STATE MONITORING IN BIO-ACTUATORS OF MIMO BIOPROCESS: AN APPLICATION TO HUMAN ARM

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Abstract: This paper attempts to present state monitoring in bio-actuators of a time varying human multijoint arm dynamics with uncertainty factors consisting of measurement noises and modeling error of the rigid body dynamics, where the uncertainty factors include non-Gaussian noises. First, a general robust filter system based on a score function approach is given. The proposed filter is designed to have the one-to-one correspondence between shape parameters and all-order even moments. Second, design procedure is given. Finally, examples using an experiment-based human arm model show that the proposed filter has desired accuracy and robustness.

Keywords: Bio-actuators state monitoring, human multijoint arm dynamics, viscoelasticity, shape parameter

1. INTRODUCTION

Fault detection and diagnosis in bioprocesses became a challenging research topic. One of the most interesting approaches is of detecting and diagnosing bio-actuator states. In this paper, the actuator states are considered as human arm viscoelasticity. Because life system actuator parameters are adjusted directly based on physical change and motor command from central nervous system (CNS), the effective estimation of the human neuromusculoskeleton system under normal conditions is a research topic of growing importance. For example, human arm is derived by the multijoint muscle generated torque, which is assumed to be a function of angular position, velocity and motor command of CNS. The change of the torque is caused by arm viscoelasticity. And the arm viscoelasticity consists of joint stiffness, which is regulated by muscle inherent spring-like properties and neural feedbacks, and viscosity. Therefore, to estimate joint stiffness and viscosity properties of arm is important in regulating posture and movement, interacting environments and representing the interface between the neural commands and environment.

For the estimation of the actuator state during voluntary movements, Gomi and Konno (1998) considered a method using single trial data for multijoint joint movements, the method was based on Kalman filter. Because the method does not require many trials, variability of trials can be avoided. In most cases, however, uncertainties arise from arm modeling error and measurement

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noises which cannot satisfactorily be presented as stochastic signals with known distribution. For these cases, Kalman filter estimate can be degraded. That is, the above uncertain factor is non-Gaussian. Recently, one of the most effective schemes proposed by Deng *et al.* (2005) is based on the nonlinear score function approach (Niehsen, 2002; Wu and Kundu, 1996) and robust design (Deng and Gomi, 2003). Compared with standard Kalman filter, for human arm innovations process including the measurements of torque generated by multijoint muscle, the design scheme achieves significant improvements with respect to stationary mean square error and rate of convergence. Meanwhile, the ill-conditioned covariance update equation of the estimator and a derivative of the score function in the covariance update equation are avoided.

This paper is concerned with designing filter using all-order even moment by extending the design scheme given in Deng *et al.* (2005). That is, the proposed filter is a general case filter. For the proposed filter, the selection of the shape parameter in the filter is discussed. The proposed filter is applied to an experiment-based human arm model derived from Gomi and Kawato(1996, 1997).

2. GENERAL ACTUATOR STATE MONITORING FILTER STRUCTURE

In this paper, the arm viscoelasticity is defined as an actuator state. Therefore, the problem is to estimate the viscoelasticity from measured data of the multijoint muscle generated torques. In this section, to estimate the viscoelasticity, the human arm dynamics equation is first introduced. Then, a general actuator state estimating filter is derived on the basis of the human arm dynamics model.

2.1 Human Arm Dynamics Model

Two-link rigid human arm dynamics on the horizontal plane can be modeled by the following equation (Gomi and Kawato, 1997).

$$\begin{pmatrix} Z_1 + 2Z_2 cos\theta_2 & Z_3 + Z_2 cos\theta_2 \\ Z_3 + Z_2 cos\theta_2 & Z_3 \end{pmatrix} (\boldsymbol{q})\ddot{\boldsymbol{q}} + \begin{pmatrix} -Z_2 sin\theta_2(\dot{\theta_2}^2 + 2\dot{\theta}_1\dot{\theta}_2) \\ Z_2\dot{\theta_1}^2 sin\theta_2 \end{pmatrix} (\dot{\boldsymbol{q}}, \boldsymbol{q}) = \tau_{in}(\dot{\boldsymbol{q}}, \boldsymbol{q}, u) + \tau_{ext} \quad (1)$$

where, $\tau_{ext} = (\tau_{s\_ext}, \tau_{e\_ext})^T$ denotes the external force, the subscripts s and e denote shoulder and elbow, respectively. τ_{in} is the multijoint muscle generated torque, which is assumed to be a function of angular position, velocity and motor command u. $\boldsymbol{q}$, $\dot{\boldsymbol{q}}$ and $\ddot{\boldsymbol{q}}$ are angular position, velocity and acceleration vector, respectively, where

$$\boldsymbol{q} = (\theta_1(t), \theta_2(t))^T$$
$$\tau_{in} = (\tau_s, \tau_e)^T \quad (2)$$

$\theta_1(t)$ is shoulder angle and $\theta_2(t)$ is elbow angle shown in Fig.2. Z_1, Z_2 and Z_3 are structural dependent parameters. For estimating arm viscoelasticity, a pseudo-random perturbation that contains sufficient frequency components is employed (Gomi and Kawato, 1996,1997). The related explanation is omitted in this paper.

By using a band-pass filter for the model (1), the effect from u can be neglected (Gomi and Konno, 1998; Deng and Gomi, 2003). Then, the filtered torque τ_{in}^f, the filtered positions $\theta_1^f(t)$ and $\theta_2^f(t)$, and the filtered velocities $\dot{\theta}_1^f(t)$ and $\dot{\theta}_2^f(t)$ satisfy the relation: $\tau_{in}^f = XU + \Delta + \zeta_1$, where X is the regression vector, U is the time-varying parameter vector to be estimated, where

$$X = \begin{pmatrix} \theta_1^f & \theta_2^f & \dot{\theta}_1^f & \dot{\theta}_2^f & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \theta_1^f & \theta_2^f & \dot{\theta}_1^f & \dot{\theta}_2^f \end{pmatrix}$$
$$U = \begin{pmatrix} R_{ss} & R_{se} & D_{ss} & D_{se} & R_{es} & R_{ee} & D_{es} & D_{ee} \end{pmatrix}^T \quad (3)$$

$\Delta = [\Delta_1, \Delta_2]^T$ consists of the structured uncertainty of the left side of (1). The uncertainty is from human arm parameter (i.e., Z_i)(Deng and Gomi, 2003).

Following the score function, Δ_1 and Δ_2 are assumed to be Gaussian, $\zeta_1 = (\bar{\zeta}_{11}, \bar{\zeta}_{22})^T$ is the non-Ganssian measurement error matrix vector of τ_{ext}. The subscripts ss of D and R represent the shoulder single-joint effect on each coefficient. Similarly, se and es denote cross-joint effects, and ee denotes the elbow single-joint effect. Here, the effect from u can be neglected by applying band-pass filtering.

The problem considered in this paper is to estimate D_{ij} and R_{ij} in (3) from measured data of multijoint muscle generated torques τ_s and τ_e with considering the effect of the uncertainty factor $\Delta + \zeta_1$.

2.2 The General Actuator State Monitoring Filter

To design the filtering algorithm, we need to prepare the above model in the discrete time state-space form as follows.

$$U(t+1) = U(t) + \zeta_2, \quad t = 1, 2, \cdots$$
$$\tau_{in}^f(t+1) = X(t+1)U(t) + \Delta(t) + \zeta_1(t) \quad (4)$$

where, $\tilde{\zeta}_2$ is white noise, $\Delta(t) = C(z^{-1})\zeta_2$, $\zeta_2 = (\zeta_{21}, \cdots, \zeta_{28})^T$ and

$$C(z^{-1}) = \begin{pmatrix} C_1(z^{-1}) \\ C_2(z^{-1}) \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{n_c} C_{1,i} z^{-i} \\ \sum_{i=0}^{n_c} C_{2,i} z^{-i} \end{pmatrix}$$
$$C_{j,i} = (C_{j,i1}, \cdots, C_{j,i8}), \quad j = 1, 2 \tag{5}$$

The fundamental problem associated with human arm system is to estimate viscoelasticity by using the generated torques τ_s and τ_e. For the simplicity of analysis, it is not unusual that a multidimensional noise exhibits similar dynamic characteristics to a reduced dimensional disturbance. Here, we consider a matrix disturbance sequence instead of multi-dimensional $C(z^{-1})\zeta_2$. Then, the design method can be extended to multiple innovations process (Deng *et al*, 2005). Further, we can calculate variance $\sigma^2_{\Delta_i}(i = 1, 2)$ of element of the new matrix disturbance sequence. The calculating produce is summarized as follows.

Define a scalar $\bar{\zeta}_2 = \sum_{i=1}^{8} \zeta_{2i}$ and polynomical matrix $C_j^*(z^{-1}) = \sum_{i=0}^{n_c} C_{j,i}^* z^{-i} (j = 1, 2)$, where $C_{j,0}^* = 1$. In order to use $C^*(z^{-1})\bar{\zeta}_2$ instead of $C(z^{-1})\zeta_2$, where $C^*(z^{-1}) = \begin{pmatrix} C_1^*(z^{-1}) \\ C_2^*(z^{-1}) \end{pmatrix}$, we must make mean and variance equal in value of the two matrices respectively, namely,

$$E\{C_j^*(z^{-1})\bar{\zeta}_2\} = E\{C_j(z^{-1})\zeta_2\}, \quad j = 1, 2$$
$$E\{[C_j^*(z^{-1})\bar{\zeta}_2]^2\} = E\{[C_j(z^{-1})\zeta_2]^2\}$$

Calculation of the coefficients of $C(z^{-1})$ is given as follows. Using

$$E\{\bar{\zeta}_2\} = 0$$
$$E\{[\bar{\zeta}_2]^2\} = \sum_{i=1}^{8} L_i$$
$$L_i = E\{[\zeta_{2i}]^2\} \tag{6}$$

we have

$$E\{[C_{j,i}^*\bar{\zeta}_2]^2\} = (C_{j,i}^*)^2 \sum_{k=1}^{8} L_k \tag{7}$$

$$E\{[\sum_{j=1}^{8} C_{l,ij}\zeta_{2j}]^2\} = \sum_{j=1}^{8} C_{l,ij}^2 L_j, \quad l = 1, 2 \tag{8}$$

Finally,

$$(C_{l,i}^*)^2 = \frac{\sum_{j=1}^{8} C_{l,ij}^2 L_j}{\sum_{k=1}^{8} L_i}, \quad l = 1, 2 \tag{9}$$

Then, we can calculate variance $\sigma^2_{\Delta_i}(i = 1, 2)$ of element of the new matrix disturbance sequence by using (9).

In the following, the problem is to design general estimating filter based on score function approach (Deng *et al.*, 2005) for the arm model with uncertainty factor. The score function approach along with generalized Gaussian approximation of probability density function (pdf) of the innovations process can be used for state estimation of non-Gaussian system. The shape parameter of the pdf controls the shape of the distribution. The pdf of generalized Gaussian uncertainty factor $\Delta_i(t) + \bar{\zeta}_{ii}(t)(i = 1, 2)$ with zero mean, variance σ_i^2 and shape parameter γ_i is given by Niehsen (1999)

$$p_i(x_i; \sigma_i, \gamma_i) = \frac{\alpha_i(\gamma_i)\gamma_i}{2\sigma_i\Gamma(1/\gamma_i)} e^{-[\alpha_i(\gamma_i)|x_i/\sigma_i|]^{\gamma_i}}$$
$$x_i \in R, \quad i = 1, 2 \tag{10}$$

$$\alpha_i(\gamma_i) = \sqrt{\frac{\Gamma(3/\gamma_i)}{\Gamma(1/\gamma_i)}} \tag{11}$$

where $\Gamma(\cdot)$ is the Gamma function. The shape parameter is determined by the one-to-one correspondence between γ_i and the fourth-order even moment $\phi_i(\gamma_i)$. In this paper, the all-order case is considered as follows.

$$\phi_i(\gamma_i) = \frac{E(\tau_i^{2m})}{\sigma_i^{2m}}$$
$$= \frac{\Gamma(\frac{2m+1}{\gamma_i})\Gamma^{m-1}(1/\gamma_i)}{\Gamma^m(3/\gamma_i)}, m = 1, 2, \cdots \tag{12}$$

where

$$\sigma_i^2 = \sigma^2_{\Delta_i} + \sigma^2_{\bar{\zeta}_{ii}} \tag{13}$$

$E(\tau_i^{2m})$ is a function of $\sigma^2_{\Delta_i}$, γ_{Δ_i}, $\sigma^2_{\bar{\zeta}_{ii}}$ and $\gamma_{\bar{\zeta}_{ii}}$. Variables $\sigma^2_{\Delta_i}$, γ_{Δ_i}, $\sigma^2_{\bar{\zeta}_{ii}}$ and $\gamma_{\bar{\zeta}_{ii}}$ are variance of Δ_i, shape parameter of Δ_i, variance of $\bar{\zeta}_{ii}$ and shape parameter of $\bar{\zeta}_{ii}$, respectively. The odd moments vanish, because the pdf is the symmetry. From Fig.1, the generalized Gaussian pdf decay rate increases for increasing the shape parameter.

Consider a relation from (12), we assume that

$$\phi_i(\gamma_i) = \frac{l_{2i}e^{-l_{1i}\gamma_i}}{\sigma_i^{2m}} \tag{14}$$

where the design parameters l_{0i} and l_{1i} can be obtained by matching (12) in pre-experiment. The unmatched part will be of uncertainty factor.

Considering the generalized Gaussian pdf, the score function-based general algorithm is obtained.

$$\hat{U}(t+1) = \hat{U}(t) + \boldsymbol{k}(t) \begin{pmatrix} \gamma_1(\frac{\alpha_1(\gamma_1)}{\sigma_1})^{\gamma_1}\tau_1^{\gamma_1 - 1} \\ \gamma_2(\frac{\alpha_2(\gamma_2)}{\sigma_2})^{\gamma_2}\tau_2^{\gamma_2 - 1} \end{pmatrix} \tag{15}$$
$$\tau_i > 0 (i = 1, 2), \tau_1 = \tau_s, \tau_2 = \tau_e$$

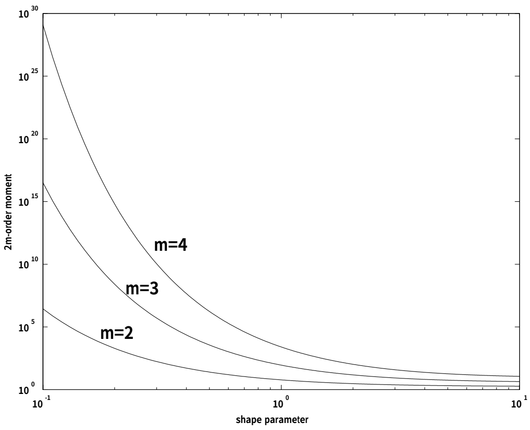

Fig. 1. The relation between moment and shape parameter

$$\boldsymbol{k}(t) = (W(t)N(t)W(t)^T + L)X^T \qquad (16)$$

where $N(t)$ is a diagonal matrix and $W(t)$ is an upper-triangular matrix with unit entries along the diagonal. L is positive definite and is the covariance matrix of ζ_2. $\hat{U}$ is an estimate parameter vector of U.

The main differences between the above filter and the filter in Niehsen (2002) are : 1) Equation (15) is multiple innovations process; 2) Using $\bar{U}D$ factorization algorithm $W(t)N(t)W(t)^T$ in (21) for avoiding ill-conditioned matrix (Thornton and Bierman, 1978) and the derivative of the score function; 3) The shape parameter can be obtained on-line (see (20)). Meanwhile, using the result in Deng *et al.*(2005), the proposed algorithm guarantees that all the estimated elements of viscoelasticity are bounded.

3. AN EXAMPLE OF FILTER DESIGN PROCEDURE AND NUMERICAL SIMULATIONS

The purpose of this section is to demonstrate the design procedure of the proposed filter and to show the effectiveness by simulation.

3.1 Filter Design Procedure for Case of m=3

In the actual estimation, the moment order needs to be decided. In this paper, $m = 3$ is selected. Then, we have

$$\phi_i(\gamma_i) = \frac{E(\tau_i^6)}{\sigma_i^6} = \frac{\Gamma(7/\gamma_i)\Gamma^2(1/\gamma_i)}{\Gamma^3(3/\gamma_i)} \qquad (17)$$

where

$$E(\tau_i^6) = \sigma^6_{\Delta_i}\phi_i(\gamma_{\Delta_i}) + 15\sigma^4_{\Delta_i}\phi_i(\gamma_{\Delta_i})\sigma^2_{\bar{\zeta}_{ii}} + 15\sigma^2_{\Delta_i}\sigma^4_{\bar{\zeta}_{ii}}\phi_i(\gamma_{\bar{\zeta}_{ii}}) + \sigma^6_{\bar{\zeta}_{ii}}\phi_i(\gamma_{\bar{\zeta}_{ii}}) \qquad (18)$$

$$\phi_i(\gamma_{\Delta_i}) = \phi_i(2) = 3 \qquad (19)$$

Note that $E(\tau_i^6) = l_{2i}e^{-l_{1i}\gamma_i}$ from (17), (18) and (19), $E(\tau_i^6)$ is solved for each processing time step, then the shape parameter is given as follows.

$$\gamma_i = -\frac{1}{l_{1i}} log(E/l_{2i}) \qquad (20)$$

$$\sigma^2_{\Delta_1} = X(W(t)N(t)W(t)^T + L)X^T(1,1) \qquad (21)$$

$$\sigma^2_{\Delta_2} = X(W(t)N(t)W(t)^T + L)X^T(2,2) \qquad (22)$$

The arm dynamics model used to generate the simulated data sets is based on the following relationships (Gomi and Kawato, 1996; Gomi and Kawato, 1997).

$$R_{ss} = A_{ss}|\tau_{s\_m}| + B_{ss} \qquad (23)$$

$$R_{se} = A_{se}|\tau_{e\_m}| + B_{se} \qquad (24)$$

$$R_{es} = R_{se} \qquad (25)$$

$$R_{ee} = A_{ee}|\tau_{e\_m}| + B_{ee} \qquad (26)$$

$$D_{ss} = C_{ss}|\tau_{s\_m}| + E_{ss} \qquad (27)$$

$$D_{se} = C_{se}|\tau_{e\_m}| + E_{se} \qquad (28)$$

$$D_{es} = D_{se} \qquad (29)$$

$$D_{ee} = C_{ee}|\tau_{e\_m}| + E_{ee} \qquad (30)$$

where

$$\begin{pmatrix} \tau_{s\_m} \\ \tau_{e\_m} \end{pmatrix} = \boldsymbol{I}(\boldsymbol{q}_d)\ddot{\boldsymbol{q}}_d + \boldsymbol{H}(\dot{\boldsymbol{q}}_d, \boldsymbol{q}_d) \qquad (31)$$

τ_{s_m} and τ_{e_m} are the desired shoulder and elbow torques, respectively. $\boldsymbol{q}_d$ is the desired angular position vector. The estimation results are evaluated by using the following formulations.

$$E_R = (|\Delta R_{ss}| + |\Delta R_{se}| + |\Delta R_{es}| + |\Delta R_{ee}|)/4$$

$$E_D = (|\Delta D_{ss}| + |\Delta D_{se}| + |\Delta D_{es}| + |\Delta D_{ee}|)/4$$

In the simulation, the multijoint muscle generated torque is obtained as follows.

$$\tau_{in} = R(\boldsymbol{q}_{eq} - \boldsymbol{q}) - D\dot{\boldsymbol{q}} \qquad (32)$$

where $\boldsymbol{q}_{eq}$ is the equilibrium point.

3.2 Simulation Results

Concerning with the real values of human arm parameters, the following parameters are considered based on the result in Gomi and Kawato (1996) and Gomi and Kawato (1997).

For arm viscoelasticity, we use

$$A_{ss} = 20, \quad B_{ss} = 20$$

$$A_{se} = 12, \quad B_{se} = 6$$

$$A_{ee} = 28, \quad B_{ee} = 15$$

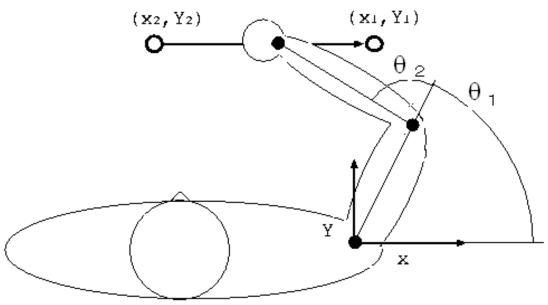

Fig. 2. One of the movement descriptions of the arm model in the simulations

$$C_{ss} = 0.6, \quad E_{ss} = 0.6$$
$$C_{se} = 0.4, \quad E_{se} = 0.3$$
$$C_{ee} = 0.8, \quad E_{ee} = 0.7 \tag{33}$$

For the two-link rigid arm in (1), the structural parameters Z_1, Z_2 and Z_3 are unknown, and in the simulation we select the true values of the parameters as $Z_1 = 0.4507$, $Z_2 = 0.1575$ and $Z_3 = 0.1530$. The error range is selected as 0.05%. The cut-off frequencies of the third-order band-pass filter to generate τ_{in}^f, $\theta_i^f(t)$ and $\dot{\theta}_i^f(t)$ are 2.5[Hz] and 20[Hz]. Besides the above 0.05% uncertainty the filtered noise applied in τ_{in}^f is

$$\begin{pmatrix} 0.09 + 0.045 * \text{rand}(r_1) \\ 0.09 + 0.045 * \text{rand}(r_2) \end{pmatrix}$$

where, rand(r_i) is a function to generate random noise with the initial value r_i.

In order to compare to the existed filters (Gomi and Konno, 1998; Deng and Gomi, 2003), the same movements are selected. That is, during multijoint viscoelasticity measurement, the arm model was instructed to move from the start position (x,y)=[-0.2,0.35](m) to the end position (x,y)=[0.2,0.35](m) directly (Fig. 2). The arm simulation procedure is described as follows. The arm keeps unmoving at the start position for $1s$, then it moves with a uniform velocity for $3s$ and keeps unmoving at end position for $1s$. The whole simulation time is $5s$. External torque produced randomly are the filtered torque of $\tau_{s\_ext} = 40 * (rand(r_3) - 0.5)$ and $\tau_{e\_ext} = 30 * (rand(r_4) - 0.5)$ by fourth order Butterworth filter. For shoulder, the filter cut-off frequency is 4Hz $\sim$ 16Hz. For elbow, the filter cut-off frequency is 8Hz $\sim$ 24Hz, where rand(r_3) and rand(r_4) are random signals. Using the conventional Kalman filter to estimate viscoelastic parameters for the model with uncertainty, Fig.3 shows the mean error of the estimation of the arm model with 5% uncertainty of Z_i (Deng and Gomi, 2003). Considering the estimation algorithm given in Deng and Gomi(2003), as the same uncertainty with the above simulation, the simulation result is shown in Fig.4. In

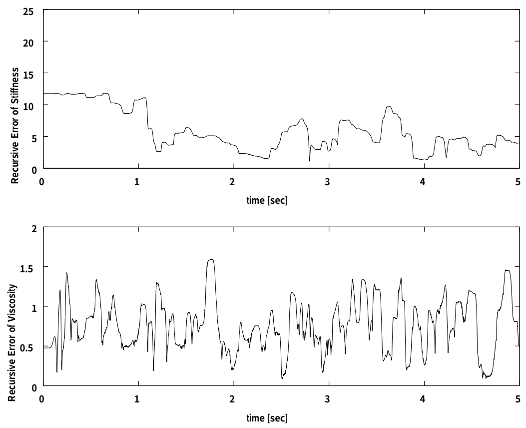

Fig. 3. Time-variation of mean error of stiffness and viscosity by using Kalman filter with 5% uncertainty of Z_i

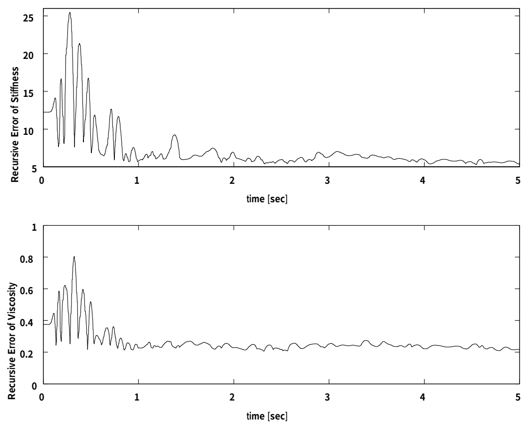

Fig. 4. Time-variation of mean error of stiffness and viscosity by using the algorithm in Deng and Gomi (2003) with 5% uncertainty of Z_i

the simulation in Fig.4, the design parameters are the same with the case in Fig. 3, but the $\bar{U}D\bar{U}^T$ term for avoiding ill-conditioned matrix (Thornton and Bierman, 1978) is added, where the dimensional partial state innovations variance is 1.8. Comparing the simulation results in Figs. 3 and 4, the algorithm used in Fig. 4 shows a better convergent performance after 1 s. It is worthy to say that the robust estimation scheme in Deng and Gomi (2003) was considered to reduce the effect of uncertainty factor by using prior information of noises. Namely, for each processing step, if the upper bound of the uncertainty factor is known, the algorithm ensures the stability in the worst uncertainty factor case. Therefore, this is a conservative design method.

Considering the estimation algorithm given in Section 3.1, the simulation results are shown in Figs. 5 and 6, where $l_{11} = 13.188$, $l_{12} = 12.176$, $l_{21} = l_{22} = 1.645e^{12}$. Fig. 6 shows the stiffness ellipses calculated during movement. The ellipses represent the direction and magnitude of elastic, resisting forces to unit-length position perturba-

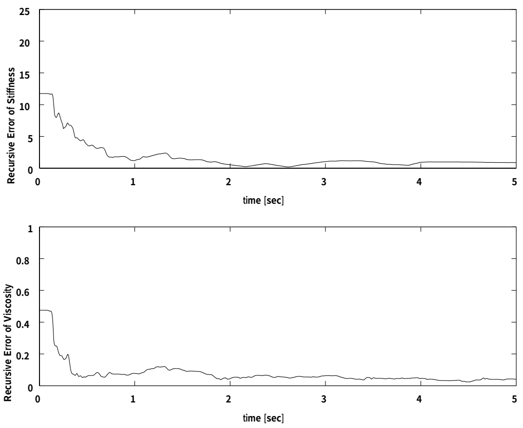

Fig. 5. Time-variation of mean error of stiffness and viscosity by using the proposed algorithm with 5% uncertainty of Z_i

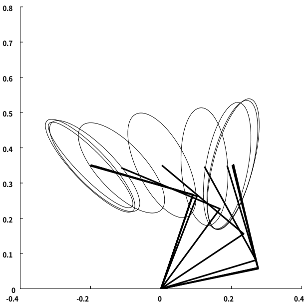

Fig. 6. Stiffness ellipse estimated by using the proposed algorithm with 5% uncertainty of Z_i

tions in all directions. The long axis of each ellipse represents maximum force, indicating the greatest stiffness. The short axis represents minimum force, indicating the least stiffness (Gomi and Kawato, 1996). Comparing the simulation results in Figs. 4 and 5, the proposed algorithm shows a better performance.

In the following, three simulations with different movements are conducted (see Table 1). The movement descriptions are shown as follows. In simulation run 2, the arm model was instructed to move from the start position [0,0.5](m) to the end position [0,0.2](m) directly. In simulation run 3, the arm model is instructed to move from the start position [-0.2,0.4465](m) to the end position [0.2,0.4465](m) as an arc. In simulation run 4, the arm model is instructed to move from the start position [-0.2,0.25](m) to the end position [0.2,0.45](m) directly. Simulation results of the three filters show that the influence from the moving directions is not so large. The above simulation results are omitted for brevity.

Simulation run	Movements
1(5% error)	[-0.2,0.35] to [0.2,0.35]
2(5% error)	[0,0.5] to [0,0.2]
3(5% error)	[-0.2,0.4465] to [0.2,0.4465]
4(5% error)	[-0.2,0.25] to [0.2,0.45]

Table 1

4. CONCLUSION

This paper focused on introduction of the actuator state monitoring of a human multijoint arm dynamics. General filter system is given based on a score function approach. The detailed design procedure for the case of $m = 3$ is shown. Further, examples using an experiment-based human arm model show that the proposed filter has desired accuracy and robustness.

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