RECURSIVE FILTER DESIGN FOR ESTIMATING TIME VARYING MULTIJOINT HUMAN ARM VISCOELASTICITY

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ABSTRACT

The time varying human multijoint arm dynamics can be modeled by two factors, simplified musculoskeletal dynamics and the uncertainty factor consisting of measurement noises and modeling error of a rigid body dynamics. In some cases, the uncertainty factor may not be Gaussian; the Kalman filter is no longer the optimal filter. In this paper, for the non-Gaussian environment, a recursive filter design method for estimating time varying human multijoint arm viscoelasticity during the arm is moving is presented. The method is based on a score function approach associated with $\bar{U}D$ factorization algorithm and equivalent noise technique for multiple innovations process. The proposed method for an experiment-based human arm model provides greater accuracy and robustness in capturing texture information of the model under the case of non-Gaussian noises, while the performance of standard Kalman filter degrades significantly.

Keywords: viscoelasticity, multijoint arm, robust estimation, score function.

1. INTRODUCTION

The study of human arm viscoelasticity is very important for the development of fields, such as, industrial robots, rehabilitation and sports, etc. For example, we can design a robot arm based on the knowledge of human impedance, then the robot arm can handle various objects as a human arm does. Especially, joint stiffness properties are important in regulating posture and movement, and interacting environments (Hogan, 1985; Lacquaniti, 1993). The stiffness properties are determined by muscle inherent spring-like properties and neural feedbacks.

For the identification of the stiffness properties during voluntary movements, several methods using ensemble data are reported (Bennett, 1992; Gomi, 1996; Lacquaniti, 1993; MacNeil, 1992), in which data of restoring forces and positional responses of many trials were required. Recently, a nonparametric system identification algorithm was used to estimate endpoint stiffness from the measured force and displacement (Perreault, 2001). However, the problem is that the above methods require many trials. Alternative method using single trial data was reported for single joint movements (Xu, 1998). Because this method does not require many trials, the effect of subject for each trial can be extremely reduced and physical variability from trial to trial can be avoided. Due to the increased number of parameters, potential modeling error, and measurement noises, however, it would not be possible to simply apply this method for estimating multijoint arm viscoelasticity. Meanwhile, based on the previous studies (Gomi, 1996; Gomi, 1998a), researchers (Gomi, 1998b) have worked on the estimation of multijoint arm viscoelasticity based on Kalman filter. However, the estimate can be degraded under the existence of arm modeling error and measurement noises. Robust estimation scheme was considered to reduce the effect of uncertainty factor by using prior information of noises (Deng, 2003). 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.

In this paper, for improvement of the on-line estimation characteristics and reduction of the number of trials, a recursive filter design method of multijoint arm viscoelasticity during the arm is moving is provided. The proposed design scheme has three features, namely, 1) using single trial data; 2) estimating multijoint arm viscoelasticity; 3) for obtaining real uncertainty factor situation, using generalized Gaissian instead of upper bound evaluation. The detailed explanation of the contribution in this paper is given as follows.

Considering the real time system identification, we have to deal with the above uncertainty factor which is highly non-Gaussian. In the non-Gaussian environment, one of the most effective schemes ever proposed (Niehsen, 2002) is based on the nonlinear score function approach (Masreliez, 1975; Wu, 1996). Compared with standard Kalman filter, for a scalar innovation process the design scheme achieves significant improvements with respect to stationary mean square error and rate of convergence. However, because of noises in several sources, one of the major problems in (Niehsen, 2002) is the ill-conditioned covariance update equation of the estimator. Namely, the algorithm may lead to a negative-definite solution and then to inaccurate result (Thornton, 1978). Also, the existing method (Niehsen, 2002) requires a derivative of the score function in the covariance update equation and this is not practical to real time application. Further, the human arm innovations process has to include the measurements of multijoint muscle generated torque. To treat these problems, we consider the following techniques in our filter design. The first step is to use the $\overline{U}D\overline{U}^T$ form to make the solution of the covariance update equation be positive definite. Meanwhile, by using the form, the derivative of the score function is avoided. As a result, relatively high identification accuracy and robustness can be attained. The second step is, using an equivalent noise technique (Deng, 1991), to solve the multiple measurements problem. That is, for estimating multijoint human arm viscoelasticity, we extend the design scheme in (Niehsen, 2002) to multiple innovations process.

2. THEORY

2.1 Human arm dynamics model and noises treatment

This section considers modeling and noise treatment problem of a human arm depicted in Fig. 1.

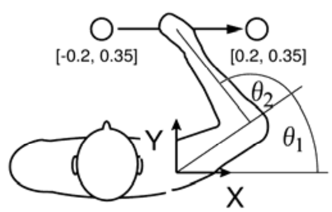

Figure 1. The movement description of the arm model

A model which is given in Appendix A is

$$I(q)\ddot{q} + H(\dot{q},q) = \tau_{in}(\dot{q},q,u) + \tau_{ext}$$

where $q = [\theta_1(t), \quad \theta_2(t)]^T$ is arm angle matrix, τ_{in} and τ_{ext} are torque, and $I(q)\ddot{q}$ and $H(\dot{q},q)$ are given by (34) and (35). By using a band-pass filter for the model, 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 following relation.

$$\tau_{\boldsymbol{in}}^{\boldsymbol{f}} = \boldsymbol{XU} + \Delta + \zeta_1 \tag{1}$$

where X is the regression vector, $\boldsymbol{U}$ is the time-varying parameter vector to be estimated, and

$$X = \begin{bmatrix} \theta_1^f(t) & \theta_2^f(t) & \dot{\theta}_1^f(t) & \dot{\theta}_2^f(t) & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \theta_1^f(t) & \theta_2^f(t) & \dot{\theta}_1^f(t) & \dot{\theta}_2^f(t) \end{bmatrix}$$

$$U = [R_{ss}(t) \quad R_{se}(t) \quad D_{ss}(t) \quad D_{se}(t) \quad R_{es}(t) \quad R_{ee}(t) \quad D_{es}(t) \quad D_{ee}(t)]^T \tag{2}$$

where $\Delta = [\Delta_1(t), \quad \Delta_2(t)]^T$ consists of the structured uncertainty of the term $\{I(q)\ddot{q} + H(\dot{q},q)\}$. The uncertainty is from human arm parameter (i.e., Z_i in (36)-(38)). Following the score function approach in Niehsen (2002), Δ_1 and Δ_2 are assumed to be Gaussian, $\zeta_1 = [\bar{\zeta}_{11}(t), \quad \bar{\zeta}_{22}(t)]^T$ is the non-Ganssian measurement error matrix of τ_{ext}. In the actual estimation, the above uncertainty factor should be considered to avoid estimation errors. In this paper, to reduce the effect of the uncertainty factor, we will consider a filtering algorithm for estimating multijoint human arm viscoelasticity.

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

$$U(t+1) = U(t) + \zeta_2,\ t = 1,2,$$
$$\tau_{in}^f(t+1) = X(t+1)U(t) + \Delta(t) + \zeta_1(t), \tag{3}$$

where, ζ_2 is white noise, $\Delta(t) = C(z^{-1})\bar{\zeta}_2$, and

$$C(z^{-1}) = \begin{pmatrix} C_1(z^{-1}) \\ C_2(z^{-1}) \end{pmatrix} = \begin{pmatrix} \sum_{i=0}^{n_c} C_{1,i} z^{-i} \\ \sum_{i=0}^{n_c} C_{2,i} z^{-i} \end{pmatrix},\ C_{j,i} = \left[C_{j,i1}, \cdots, C_{j,i8}\right],\ j = 1,2 \tag{4}$$

$$\zeta_2 = \left[\zeta_{21}, \cdots, \zeta_{28}\right]^T \tag{5}$$

The fundamental problem associated with human arm system is to estimate viscoelasticity by using the generated torques τ_s and τ_e. However, the score function approach described in Niehsen (2002) was confined to scalar measurements. Here, we consider a new matrix disturbance sequence instead of multi-dimensional $C(z^{-1})\zeta_2$. Then, the design method can be extended to multiple innovations process.

Define a scalar $\bar{\zeta}_2 = \sum_{i=1}^{8} \zeta_{2i}$ and polynomial matrix $C_j^*(z^{-1}) = \sum_{i=0}^{n_c} C_{j,i}^* z^{-i},\ j = 1,2,$ where $C_{j,0}^*(z^{-1}) = 1$. 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,

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

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

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

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

Finally,

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

Then, we can calculate variance $\sigma_{\Delta_i}^2\ (i = 1,2)$ of element of the new matrix disturbance sequence by using (9). In the following, the objective is to design the recursive filter based on score function approach for the arm model with uncertainty factor.

2.2 Filter design based on the score function approach

The score function approach along with generalized Gaussian approximation of the innovations process probability density function can be used for state estimation of non-Gaussian system. The shape parameter of the probability density function (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)

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

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

where $\Gamma(\cdot)$ is the Gamma function given by

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt \tag{12}$$

If $\gamma_i = 2$, the uncertainty factor is completely characterized by its second-order moment. Otherwise, the uncertainty factor is completely characterized by its second-order moment and fourth-order moment. In this paper, the shape parameter is determined by the one-to-one correspondence between γ_i and the following fourth-order even moment

$$\phi_i(\gamma_i) = \frac{E(\tau_i^4)}{\sigma_i^4} = \frac{\Gamma(5/\gamma_i)\Gamma(1/\gamma_i)}{\Gamma^2(3/\gamma_i)} \tag{13}$$

where

$$E(\tau_i^4) = \phi_i(\gamma_i)\sigma_i^4 = \sigma_{\Delta_i}^4 \phi_i(\gamma_{\Delta_i}) + \sigma_{\bar{\zeta}_{ii}}^4 \phi_i(\gamma_{\bar{\zeta}_{ii}}) + 6\sigma_{\Delta_i}^2 \sigma_{\bar{\zeta}_{ii}}^2 \tag{14}$$

$$\sigma_i^2 = \sigma_{\Delta_i}^2 + \sigma_{\bar{\zeta}_{ii}}^2 \tag{15}$$

$$\phi_i(\gamma_{\Delta_i}) = \phi_i(2) = 3 \tag{16}$$

where $\sigma_{\Delta_i}^2$, γ_{Δ_i}, $\sigma_{\bar{\zeta}_{ii}}^2$ 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.

Considering the generalized Gaussian pdf given in (10), the score function is given by

$$g_i(\tau_i) = \gamma_i \left(\frac{\alpha_i(\gamma_i)}{\sigma_i} \right)^{\gamma_i} \tau_i^{\gamma_i - 1},\ \tau_i > 0,\ i = 1,2,\ \tau_1 = \tau_s,\ \tau_2 = \tau_e \tag{17}$$

According to the above discussions and the result in Niehsen (2002), we can also design a filter to estimate arm viscoelasticity. However, one of the major problems in filtering applications is that the covariance update equation is often ill-conditioned and the algorithm stability under the structured uncertainties of arm and measurement noises is not guaranteed in general. Further, the covariance update equation in Niehsen (2002) includes the derivative of the score function. Then, we propose the following algorithm.

$$\hat{U}(t+1) = \hat{U}(t) + k(t)\begin{pmatrix} g_1 \\ g_2 \end{pmatrix} \tag{18}$$

$$k(t) = M(t)X^T \tag{19}$$

$$M(t) = P(t) + L \tag{20}$$

$$P(t) = W(t)N(t)W(t)^T \tag{21}$$

where $N(t)$ is a diagonal matrix and $W(t)$ is an upper-triangular matrix with unit entries along the diagonal and 4×4 right upper-triangular zero matrix. L is positive definite and is the covariance matrix of ζ_2. $\hat{\boldsymbol{U}}$ is an estimate parameter vector of $\boldsymbol{U}$. The main differences between this paper and Niehsen (2002) are: 1) Equation (18) is multiple innovations process; 2) Using $\bar{\boldsymbol{U}}\boldsymbol{D}$ factorization algorithm (21) for avoiding ill-conditioned matrix and the derivative of the score function. To assist the development, the detailed formulation of the $\bar{\boldsymbol{U}}\boldsymbol{D}\bar{\boldsymbol{U}}^{\boldsymbol{T}}$ method is given as follows.

$$f = W^T(t-1)X^T(t) \tag{22}$$

$$b = Z(t-1)f \tag{23}$$

$$\alpha_{j,i}(t) = \alpha_{j-1,i} + f_{j,i}b_{j,i},\ \alpha_{0,i} = V_i \tag{24}$$

$$N_{j,j}(t) = (\alpha_{j-1,i}/\alpha_{j,i})N_{j,j}(t-1) \tag{25}$$

$$v_{j,i} = b_{j,i} \tag{26}$$

$$l_{m,i} = -f_{j,i}/\alpha_{j-1,i} \tag{27}$$

where $\boldsymbol{f}$ and $\boldsymbol{b}$ are an 8×8 matrix, respectively. $\boldsymbol{V_i}$ is $\boldsymbol{ii-th}$ element of $\boldsymbol{V}$. For $\boldsymbol{i} = 1$, $\boldsymbol{j} = 1,2,3,4$; for

$\boldsymbol{i} = 2$, $\boldsymbol{j} = 5,6,7,8$. $\boldsymbol{V}$ is positive definite and is the covariance matrix of $\Delta(\boldsymbol{t}) + \zeta_1(\boldsymbol{t})$. The dimension of $\boldsymbol{W}$ and $\boldsymbol{N}$ is 8. Meanwhile, $\boldsymbol{W}$ matrix will be updated by the following equations.

$$W_{j,m}(t) = W_{j,m}\ (t-1) + v_{j,i} l_{m,i} \tag{28}$$

$$v_{j,i} := v_{j,i} + W_{j,m}(t-1) v_{m,i} \tag{29}$$

Therefore, we described the proposed filter described by (18)-(21). This filter is designed by using the noise treatment technique give in Section 2.1. For the situation of a non-Gaussian structured uncertainty noise $\Delta_{\boldsymbol{i}}$ but Gaussian measurement noise $\bar{\zeta}_{\boldsymbol{ii}}$, we can employ another filter given in Masreliez（1975), and the proposed design techniques are same.

3. SIMULATION

3.1 Simulation model

In this section, we examine the proposed method based on an arm model obtained by experimental data. The analysis and setting of viscoelasticity-torque relationship are given in **Appendix B**. Here, the task of the arm movement is drawing a line as described in Fig.1. The ideal human arm viscoelasticity model is set by the experimental data (Gomi, 1996; Gomi, 1998a) from a parallel link drive air-magnet floating manipulandum system.

The structural parameters $\boldsymbol{Z}_1$, $\boldsymbol{Z}_2$ and $\boldsymbol{Z}_3$ are unknown, in the simulation we select the true values of the parameters as $\boldsymbol{Z}_1 = 0.4507$, $\boldsymbol{Z}_2 = 0.1575$ and $\boldsymbol{Z}_1 = 0.1530$ based on the result in Gomi（1997). The error range is selected as 0.05%. The cut-off frequencies of the third-order band-pass filter to generate $\tau_{\boldsymbol{in}}^{\boldsymbol{f}}$, $\theta_{\boldsymbol{i}}^{\boldsymbol{f}}$ and $\dot{\theta}_{\boldsymbol{i}}^{\boldsymbol{f}}$ are 2.5[Hz] and 20[Hz]. Besides the above 0.05% uncertainty the filtered noise applied in $\tau_{\boldsymbol{in}}^{\boldsymbol{f}}$ is

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

where, $\boldsymbol{rand}(\boldsymbol{r_i})$ is a function to generate random noise with the initial value $\boldsymbol{r_i}$. Meanwhile, the parameters of the proposed filter are designed as follows.

$$\begin{pmatrix} V_1 & 0 \\ 0 & V_1 \end{pmatrix} = \begin{pmatrix} 1.8 & 0 \\ 0 & 1.8 \end{pmatrix}$$

$$L = diag([1,1,0.35,0.35,1,1,0.35,0.35])$$

$$W(0) = \begin{pmatrix} 1 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

$$\boldsymbol{N}(0) = \boldsymbol{diag}([1.0\boldsymbol{e}^5, 1.0\boldsymbol{e}^5, 1.0\boldsymbol{e}^3, 1.0\boldsymbol{e}^2, 1.0\boldsymbol{e}^5, 1.0\boldsymbol{e}^5, 1.0\boldsymbol{e}^2, 1.0\boldsymbol{e}^2])$$

During multijoint viscoelasticity measurement, the arm model was instructed to move from the start position $(\boldsymbol{x}, \boldsymbol{y}) = [-0.2, 0.35](\boldsymbol{m})$ to the end position $(\boldsymbol{x}, \boldsymbol{y}) = [0.2, 0.35](\boldsymbol{m})$ directly (Fig. 1). The arm simulation procedure is described as follows. The arm keeps unmoving at the start position for 1(s), then it moves in the uniform velocity for 3(s) and keeps unmoving at end position for 1(s). The whole simulation time is 5(s). Since the moving velocity is slow, the shape parameter in the simulation is chosen to be: $\gamma_1 = \gamma_2 = 1.7$. External torque produced by random are the filtered torque of $\tau_{\boldsymbol{s\_ext}} = 40 * (\boldsymbol{rand}(r_3) - 0.5)$ and $\tau_{e\_ext} = 30 * (rand(r_4) - 0.5)$ by fourth order Butterworth filter. For shoulder, the filter cut-off frequency is 4Hz~16Hz. For elbow, the filter cut-off frequency is 8Hz~24Hz, where $\boldsymbol{rand}(\boldsymbol{r}_3)$ and $\boldsymbol{rand}(\boldsymbol{r}_4)$ are random signals. In this paper, all of the dotted lines in figures describe the corresponding true values based on the relationships in **Appendix B**, and

$$A_{ss} = 20, B_{ss} = 20, A_{se} = 12, B_{se} = 6, A_{ee} = 28, B_{ee} = 15$$

$$C_{ss} = 0.6, E_{ss} = 0.6, C_{se} = 0.4, E_{se} = 0.3, C_{ee} = 0.8, E_{ee} = 0.7 \quad (30)$$

Namely, the reference viscoelasticities are varying around the following values

$$R_{ss} = 20[Nm/rad], R_{se} = 6[Nm/rad], R_{ee} = 15[Nm/rad], R_{es} = 6[Nm/rad]$$

$$D_{ss} = 0.6[Nm/(rad/s)], E_{se} = 0.3[Nm/(rad/s)], D_{ee} = 0.7[Nm/(rad/s)], D_{es} = 0.3[Nm/(rad/s)]$$

Meanwhile, the estimation results are evaluated by using the following formulations.

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

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

3.1 Simulation results

Kalman filter can be successfully used in estimating viscoelastic parameters if the arm dynamic model is exactly known. Using the conventional Kalman filter to estimate viscoelastic parameters for the model with uncertainty, Fig. 2-4 show the estimated viscoelasticy, mean error of the estimation and stiffness ellipse of the arm model.

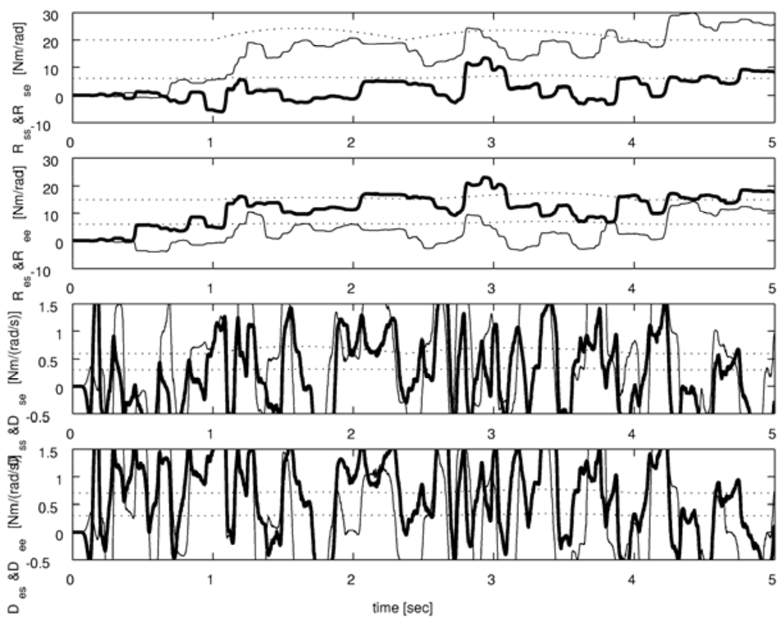

Figure 2. Estimated stiffness and viscosity by using Kalman filter with 5% uncertainty of $\boldsymbol{Z_i}$

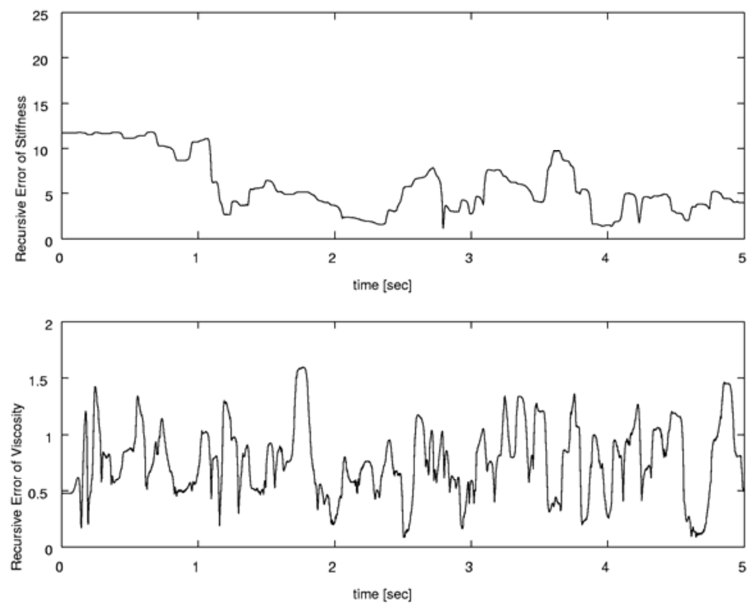

Figure 3. Time-variation of mean error of stiffness and viscosity by using Kalman filter with 5% uncertainty of $\boldsymbol{Z_i}$

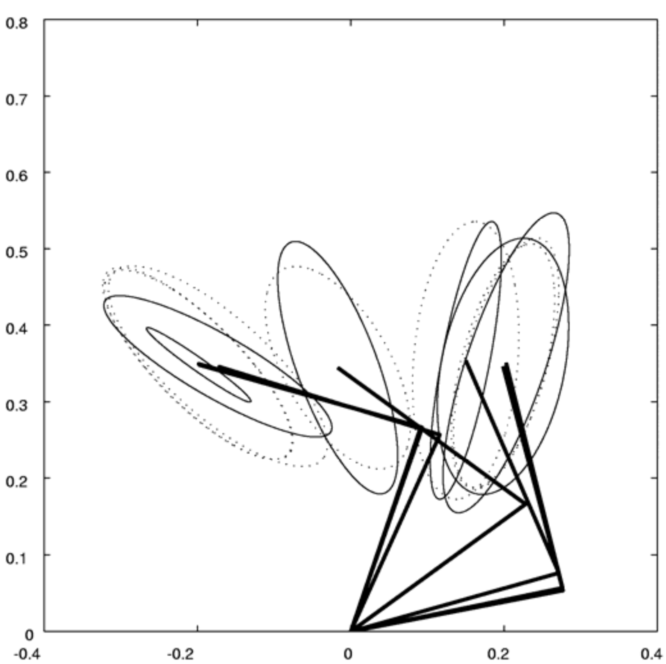

Figure 4. Stiffness ellipse estimated by using Kalman filter with 5% uncertainty of $\boldsymbol{Z_i}$ (the dotted circle describes the true value)

Since there exist the structural uncertainty and the measurement error described above, the estimated results of the arm viscoelasticity are undesirable. Considering the estimation algorithm given in Section 2, the simulation results are shown in Figs. 5~7.

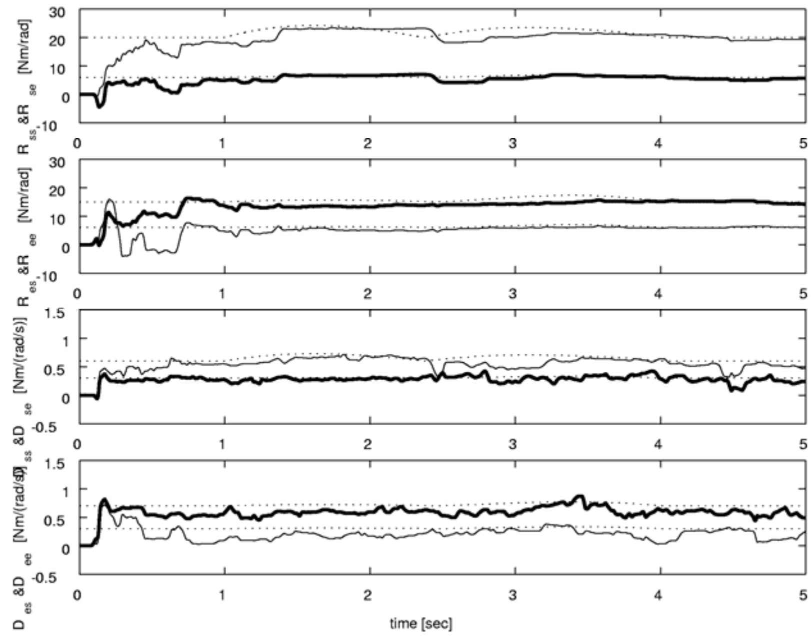

Figure 5. Estimated stiffness and viscosity by using the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$

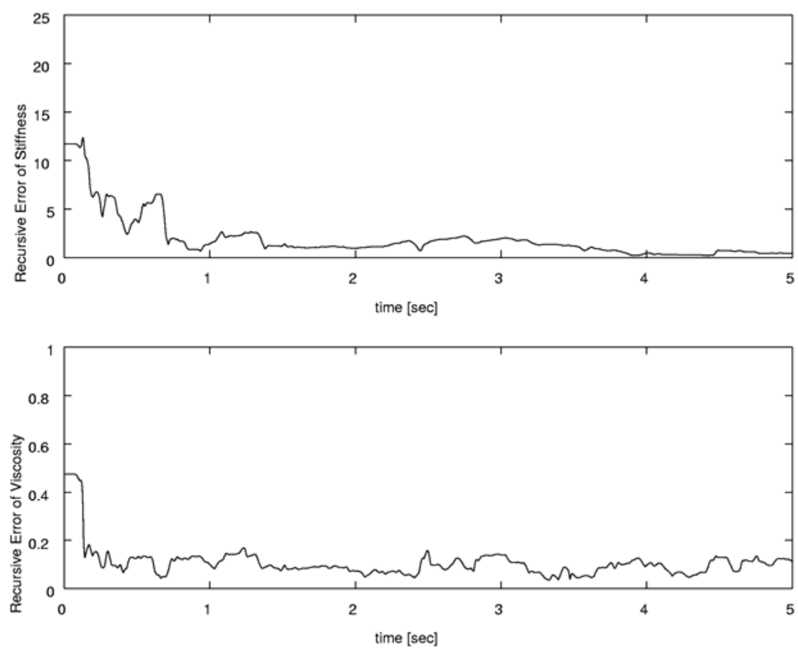

Figure 6. Time-variation of mean error of stiffness and viscosity by using the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$

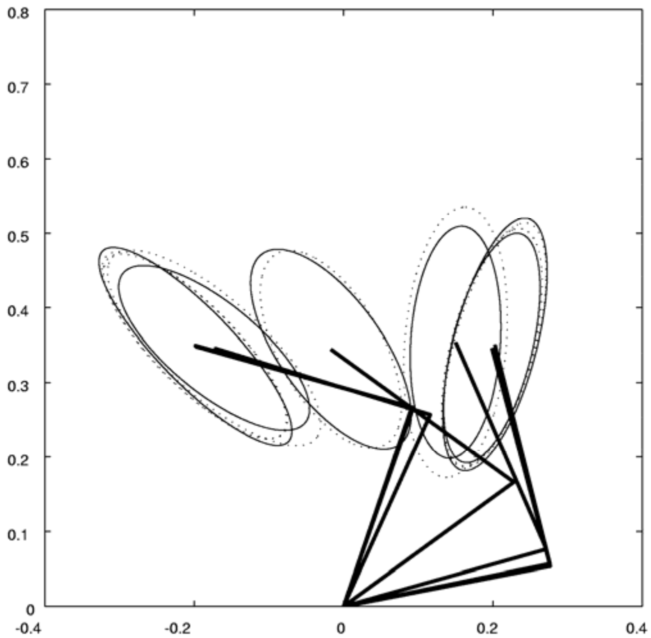

Figure 7. Stiffness ellipse estimated by the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$ (the dotted circle describes the true value)

In these simulations, the design parameters are the same, but the $\overline{\boldsymbol{U}}\boldsymbol{D}\overline{\boldsymbol{U}}^{\boldsymbol{T}}$ term is added, further, uncertainty and noise treatment are also considered. Comparing the simulation results, the proposed algorithm shows a better performance. In the following, to show the effect of difference of movements, three simulations with different movements are conducted. During multijoint viscoelasticity measurement, under the same design condition with the proposed robust filter in the case of 5% uncertainty of $\boldsymbol{Z_i}$, the arm model was instructed to move from the start position $(\boldsymbol{x},\boldsymbol{y}) = [0,0.5](\boldsymbol{m})$ to the end position $(\boldsymbol{x},\boldsymbol{y}) = [0,0.2](\boldsymbol{m})$ directly. The estimated viscoelasticity, mean error of the estimation and stiffness ellipse of the arm model are described in Figs. 8~10.

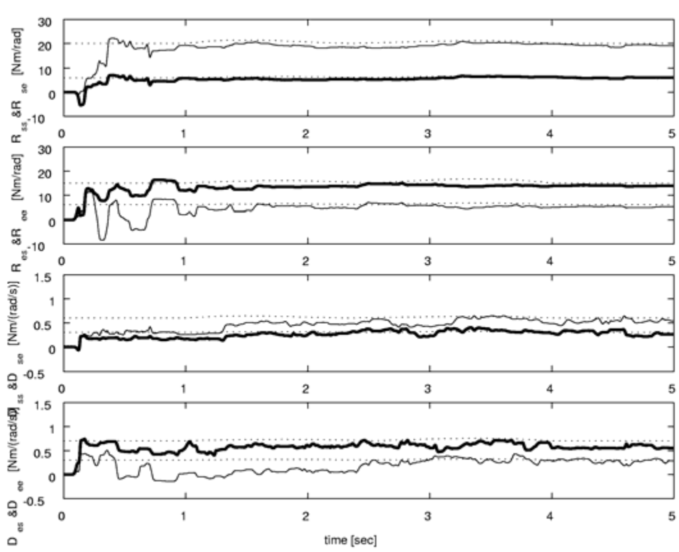

Figure 8. Estimated stiffness and viscosity by using the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$

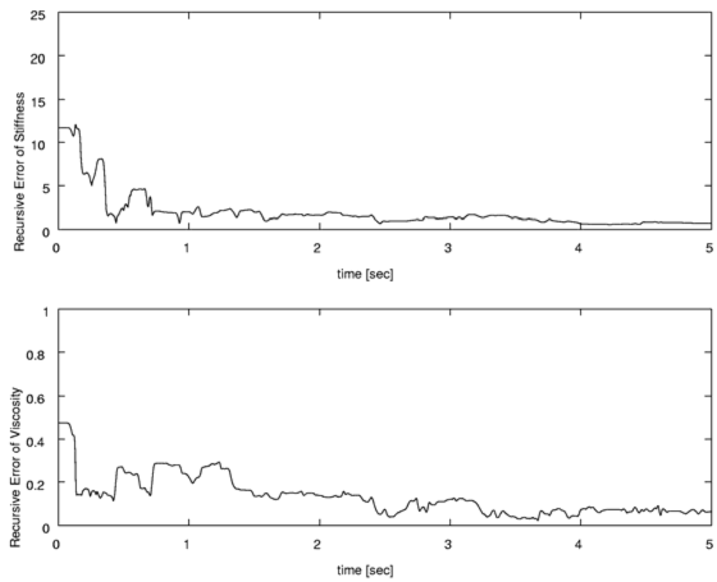

Figure 9. Time-variation of mean error of stiffness and viscosity by using the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$

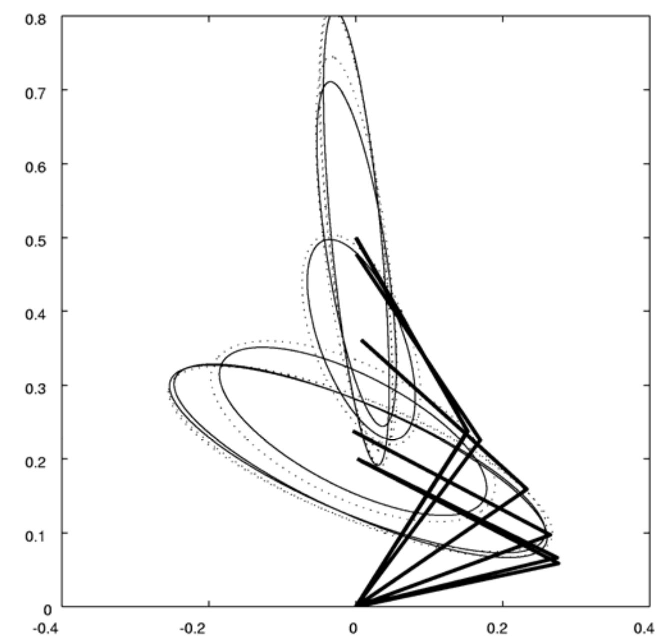

Figure 10. Stiffness ellipse estimated by the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$ (the dotted circle describes the true value)

Further, for the case of the arm model being instructed to move from the start position $(\boldsymbol{x}, \boldsymbol{y}) = [-0.2, 0.25](\boldsymbol{m})$ to the end position $(\boldsymbol{x}, \boldsymbol{y}) = [0.2, 0.45](\boldsymbol{m})$ directly, the simulation results are shown in Figs. 11~13, for the case of the arm model being instructed to move from the start position $(\boldsymbol{x}, \boldsymbol{y}) = [-0.2, 0.4465](\boldsymbol{m})$ to the end position $(\boldsymbol{x}, \boldsymbol{y}) = [0.2, 0.4465](\boldsymbol{m})$ as an arc, the simulation results are shown in Figs.14~16. Based on the above simulation results, the influence from the moving directions is not so large.

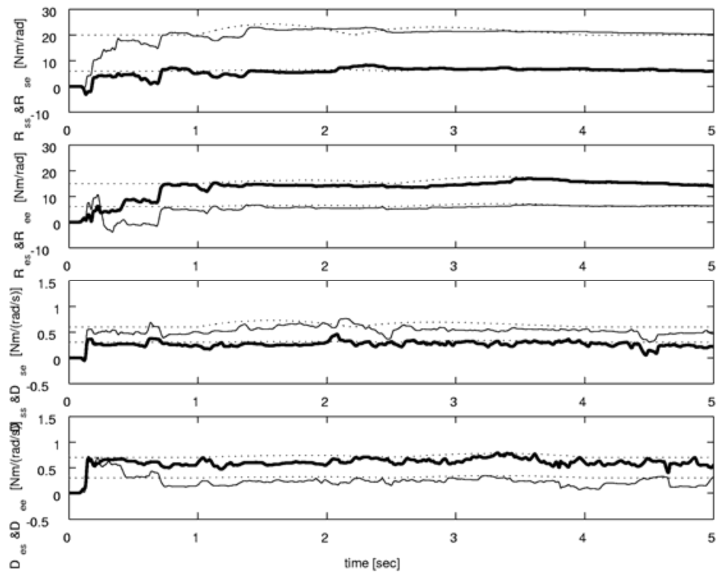

Figure 11. Estimated stiffness and viscosity by using the proposed algorithm with 5% uncertainty of Z_i

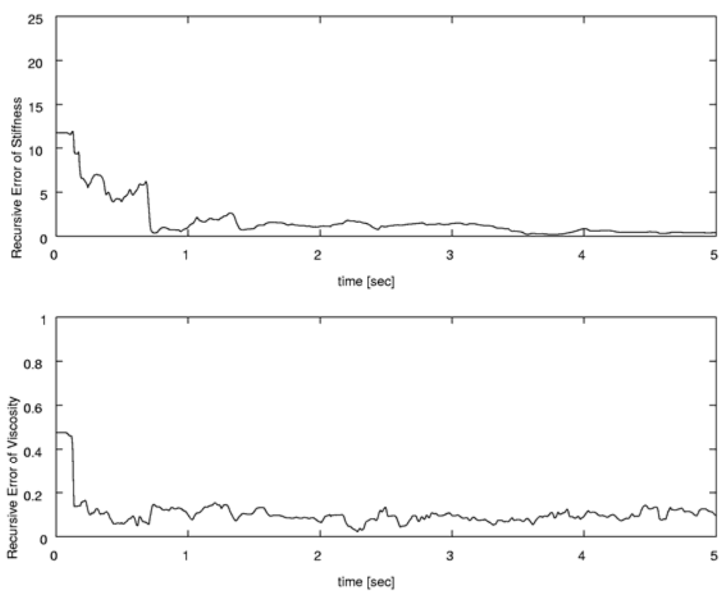

Figure 12. Time-variation of mean error of stiffness and viscosity by using the proposed algorithm with 5% uncertainty of Z_i

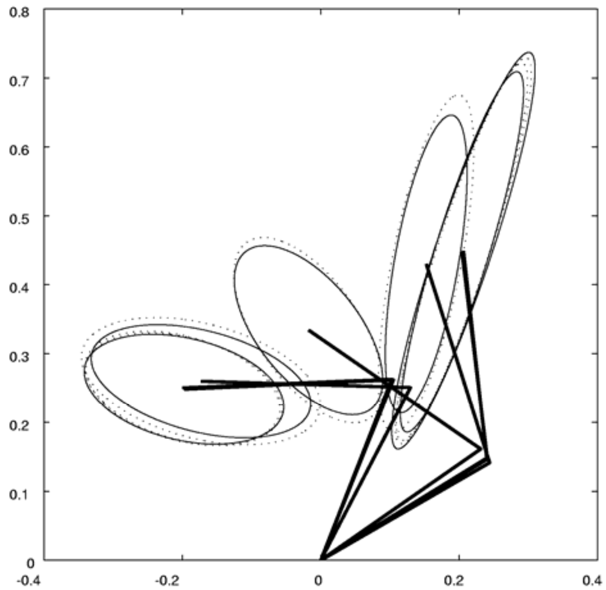

Figure 13. Stiffness ellipse estimated by the proposed algorithm with 5% uncertainty of Z_i (the dotted circle describes the true value)

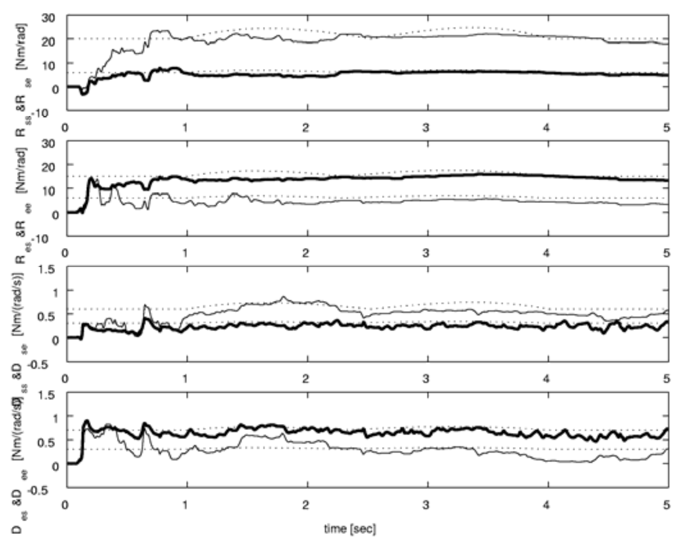

Figure 14. Estimated stiffness and viscosity by using the proposed algorithm with 5% uncertainty of Z_i

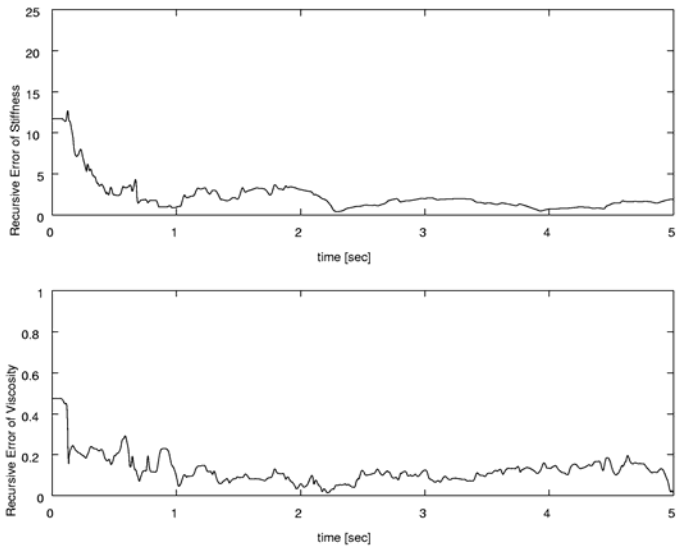

Figure 15. Time-variation of mean error of stiffness and viscosity by using the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$

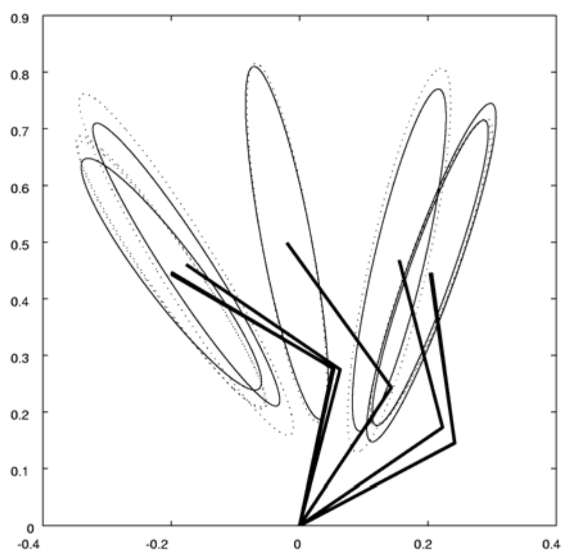

Figure 16. Stiffness ellipse estimated by the proposed algorithm with 5% uncertainty of $\boldsymbol{Z_i}$ (the dotted circle describes the true value)

Even though the uncertainty range of $\boldsymbol{Z_i}$ is selected as 15%, the good results of viscoelastic parameters are obtained (Figs. 17~19). All simulation descriptions are also summarized in Table 1.

Table 1

Simulation run	Movements	Simulation results	Viscoelastic parameters
1	[-0.2, 0.35] to [0.2, 0.35]	Figs. 2,3,4	Fig.2(Kalman filter)
2	[-0.2, 0.35] to [0.2, 0.35]	Figs. 5,6,7	Fig.5(Proposed method)
3	[0, 0.5] to [0. 0.2]	Figs. 8,9,10	Fig.8(Proposed method)
4	[-0.2, 0.25] to [0.2, 0.45]	Figs. 11,12,13	Fig.11(Proposed method)
5	[-0.2, 0.4465] to [0.2, 0.4465]	Figs. 14,15,16	Fig.14(Proposed method)
6	[-0.3, 0.35] to [0.2, 0.35]	Figs. 17,18,19	Fig.17(Proposed method)

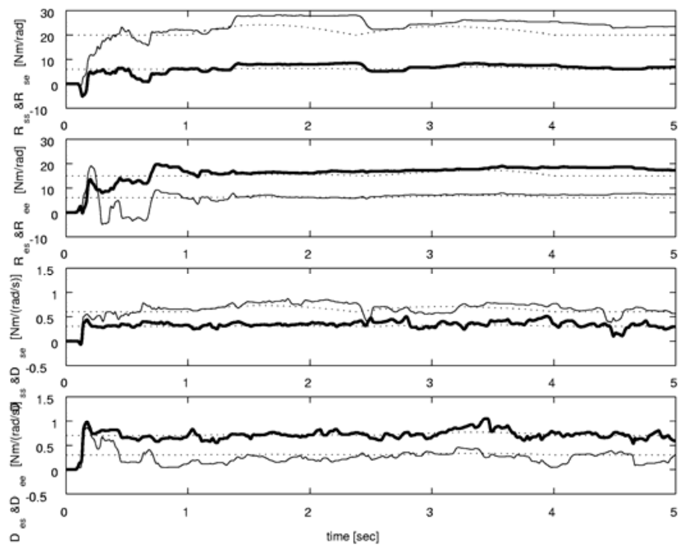

Figure 17. Estimated stiffness and viscosity by using the proposed algorithm with 15% uncertainty of $\boldsymbol{Z_i}$

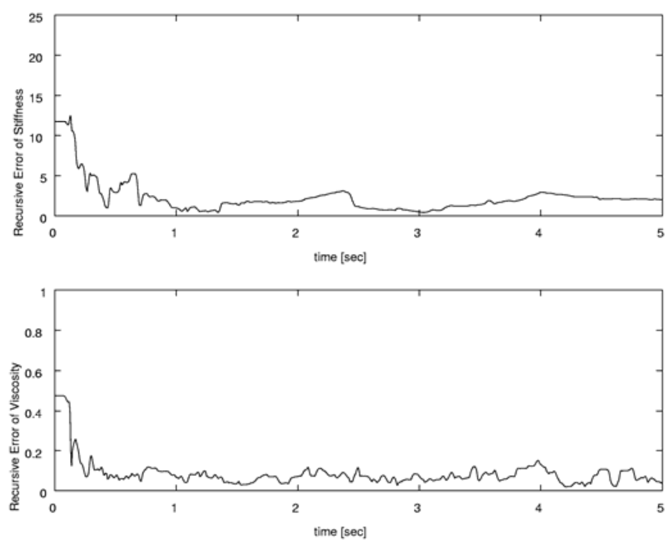

Figure 18. Time-variation of mean error of stiffness and viscosity by using the proposed algorithm with 15% uncertainty of $\boldsymbol{Z_i}$

4. CONCLUSION

Recursive filter design of time varying human multijoint arm viscoelasticity during movement has been developed. For estimating multijoint human arm viscoelasticity, the design scheme based on the score function approach to multiple innovations process is considered. Concerning the real time issues on the estimation, the $\overline{\boldsymbol{U}}\boldsymbol{D}$ factorization algorithm and equivalent noise technique for the multiple innovations process have been applied successfully. We have illustrated an efficacy of the proposed method with simulations for human arm model, where the human arm model used in the simulation is chosen from matching of the experimental results.

APPENDIX A

In this appendix, the equation (1) to be identified is derived from equation (31). The human arm dynamics and pseudo-random perturbation method to estimate the arm viscoelasticity are introduced based on the results in Gomi (1996) and Gomi (1997).

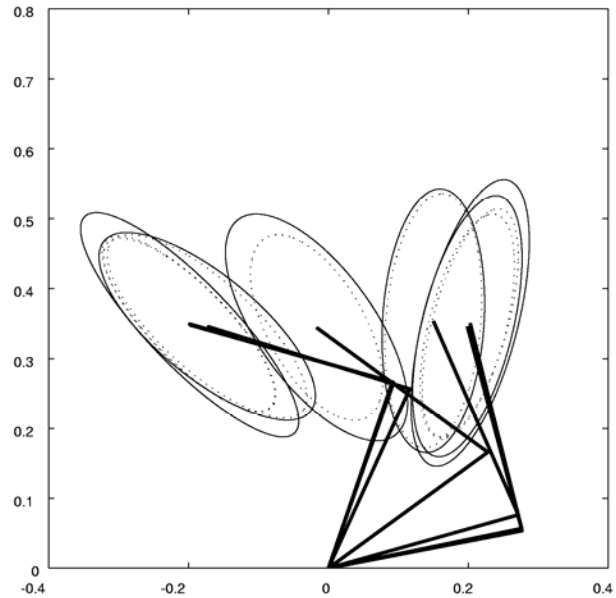

Figure 19. Stiffness ellipse estimated by the proposed algorithm with 15% uncertainty of Z_i (the dotted circle describes the true value)

Two-link rigid human arm dynamics on the horizontal plane can be modeled by the following equation.

$$I(q)\ddot{q} + H(\dot{q}, q) = \tau_{in}(\dot{q}, q, u) + \tau_{ext} \quad (31)$$

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. q, $\dot{q}$ and $\ddot{q}$ are angular position, velocity and acceleration vector, respectively, where

$$q = [\theta_1(t), \quad \theta_2(t)]^T \quad (32)$$

$$\tau_{in} = [\tau_s, \tau_e]^T \quad (33)$$

$\theta_1(t)$ is shoulder angle and $\theta_2(t)$ is elbow angle. I and H denote the inertial matrix and coriolis-centrifugal force vector respectively, which can be expressed as follows.

$$\mathbf{I} = \begin{pmatrix} Z_1 + 2Z_2 \cos\theta_2 & Z_3 + Z_2 \cos\theta_2 \\ Z_3 + Z_2 \cos\theta_2 & Z_3 \end{pmatrix} \quad (34)$$

$$\mathbf{H} = \begin{pmatrix} -Z_2 \sin\theta_2 (\dot{\theta}_2^{\,2} + 2\dot{\theta}_1\dot{\theta}_2) \\ Z_2\dot{\theta}_1^{\,2} \sin\theta_2 \end{pmatrix} \quad (35)$$

$$Z_1 = m_1 l_{g1}^2 + m_2(l_1^2 + l_{g2}^2) + \bar{I}_1 + \bar{I}_2 \quad (36)$$

where, Z_1, Z_2 and Z_3 are structural dependent parameters, which can be presented as follows.

$$Z_2 = m_2 l_1 l_{g2} \quad (37)$$

$$Z_3 = m_2 l_{g2}^2 + \bar{I}_2 \quad (38)$$

Here, m_1 and m_2 denote the masses of upper arm and forearm links, l_{g1} and l_{g2} denote the length from each joint to the center of gravity for each link, $\bar{I}_1$ and $\bar{I}_2$ denote the inertia for each link, and l_1 denotes the length of the upper arm. By using pre-estimated arm structural parameters m_1, m_2, l_{g1}, l_{g2} and l_1, values of parameters Z_1, Z_2 and Z_3 can be obtained. Then the number of identification was reduced (Gomi, 1997). However, the real values of these parameters are difficult to know in real experiment.

For estimating arm viscoelasticity, a pseudo-random perturbation that contains sufficient frequency components is employed. Because multijoint muscle generated torque, τ_{in}, is a function of position, velocity, and motor command, its variational component, $\delta\tau_{in}$, can be represented as follows,

$$\delta\tau_{in} = -\mathbf{D}\delta\dot{\mathbf{q}} + \frac{\partial\tau_{in}}{\partial u}\delta u\,, \tag{39}$$

$$-\frac{\partial\tau_{in}}{\partial\dot{\mathbf{q}}^T} = \mathbf{D} = \begin{pmatrix} D_{ss} & D_{se} \\ D_{es} & D_{ee} \end{pmatrix}, \tag{40}$$

here, $\boldsymbol{D}$ and $\boldsymbol{R}$ present muscle viscosity and stiffness matrix, and

$$-\frac{\partial\tau_{in}}{\partial\mathbf{q}^T} = \mathbf{R} = \begin{pmatrix} R_{ss} & R_{se} \\ R_{es} & R_{ee} \end{pmatrix}. \tag{41}$$

The subscripts $\boldsymbol{ss}$ of $\boldsymbol{D}$ and $\boldsymbol{R}$ represent the shoulder single-joint effect on each coefficient. Similarly, $\boldsymbol{se}$ and $\boldsymbol{es}$ denote cross-joint effects, and $\boldsymbol{ee}$ denotes the elbow single-joint effect. Here, if we can assume that the change of voluntary component $\frac{\partial\tau_{in}}{\partial\boldsymbol{u}}\delta\boldsymbol{u}$ is sufficiently slow compared with external perturbation; this term can be neglected by applying high pass filtering. Namely, by using high-pass (or band-pass) filtering to obtain variational components of τ_{in}, $\boldsymbol{q}$ and $\dot{\boldsymbol{q}}$, we can estimate viscoelastic parameters using the above equation as in Gomi (1998b) and Xu (1998).

APPENDIX B

In this appendix, the analysis and setting of viscoelasticity-torque relationship are given. By the experimental results in Gomi (1996) and Gomi (1998a), the correlation values of viscosity are lower than those in the stiffness cases. In general, the slopes of viscosity change against the elbow joint are greater than those at the shoulder joint, the trends of viscosity changes in positive and negative directions are asymmetrical. Meanwhile, stiffness component increased monotonically as force magnitude increased in all force directions, each stiffness component greatly changed according to the force direction and this resulted in a change in ratios between the stiffness components. Here, we assume an approximate stiffness-torque relationship and viscosity-torque relationship using the above discussions.

$$R_{ss} = A_{ss}\,|\,\tau_{s\_m}\,| + B_{ss}$$
$$R_{se} = A_{se}\,|\,\tau_{e\_m}\,| + B_{se}$$
$$R_{es} = R_{se}$$
$$R_{ee} = A_{ee}\,|\,\tau_{e\_m}\,| + B_{ee}$$
$$D_{ss} = C_{ss}\,|\,\tau_{s\_m}\,| + E_{ss}$$
$$D_{se} = C_{se}\,|\,\tau_{e\_m}\,| + E_{se}$$
$$D_{es} = D_{se}$$
$$D_{ee} = C_{ee}\,|\,\tau_{e\_m}\,| + E_{ee}$$

where, $\begin{pmatrix} \tau_{s\_m} \\ \tau_{e\_m} \end{pmatrix} = \mathbf{I}(\mathbf{q}_d)\ddot{\mathbf{q}}_d + \mathbf{H}(\dot{\mathbf{q}}_d, \mathbf{q}_d)$; τ_{s_m} and τ_{e_m} are the desired shoulder and elbow torques, respectively. $\boldsymbol{q_d}$ is the desired angular position vector. Obviously, we can also obtain the relation between $\boldsymbol{R_{se}}$ and $|\,\tau_{s\_m}\,|$, $\boldsymbol{D_{se}}$ and $|\,\tau_{s\_m}\,|$, but we assumed $\boldsymbol{R_{es}} = \boldsymbol{R_{se}}$ and $\boldsymbol{D_{es}} = \boldsymbol{D_{se}}$. The coefficients of $\boldsymbol{D_{ii}}$, $\boldsymbol{B_{ii}}$, $\boldsymbol{C_{ii}}$ and $\boldsymbol{E_{ii}}$ can be chosen from matching the experimental results described in Gomi (1996), Gomi (1998a). In the simulation, the multijoint muscle generated torque is obtained as $\tau_{in} = R(\mathbf{q}_{eq} - \mathbf{q}) - D\dot{\mathbf{q}}$, where $\boldsymbol{q_{eq}}$ is the equilibrium point (Bizzi, 1984; Feldman, 1986).

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