Proceedings of the 2003 IEEE
International Conference on Robotics & Automation
Taipei, Taiwan, September 14-19, 2003

Kalman Filter Analysis for Quantitative Comparison of Sensory Schemes in Bilateral Teleoperation Systems

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***Abstract*— An important area of research in the teleoperation literature is to develop systematic methods to quantitatively compare different manipulator designs in application critical tasks. Such quantitative methods are especially important during design of the manipulators to make an informed decision among various design alternatives. In this paper, a novel method to quantitatively compare different sensory schemes for a teleoperation system is introduced. This method evaluates the sensory schemes by comparing the norm of the *a posteriori* error covariance matrices of the Kalman filters for each configuration. The main advantage of this method is that it allows to quantitatively compare arbitrary sensory configurations.**

Keywords — Bilateral Teleoperation Control Design, Haptics, Telemanipulation, Teleoperation, Telesurgery

I. INTRODUCTION

An important area of research in the teleoperation literature is to develop systematic methods to quantitatively compare different manipulator designs in application critical tasks. Such quantitative methods are especially important during design of a system to make an informed decision between various design alternatives. There are three main aspects of the teleoperation system that needs to be evaluated are kinematic design, actuation mechanisms, and sensory systems to be used. All these three aspects of the system needs to be considered together with the bilateral controller design to optimize the performance of the system with respect to application-based performance criteria.

There are a number of earlier studies in the literature that looked at the different aspects of this problem. Hannaford [8], [9] studied the bilateral control design problem using two-port network models, looked at how to achieve 'ideal' teleoperator response, and studied the two most common bilateral controller architectures, namely position error based force feedback (PERR) and kinesthetic force feedback (KFF) architectures. Eppinger and Seering [7] studied the effects of the relative locations of the sensors and actuators of a mechanism on the contact stability of the system. Although this study was not done for teleoperation systems in particular, it gave design intuitions applicable to teleoperation systems as well. Colgate [6] looked at the effects of number of communication channels in a bilateral control architecture on ability of the system to achieve or approximate ideal teleoperator response. In more recent works, the authors have proposed a new metric called *alpha*-curve to quantitatively evaluate the improvement offered by using a force sensor in a bilateral teleoperation system by using a task-based performance objective optimization method [3]. The authors have also proposed a workspace analysis method to quantitatively evaluate the kinematic ability of teleoperated surgical manipulators to perform the critical tasks of suturing and knot tying [5].

The motivation behind this study is robotic telesurgery, where a surgical operation is performed by robotic instruments controlled by surgeons through teleoperation [4]. During the design of a telesurgical robot, we would like to know if the use of a force sensor on the slave manipulator is necessary for sufficient fidelity. For better performance, it is almost always desirable to use additional sensors; however, as this sensor will be located on the part of the instrument that will be inside the patient, it is a source of complications in the manipulator design, sterilization requirements, and adds to the cost of the final system. Therefore it is important to have theoretical analysis tools to compare different sensory schemes in terms of performance. This way, it is possible to make informed decisions in choosing sensors for the system.

Kalman filter [10], [1] gives the optimal linear state estimator for a linear system given the process and measurement noise characteristics. The error statistics of the state estimates is a limiting factor on the performance achievable with a state feedback controller, as the controller needs to be slower than the observer (state estimator) poles which are in turn dictated by the error in the estimates.

In this paper, we propose a new method to quantitatively compare different sensory schemes for a teleoperation system by comparing the norm of the *a posteriori* error covariance matrices of the Kalman filters for each configuration. The main advantage of this method is that it allows to quantitatively compare arbitrary sensory configurations.

II. KALMAN FILTER OVERVIEW

The discussion in this section follows the notation and formulation of Lewis [10]. Given the following continuous time stochastic linear system in state space representation which will be controlled with a discrete time controller:

$$\dot{z} = A^c z + B^c u + G^c w \tag{1}$$

$$y = Cz + v \tag{2}$$

where, $z(t) \in \Re^n$ is the state vector, $u(t) \in \Re^p$ is the control input, $w(t) \in \Re^q$ is the process noise, $y(t) \in \Re^m$ is the measurement vector, and $v(t) \in \Re^m$ is the measurement noise. Suppose the $w(t)$ and $v(t)$ are zero mean white noise processes, with covariances Q^c and R^c respectively. The discrete time equivalent of this system is given by

$$z_{k+1} = Az_k + Bu_k + Gw_k \tag{3}$$

$$y_k = Cz_k + v_k \tag{4}$$

with

$$A = e^{A^c T} \tag{5}$$

$$B = \int_0^T e^{A^c \tau} B^c d\tau \tag{6}$$

$$G = I \tag{7}$$

$$w_k \sim (0, Q) \tag{8}$$

$$Q = \int_0^T e^{A^c \tau} G^c Q (G^c)^T e^{(A^c)^T \tau} d\tau \approx G^c Q^c (G^c)^T \tag{9}$$

$$v_k \sim (0, R) \tag{10}$$

$$R = R^c / T \tag{11}$$

where T is the sampling time, $z_k = z(kT)$ is the sampled state vector. Other sampled signals are defined similarly. Here it is assumed that $u(t)$ is constant between the samples, i.e. digital controller output has a zero order hold at the output. If (A, C) is detectable, $(A, G\sqrt{Q})$ is stabilizable, and $R > 0$, then the steady state Kalman filter for the discrete time system of (3),(4) is given as

$$\hat{z}_{k+1} = A\hat{z}_k + Bu_k + AK(y_k - C\hat{z}_k) \tag{12}$$

where $\hat{z}_k$ are the state estimates, and the Kalman filter gain K is given by

$$K = PC^T (CPC^T + R)^{-1} \tag{13}$$

which is a constant $n \times m$ matrix. P is the steady state *a priori* error covariance matrix, which is the solution of the following algebraic Ricatti equation:

$$P = A\left(P - PC^T (CPC^T + R)^{-1} CP\right) A^T + GQG^T. \tag{14}$$

Then, the steady state *a posteriori* error covariance matrix for the state estimates is

$$P^+ = P - PC^T (CPC^T + R)^{-1} CP. \tag{15}$$

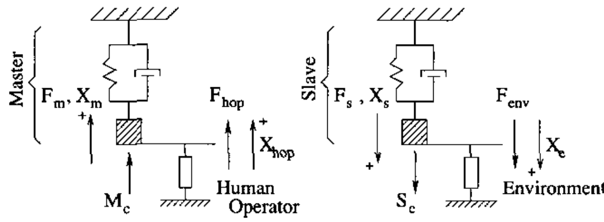

Fig. 1. Physical model of the teleoperation system.

III. MODELING THE TELEOPERATION SYSTEM AND SENSORS

A state space representation of the teleoperator model of Fig. 1 is as follows

$$\frac{d}{dt}\begin{bmatrix} x_s \\ \dot{x}_s \\ x_m \\ \dot{x}_m \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\frac{K_s}{M_s} & -\frac{B_s}{M_s} & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & -\frac{K_m}{M_m} & -\frac{B_m}{M_m} \end{bmatrix} \begin{bmatrix} x_s \\ \dot{x}_s \\ x_m \\ \dot{x}_m \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 & 0 \\ \frac{1}{M_s} & \frac{1}{M_s} & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{M_m} & \frac{1}{M_m} \end{bmatrix} \begin{bmatrix} S_c \\ F_{env} \\ M_c \\ F_{hop} \end{bmatrix} \tag{16}$$

where F_{env} and F_{hop} are respectively the environment and human operator interaction forces, and M_c and S_c are respectively the master and slave actuator forces.

Here, we consider the environment and human operator forces as process noise. We also assume that they are uncorrelated first order Markov processes, which are modeled as low pass filtered white noise sources. Incorporating these into the model, we get the following state space representation

$$z = \left[x_s \, \dot{x}_s \, F_{env} \, x_m \, \dot{x}_m \, F_{hop}\right]^T \tag{17}$$

$$\dot{z} = \underbrace{\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ -\frac{K_s}{M_s} & -\frac{B_s}{M_s} & \frac{1}{M_s} & 0 & 0 & 0 \\ 0 & 0 & -\beta_{env} & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -\frac{K_m}{M_m} & -\frac{B_m}{M_m} & \frac{1}{M_m} \\ 0 & 0 & 0 & 0 & 0 & -\beta_{hop} \end{bmatrix}}_{A^c} z + \underbrace{\begin{bmatrix} 0 & 0 \\ \frac{1}{M_s} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \frac{1}{M_m} \\ 0 & 0 \end{bmatrix}}_{B^c} \underbrace{\begin{bmatrix} \tilde{S}_c \\ \tilde{M}_c \end{bmatrix}}_{u} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \beta_{env} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \beta_{hop} \end{bmatrix}}_{G^c} \underbrace{\begin{bmatrix} \hat{F}_{env} \\ \hat{F}_{hop} \end{bmatrix}}_{w} \tag{18}$$

and

$$Q^c = \begin{bmatrix} \sigma^2_{F_{env}} & 0 \\ 0 & \sigma^2_{F_{hop}} \end{bmatrix} \tag{19}$$

where $\sigma^2_{\hat{F}_{env}}$ and $\sigma^2_{\hat{F}_{hop}}$ are the covariances and β_{env} and β_{hop} are the bandwidths of $\hat{F}_{env}$ and $\hat{F}_{hop}$ respectively. As for the notation, the variables with ^ and ~ are used to denote continuous process noise and discrete control input terms and the variables with * will be used to denote discrete measurement noise terms.

Actually, the human operator and environment forces are related when the system is in closed loop control. However, this relation is rather arbitrary, since it is a function of the existence of the contact and the properties of the object in contact. It is also a function of the controller implemented, however at this point there is no bilateral controller in the system. Therefore, considering them as uncorrelated processes is a reasonable assumption.

Roughly speaking, each sensory configuration corresponds to a different output matrix C for the system. We will consider position, velocity, acceleration, and force measurements on the master and slave manipulators.

Position and velocity sensors give measurements of the states of (18):

$$\begin{bmatrix} x_{s,meas} \\ \dot{x}_{s,meas} \\ x_{m,meas} \\ \dot{x}_{m,meas} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} z + \begin{bmatrix} \delta^*_{x_s} \\ \delta^*_{\dot{x}_s} \\ \delta^*_{x_m} \\ \delta^*_{\dot{x}_m} \end{bmatrix} \tag{20}$$

where $\delta^*_\cdot$ are the measurement noise. If the quantization of the sensor is the only form of measurement noise, which is usually the case for position sensing with encoders, the covariance of the random process is $\sigma^2 = \Delta^2/12$, Δ being the quantization step size. Assuming these random processes are uncorrelated

$$R = \mathrm{diag}\{[\ \sigma_{x_s}, \sigma_{\dot{x}_s}, \sigma_{x_m}, \sigma_{\dot{x}_m}\ ]\} \tag{21}$$

Note that here we have directly calculated R, not by $R = R^c/T$. This is because the quantization noise itself is in discrete time, it is not the result of sampling of a continuous time random process.

Accelerometers also give measurements of the states of the system. Here, we are also including the signal conditioning filters for the accelerometers, since accelerometers are analog sensors and the signal conditioning filters are an integral part of these sensors. Then, (18) augmented with the low pass filters becomes

$$\underbrace{\frac{d}{dt}\begin{bmatrix} x_s \\ \dot{x}_s \\ F_{env} \\ a_s \\ x_m \\ \dot{x}_m \\ F_{hop} \\ a_m \end{bmatrix}}_{\dot{z}} = \underbrace{\begin{bmatrix} A^c_{UL} & 0 \\ 0 & A^c_{LR} \end{bmatrix}}_{A^c} \underbrace{\begin{bmatrix} x_s \\ \dot{x}_s \\ F_{env} \\ a_s \\ x_m \\ \dot{x}_m \\ F_{hop} \\ a_m \end{bmatrix}}_{z} + \underbrace{\begin{bmatrix} 0 & 0 \\ \frac{1}{M_s} & 0 \\ 0 & 0 \\ \frac{\beta_{acc}}{M_s} & 0 \\ 0 & 0 \\ 0 & \frac{1}{M_m} \\ 0 & 0 \\ 0 & \frac{\beta_{acc}}{M_m} \end{bmatrix}}_{B^c} \underbrace{\begin{bmatrix} \tilde{S}_c \\ \tilde{M}_c \end{bmatrix}}_{u} + \underbrace{\begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \beta_{env} & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & \beta_{hop} \\ 0 & 0 \end{bmatrix}}_{G^c} \underbrace{\begin{bmatrix} \hat{F}_{env} \\ \hat{F}_{hop} \end{bmatrix}}_{w} \tag{22}$$

where a_s and a_m are the internal states of the acceleration sensor filters at slave and master respectively, and

$$A^c_{UL} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\frac{K_s}{M_s} & -\frac{B_s}{M_s} & \frac{1}{M_s} & 0 \\ 0 & 0 & -\beta_{env} & 0 \\ -\frac{\beta_{acc}K_s}{M_s} & -\frac{\beta_{acc}B_s}{M_s} & \frac{\beta_{acc}}{M_s} & -\beta_{acc} \end{bmatrix} \tag{23}$$

$$A^c_{LR} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ -\frac{K_m}{M_m} & -\frac{B_m}{M_m} & \frac{1}{M_m} & 0 \\ 0 & 0 & -\beta_{hop} & 0 \\ -\frac{\beta_{acc}K_m}{M_m} & -\frac{\beta_{acc}B_m}{M_m} & \frac{\beta_{acc}}{M_m} & -\beta_{acc} \end{bmatrix}. \tag{24}$$

Then, the output equations with accelerometer measurements are

$$\begin{bmatrix} x_{s,meas} \\ \dot{x}_{s,meas} \\ \ddot{x}_{s,meas} \\ x_{m,meas} \\ \dot{x}_{m,meas} \\ \ddot{x}_{m,meas} \end{bmatrix} = \begin{bmatrix} 1&0&0&0&0&0&0&0 \\ 0&1&0&0&0&0&0&0 \\ 0&0&0&1&0&0&0&0 \\ 0&0&0&0&1&0&0&0 \\ 0&0&0&0&0&1&0&0 \\ 0&0&0&0&0&0&0&1 \end{bmatrix} z + \begin{bmatrix} \delta^*_{x_s} \\ \delta^*_{\dot{x}_s} \\ \delta^*_{\ddot{x}_s} \\ \delta^*_{x_m} \\ \delta^*_{\dot{x}_m} \\ \delta^*_{\ddot{x}_m} \end{bmatrix} \tag{25}$$

with

$$R = \mathrm{diag}\{[\ \sigma_{x_s}, \sigma_{\dot{x}_s}, \sigma_{\ddot{x}_s}, \sigma_{x_m}, \sigma_{\dot{x}_m}, \sigma_{\ddot{x}_m}\ ]\}. \tag{26}$$

Since accelerometer is an analog sensor, it has both continuous time noise and quantization noise terms. If the spectral density of the sensor noise has magnitude ρ_{acc} (assuming white noise), and the quantization step size is Δ_{acc}, then the covariance of the accelerometer measurement noise is $\sigma_{\ddot{x}} = \rho^2_{acc}/T + \Delta^2_{acc}/12$. Note that the sensor noise and the quantization noise are uncorrelated.

Force sensor gives a measurement of the process noise rather than the states, therefore it changes the error statistics of the process noise. For example, when we put a force sensor on the slave manipulator, the slave dynamics can be written as

$$M_s\ddot{x}_s + B_s\dot{x}_s + K_s x_s = \tilde{S}_c + \underbrace{\tilde{F}_{env} + \hat{\delta}_{F_{env}}}_{F_{env}} \tag{27}$$

where F_{env} is not a completely unknown variable but rather the sum of the measured force $\tilde{F}_{env}$ and the noise (quantization + measurement) of the force sensor $\hat{\delta}_{F_{env}}$. Low pass filter for the force input is no longer needed. Then, the state space model for the system with force sensors is

$$\underbrace{\frac{d}{dt}\begin{bmatrix} x_s \\ \dot{x}_s \\ z_3 \\ x_m \\ \dot{x}_m \\ z_6 \end{bmatrix}}_{\dot{z}} = \underbrace{\begin{bmatrix} A^c_{UL} & 0 \\ 0 & A^c_{LR} \end{bmatrix}}_{A^c} \underbrace{\begin{bmatrix} x_s \\ \dot{x}_s \\ a_s \\ x_m \\ \dot{x}_m \\ a_m \end{bmatrix}}_{z} + \underbrace{\begin{bmatrix} 0 & 0 & 0 & 0 \\ \frac{1}{M_s} & 0 & \frac{1}{M_s} & 0 \\ \frac{\beta_{acc}}{M_s} & 0 & \frac{\beta_{acc}}{M_s} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & \frac{1}{M_m} & 0 & \frac{1}{M_m} \\ 0 & \frac{\beta_{acc}}{M_m} & 0 & \frac{\beta_{acc}}{M_m} \end{bmatrix}}_{B^c} \underbrace{\begin{bmatrix} \tilde{S}_c \\ \tilde{M}_c \\ \tilde{F}_env \\ \tilde{F}_{hop} \end{bmatrix}}_{u} + \underbrace{\begin{bmatrix} 0 & 0 \\ \frac{1}{M_s} & 0 \\ \frac{1}{M_s} & 0 \\ 0 & 0 \\ 0 & \frac{1}{M_m} \\ 0 & \frac{1}{M_m} \end{bmatrix}}_{G^c} \underbrace{\begin{bmatrix} \hat{\delta}_{F_{env}} \\ \hat{\delta}_{F_{hop}} \end{bmatrix}}_{w} \tag{28}$$

where

$$A^c_{UL} = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{K_s}{M_s} & -\frac{B_s}{M_s} & 0 \\ -\frac{\beta_{acc}K_s}{M_s} & -\frac{\beta_{acc}B_s}{M_s} & -\beta_{acc} \end{bmatrix} \tag{29}$$

$$A^c_{LR} = \begin{bmatrix} 0 & 1 & 0 \\ -\frac{K_m}{M_m} & -\frac{B_m}{M_m} & 0 \\ -\frac{\beta_{acc}K_m}{M_m} & -\frac{\beta_{acc}B_m}{M_m} & -\beta_{acc} \end{bmatrix} \tag{30}$$

and

$$\begin{bmatrix} x_{s,meas} \\ \dot{x}_{s,meas} \\ \ddot{x}_{s,meas} \\ x_{m,meas} \\ \dot{x}_{m,meas} \\ \ddot{x}_{m,meas} \end{bmatrix} = I_{6\times6}z + \begin{bmatrix} \delta^*_{x_s} \\ \delta^*_{\dot{x}_s} \\ \delta^*\ddot{x}_s \\ \delta^*_{x_m} \\ \delta^*_{\dot{x}_m} \\ \delta^*_{\ddot{x}_m} \end{bmatrix}. \tag{31}$$

Noise covariances for this model are

$$Q^c = \begin{bmatrix} \sigma^2_{\hat{\delta}_{F_{env}}} & 0 \\ 0 & \sigma^2_{\hat{\delta}_{F_{hop}}} \end{bmatrix} \tag{32}$$

and

$$R = \mathrm{diag}\left\{\left[\ \sigma_{x_s}, \sigma_{\dot{x}_s}, \sigma_{\ddot{x}_s}, \sigma_{x_m}, \sigma_{\dot{x}_m}, \sigma_{\ddot{x}_m}\ \right]\right\} \tag{33}$$

where $\sigma^2_{\hat{\delta}_{F_{env}}} = \rho_F^2/T + \Delta_F^2/12$ and $\sigma^2_{\hat{\delta}_{F_{hop}}} = \rho_F^2/T + \Delta_F^2/12$, assuming that force sensor noise has two components: analog white sensor noise with spectral density ρ_F, and sensor quantization with step size Δ_F

IV. ANALYSIS METHOD

The algorithm to compare the sensory configurations is as follows.

1) For each of the sensory configurations :
   a) Construct the continuous time state space model (A^c, B^c, G^c, C)
   b) Calculate the discrete time equivalent of the system (A, B, G, C)
   c) Construct the noise covariance matrices Q, R
   d) Calculate the *a priori* error covariance matrix P using (14)
   e) Calculate the *a posteriori* error covariance matrix P^+ using (15)
   f) Calculate the norm of the submatrix of P^+ corresponding to the states $(x_s, \dot{x}_s, F_{env}, x_m, \dot{x}_m, F_{hop})$
2) The relative values of the calculated norms give a quantitative estimate for the achievable performance with the sensory configurations.

At step (f) we are calculating the norm of the submatrix of P^+ corresponding the states inherent to the system in order to have a fair comparison.

V. CASE STUDY

In this section, we perform a case study to illustrate the analysis method we have described above. We use the following manipulator model parameters :

$$K_s = K_m = 0 \tag{34}$$

$$B_s = B_m = 6.46 \times 10^{-5} \tag{35}$$

$$M_s = M_m = 2.02 \times 10^{-5} \tag{36}$$

which are for a teleoperation system using two identical Phantom^{TM} (Sensable Technologies, Woburn, MA) haptic interfaces as the master and slave manipulators. This is the test-bed setup we used in a number of our teleoperation experiments [3], [2]. We assume an intentional hand motion bandwidth of 5 Hz, environment interaction force

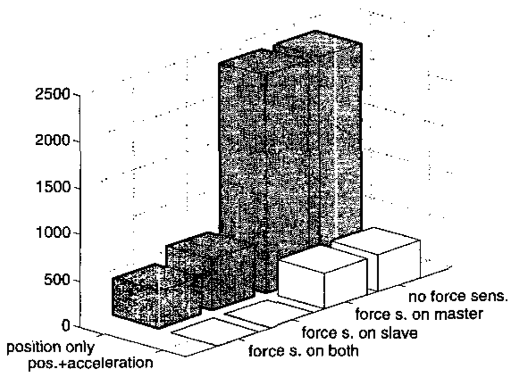

Fig. 2. Result of the Kalman filter analysis for the teleoperation system studied. Vertical axis is the induced 2-norm of the *a posteriori* error covariance matrix.

bandwidth of 100 Hz, and interaction forces of magnitude 1 N:

$$\beta_{hop} = 5\text{Hz} \quad (37)$$
$$\beta_{env} = 100\text{Hz} \quad (38)$$
$$\sigma^2_{F_{hop}} = 1 \quad (39)$$
$$\sigma^2_{F_{env}} = 1. \quad (40)$$

The following noise values are for the sensors present on the experimental testbed:

$$\Delta_{pos} = 0.03 \quad (41)$$
$$\Delta_{acc} = 11.98 \quad (42)$$
$$\beta_{acc} = 200\text{Hz} \quad (43)$$
$$\rho_{acc} = 24.06 \quad (44)$$
$$\Delta_F = 0.025 \quad (45)$$
$$\rho_F = 0.0091. \quad (46)$$

There is no velocity sensor available on our testbed.

The results of the Kalman filter analysis for this system are shown in Fig. 2 comparing eight different sensor configurations with position, acceleration, and force sensors.

Results predict that for this system, addition of force sensors and accelerometers will improve the performance, and relative improvement by adding accelerometers is more than that of force sensors. This is actually an interesting result, and it is because we are using back-drivable, low-inertia, high-bandwidth, master and slave manipulators. Results also suggest that if there will be a single force sensor, it is more desirable to put it on the slave manipulator rather than the master manipulator. This is because the assumed bandwidth of environment force is wider than the bandwidth of the human hand motions.

VI. DISCUSSION

Although the results discussed in the case study section is specific to the manipulators and sensors used in the analysis, it illustrates how the method can be used to quantitatively evaluate different sensory configurations for a teleoperation system.

The advantages of the method presented here over the earlier ones are: 1) there is no assumed control architecture; 2) sensor noise, which is an important factor in teleoperator performance, is explicitly included in the analysis. However, this method is indirect, i.e. it doesn't directly give the relative achievable performances but rather look at an indirect indicator of performance, namely the best possible *a posteriori* error covariance achievable with a state estimator.

For future work, we are looking at developing a more comprehensive methodology which merges the method presented in this paper with the task-based performance objectives as highlighted in Çavuşoğlu *et al* [3] with the *alpha*-curve method.

VII. ACKNOWLEDGMENTS

This research was supported in part by NSF under grants IRI-95-31837, CISE CDA-9726362, CISE IIS-0083472, and CISE IIS-0222743, ONR under MURI grant N14-96-1-1200, ARO under MURI grant DaaH04-96-1-0341, and US Air Force Research Laboratory under grant F30602-01-2-0588.

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