$, $\sigma_{\xi 2}^2 = 0.5$. And $w(t)$ is white noises with zero mean and its covariance is $\sigma_w^2 = 0.8$.

State estimation problem is based on the measurement $(\boldsymbol{y}_i(t+N), \boldsymbol{y}_i(t+N-1), \cdots)$, to obtain covariance intersection fusion state estimator $\hat{\boldsymbol{x}}_0(t \mid t)$.

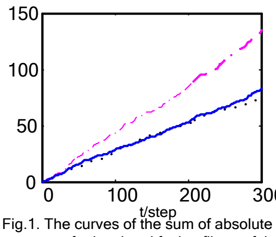

Fig.1. The curves of the sum of absolute error curve for local and fusion filters of the position

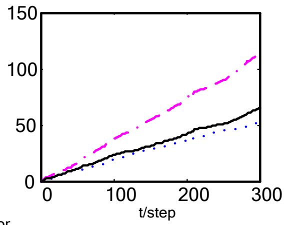

Fig.2. The curves of the sum of absolute error curve for local and fusion filters of the velocity

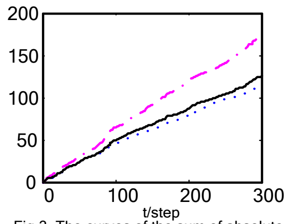

Fig.3. The curves of the sum of absolute error curve for local and fusion filters of the acceleration

The simulation results are shown in Figure 1-Figure 3. Figure 1~3 are the absolute error curve for the local and fusion state filter weighted by CI fusion. In the figure, the accuracy of the fusion state filtering is higher than any of the single sensor.

7 Conclusions

Under the linear minimum variance optimal information fusion criterion, the multi sensor optimal information fusion state estimator for descriptor and non descriptor systems is presented. The algorithm presented in this paper has many advantages. Non recursive state estimators can not only deal with the estimation problem of descriptor and non descriptor systems in a unified way, and can also handle the filtering, smoothing and prediction problems in a unified way. Non-recursive state estimators can be applied to non-square descriptor systems. Distributed information fusion rule, which adopted in this paper, is covariance intersection fusion. The estimation accuracy for the system is greatly improved compared with the single local sensor. Covariance intersection fusion has minimal computational burden because of avoiding computing the cross covariance matrix.

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