INTEGRATION OF MULTI-SENSOR MANIPULATOR ACTUATOR INFORMATION FOR ROBUST ROBOT CONTROL SYSTEMS

Minoru HASHIMOTO and Richard P. PAUL*

(Received May 31, 1989)

ABSTRACT

Robot manipulator joints with only a single state sensor (either in position or in velocity) are limited in their ability to determine both state variables (in position and in velocity). Also, if the single sensor fails, the robot becomes uncontrollable. In the present paper, we propose a method which efficiently uses multi–sensor information to obtain a more precise description of joint position and velocity, and such a method allows for a robust control system free from the affects of spurious sensor observation, one which is impervious to single sensor failure. We employ an encoder and a tachometer for each joint as sensors. A technique is described for combining both uncertain sensor observations with an observation model to provide an optimal estimation of both state variables. The estimation method does not result in more than one sample period of delay in time, as the estimator does not use a time series analysis. In order to detect a sensor failure, we use a cross–checking hypothesis test for redundant sensor information. In addition, we can detect a control failure by including the command information of the control in the hypothesis test. The algorithm for implementing the estimation and the hypothesis test is presented. Simulation results demonstrate that the technique works well.

1. INTRODUCTION

Although, many robot control schemes have been proposed to provide for more exact position and force control, the actuator sensor system itself has not been given much attention. It is, however, the basis for any form of robot control. These actuator observation are noisy and often spurious. An encoder and a tachometer, which are used often as the robot joint sensors have both quantizing and ripple noise, respectively. Further, the information from them is not precise enough over their entire range of operation needed for robot control. In order to get noise–free data, filters have been used. For example, Suehiro and Takase [1] applied a first–order lag element digital filter into the velocity feedback loop to stabilize the servo control around the resonance frequency. However, any such filter introduces a time delay which may cause both control error and control instability. Our approach is to use redundant sensor information sources. The joint position or the velocity can be obtained from both of the information sources by either differentiation or integration. If each joint has two or more sensors the system can be considered as a redundant sensor system. By combining the information from many different sources we can obtain a more accurate information of the joint state without causing any time delay.

---

* Department of Computer and Information Science, Universitv of Pennsylvania, Philadelphia, PA 19104, USA

If the sensor of a robot actuator is the only sensor and it fails then it is no longer possible to control the joint and a catastrophic accident can occur. With only one sensor, there is no way to avoid this kind of problem. Workers cannot go safely into the operating area of the robot. If we can detect a sensor failure and can continue to move the manipulator to a safe position, then the manipulator will become much safer. In order to this, it is important to use a redundant sensor system. By cross–checking the redundant sensor information sources, it is possible to detect the failure of any one sensor. Moreover, the information received from the failed sensor can be rejected from the estimation of joint state. We will be able to continue to control the manipulator until we get to a safe position to stop the manipulator.

There have been a number of multi–sensor robot systems described in the literature. These papers [2–4] investigate the manner in which multi–sensor system may be used to gain information about the environment. Allen and Bajcsy [2] have employed stereo edges to match objects to a fixed world model, then using a tactile probe to investigate occluded parts. This technique has essentially used a heuristic process to bring two different information sources together, which is difficult to extend consistently to general sensors, and provides no basis for representing uncertainty of observations. Durrant–Whyte [3, 4] has presented a theory and methodology for integrating and propagating geometric sensor observations to obtain knowledge about an uncertain geometric environment. The method is based on Bayesian techniques and on statistical decision theory; it is applicable to general sensors with Bayesian model as a basis. In our approach it is important to consider the computational burden needed to implement the technique, because the method is to be performed in the robot servo control loop.

The next Section is concerned with the optimal estimations for joint state using redundant information. We treat the observation model as a static linear system to exclude the time delay in the estimation theory of the dynamic system. We will obtain the optimal estimations as a linear function of redundant information. The weight parameters are functions of the noise variances. Cross–checking hypothesis tests are described for detecting spurious sensor information. In Section 3, the simple noise models of an encoder and a tachometer are discussed. The models involve the mean and the variance of the sensor noise. A simulation is carried out in Section 4 to verify the method described in Sections 2 and 3.

2. INTEGRATION OF REDUNDANT SENSOR INFORMATION

In this Section, the three independent information sources for each joint are taken into account.

2.1. Observation Model and Estimator

The basic observation model to be considered in this paper is the static Fisher model [5] in which the observation process is modeled as follows:

$$\mathbf{z} = \mathbf{Hx} + \mathbf{r} \tag{2.1}$$

where, $\mathbf{z}$ is an observation vector,

$$\mathbf{z} = [z_1^p \ z_2^p \ z_3^p \ z_1^\nu \ z_2^\nu \ z_3^\nu]'$$

$$\mathbf{H} = \begin{bmatrix} 1 & 0 \\ 1 & 0 \\ 1 & 0 \\ 0 & 1 \\ 0 & 1 \\ 0 & 1 \end{bmatrix}$$

The prime indicates a transpose of the matrix. The subscripts 1, 2 and 3 refer to each of the sensors. The superscripts p and v describe position and velocity. The $\mathbf{x}$ is a state vector of system which is completely unknown,

$$\mathbf{x} = [x^p \; x^v]',$$

$\mathbf{r}$ is a noise vector,

$$\mathbf{r} = [r_1^p \; r_2^p \; r_3^p \; r_1^v \; r_2^v \; r_3^v]'$$

$$E[\mathbf{r}] = \mathbf{u}$$

$$E[\mathbf{r}\mathbf{r}'] = \mathbf{R} = diagonal\,[R_1^p \; R_2^p \; R_3^p \; R_1^v \; R_2^v \; R_3^v],$$

where each diagonal element of the matrix $\mathbf{R}$, i.e. R_i, is the variance of the noise of sensor i.

It is assumed that the probability density function of the random noise is Gaussian.

$$\mathbf{r} \; is \; N(\mathbf{u}, \mathbf{R})$$

Then $\mathbf{z}$ is also Gaussian [5],

$$\mathbf{z} \; is \; N(\mathbf{x}+\mathbf{u}, \mathbf{R})$$

For the Fisher model we can make the following estimator which yields the minimum error covariance matrix.

$$\begin{aligned} \hat{\mathbf{x}} &= \mathbf{W}(\mathbf{z}-\mathbf{u}) \\ \mathbf{W} &= \Sigma \mathbf{H}'\mathbf{R} \\ \Sigma &= (\mathbf{H}'\mathbf{R}^{-1}\mathbf{H})^{-1} \end{aligned} \tag{2.2}$$

where the minimum error covariance and the mean of estimator are

$$\Sigma = E[(\mathbf{x}-\hat{\mathbf{x}})(\mathbf{x}-\hat{\mathbf{x}})'] \tag{2.3}$$

$$E[\hat{\mathbf{x}}] = \mathbf{x}. \tag{2.4}$$

In the other words, the equation for position or velocity is

$$\hat{x} = \left(\sum_{i=1}^{3} R_i^{-1}\right)^{-1} \sum_{i=1}^{3} R_i^{-1}(z_i - u_i) \tag{2.5}$$

In this estimation scheme, we can verify which combination of sensors is better than the others by computing the minimum error covariance matrix.

2.2. Spurious Information Source Detection

If bad data points are observed, a catastrophic problem might occur in the robot control. The spurious data can often be detected using hypothesis–testing concepts. In a redundant sensor system, hypothesis testing can be used to cross–check the observations in order to decide which information source is spurious.

For the cross–checking test, the following hypotheses for position or velocity observation are used.

$$H_1:\quad \mathbf{z}=\mathbf{z}_{cc},\qquad \mathbf{z}_{cc}=\mathbf{h}_{cc}x+\mathbf{r}_{cc} \tag{2.6.a}$$

where,

$$\mathbf{z}_{cc}=\begin{bmatrix} z_i \\ z_j \end{bmatrix}\qquad \mathbf{h}_{cc}=\begin{bmatrix} 1 \\ 1 \end{bmatrix}\qquad \mathbf{r}_{cc}=\begin{bmatrix} r_i \\ r_j \end{bmatrix}$$

$$\mathbf{r}_{cc}\ \textit{is}\ N(\mathbf{u}_{cc},\mathbf{R}_{cc})\qquad x\textit{: completely unknown}$$

$$H_2:\quad H_1\ \textit{is not true} \tag{2.6.b}$$

The spurious data which cannot be included in the observation model can be caused by many things, such as sensor failure, failure of A/D conversion equipment, or communication line failure. We assume that any communication and A/D converter failures relates to only one observation. We also assume that the software does not fail. Therefore, kinds of failures are classified as sensor failures or others. The Table 1 shows the relationship between sensor failure and hypothesis testing. At least three independent information sources are required, because if we have only two sensors we cannot recognize which sensor fails by the cross–checking test. Furthermore there are temporary and permanent sensor failures. If it is temporary, one can ignore the failed observation in estimating the joint status. If we were to include the failed information in the integration of data, it would result in an incorrect estimation. When the failure is permanent we have to change the control mode and to move the manipulator to a safe position. We could decide if we have a permanent failure by counting the number of the spurious observations.

Table 1: Hypothesis testing for failure detection

sensor	1-2	2-3	3-1
No. 1 sensor failure	H_2	H_1	H_2
No. 2 sensor failure	H_2	H_2	H_1
No. 3 sensor failure	H_1	H_2	H_2
the other failure	H_2	H_2	H_2

To test these hypotheses we will evaluate the log likelihood function, $\xi_j(\mathbf{z})$.

$$\xi_j(\mathbf{z})=\ln p_j(\mathbf{z}) \tag{2.7}$$

where $p_j(z)$ is the probability density of $\mathbf{z}$ for the j th hypothesis. For the hypothesis, H_1, the probability density assuming that is true is

$$p_{h1}(\mathbf{z})=[(2\pi)^2\,|\,R_{cc}\,|\,]^{-1/2}\exp(-\frac{1}{2})\left\{[(\mathbf{z}-\mathbf{u}_{cc})-\mathbf{h}_{cc}\,\hat{x}]'\mathbf{R}_{cc}^{-1}[(\mathbf{z}-\mathbf{u}_{cc})-\mathbf{h}_{cc}\,\hat{x}]\right\} \tag{2.8}$$

where, because the real state, x, is unknown, the result of estimation is being uesd.

$$\hat{x}=(\mathbf{h}_{cc}'\mathbf{R}_{cc}^{-1}\mathbf{h}_{cc})^{-1}\mathbf{h}_{cc}'\mathbf{R}_{cc}^{-1}(\mathbf{z}-\mathbf{u}_{cc}) \tag{2.9}$$

From Equation (2.7), log likelihood decision function becomes

$$\xi_{h1}(\mathbf{z})=\frac{1}{2}\left\{-2\ln(2\pi)-\ln|R_{cc}|-[(\mathbf{z}-\mathbf{u}_{cc})-\mathbf{h}\hat{x}]'\mathbf{R}_{cc}^{-1}[(\mathbf{z}-\mathbf{u}_{cc})-\mathbf{h}_{cc}\hat{x}]\right\} \tag{2.10}$$

It is more convenient to use only third term in right hand equation of Equation (2.10). With Equation (2.9), the convenient decision function is derived as follows:

$$\xi_{h1}(\mathbf{z})=R_i^{-1}[(z_i-u_i)-\hat{x}]^2+R_j^{-1}[(z_j-u_j)-\hat{x}]^2=\frac{[(z_i-u_i)-(z_j-u_i)]^2}{R_i+R_j} \tag{2.11}$$

Since $(z_i-u_i)-(z_j-u_j)$ has the variance of R_i+R_j, a reasonable choice for the tails in the Gaussian distribution yields the following decision rule:

$$\textit{Choose } H_1 \text{ if } \xi_{h1}(\mathbf{z})\leq 9 \tag{2.12.a}$$

$$\textit{Choose } H_2 \text{ if } \xi_{h1}(\mathbf{z})>9 \tag{2.12.b}$$

2.3. Including prior information

The control system can be modeled as follows:

$$\mathbf{x}_d = \mathbf{x}-\mathbf{r}_c \tag{2.13}$$

where, $\mathbf{x}_d$ is a desired information vector. The $\mathbf{r}_c$ is a control error vector whose probability density function can be modeled as Gaussian distribution.

$$\mathbf{r}_c \textit{ is } N(0, \Psi)$$

The covariance matrix is the control error matrix, Ψ.

If the joint has only two independent sensors, the prior information which is the desired data in the control, must be taken into account in the cross–checking hypothesis tests to find which information source has failed. In this case we can put the prior information, x_d, on one of the sensor observations into Equation (2.6), where the control error, r_c, is modeled as a noise for the prior information. By using the decision function, Equation (2.11), and the decision rule, Equation (2.12), not only checks for sensor failures but also for control failure. This is based on the assumption that both the sensor and the control do not fail at same time.

When the joint has three or more idependent observation sources, we do not need this assumption. In this case, the sensor failure is detected by the cross–checking tests without the control information, and then the control failure is checked by the following hypothesis tests. The estimated state, $\hat{\mathbf{x}}$, is used instead of the actual state, $\mathbf{x}$, because the $\mathbf{x}$ cannot be known.

$$\begin{bmatrix} x_d^p \\ x_d^{\nu} \end{bmatrix} = \begin{bmatrix} \hat{x}^p \\ \hat{x}^{\nu} \end{bmatrix} - \begin{bmatrix} r_c^p \\ r_c^{\nu} \end{bmatrix} \tag{2.14}$$

By including the estimation error covariance matrix, Equation (2.3), the following hypotheses are made for detecting control failure.

$$G_1:\quad \hat{x}=y_1,\ y_1\ \textit{has probability density}\ p(y_1) = N(x_d, \Psi+\Sigma) \tag{2.15.a}$$

$$G_2:\quad G_1\ \textit{is not true} \tag{2.15.b}$$

In the same manner as equations (2.7)–(2.10), the convenient decision function becomes

$$\xi_1(z)=\frac{[x_d-\hat{x}]^2}{\Psi+\sigma} \tag{2.16}$$

A reasonable choice for the tails in the Gaussian distribution yields the following decision rule:

$$\textit{Choose}\ G_1\ \text{if}\ \xi_{g1}(\hat{x})\leq 9 \tag{2.17.a}$$

$$\textit{Choose}\ G_2\ \text{if}\ \xi_{g1}(\hat{x})>9 \tag{2.17.b}$$

2.4. Algorithm for Implementation

A different algorithm must be used for two sensor systems and for joint with more than two sensors. The difference between them is in the checking method of the control failure. In the case of two sensors, the prior information is used in the cross–checking test with sensor information source. For three or more sensors, the sensor failure is checked by only sensor observations, and control failure is checked based on estimated joint state.

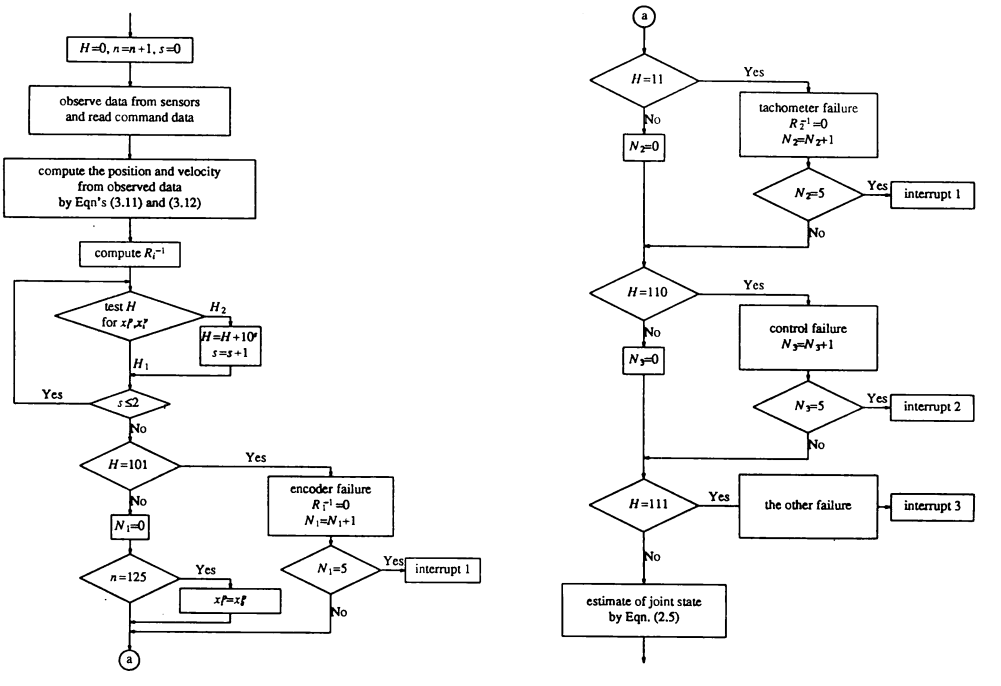

Fig. 1 Algorithm of integration of sensors

Figure 1 shows a flowchart for two sensor system which consists of an encoder and a tachometer. We apply the hypothesis testing to the position and the velocity data for each sensor. If either the tests for position or velocity chooses H_2, we would decide that the hypothesis H_1, is not true. In the flowcharts the "S" indicates types of sensors. The estimated position from velocity sensors is calibrated every 125 cycles by the position sensor observation such as encoder observation, since this data become inaccurate with repeated integration. Permanent sensor failure is detected by counting the number of spurious information observations. In this algorithm we used five as the limit of the number of spurious data observations to decide permanent failure. After a permanent failure is detected, the system interrupts to higher level to decide what action should be taken depending on the type of failure. Interrupt 1 (sensor failure) : The interrupt makes a new command trajectory to get to a safe position, the control follows the command data without the failed information source until the manipulator reaches the desired position. Interrupt 2 (control failure) : In this case the manipulator has collided with an obstacle. The interrupt changes the command position to the point of contact where the control failure happened. The control continues to stay at the position. Interrupt 3 (the other failure) : We can no longer control or get any correct observation. The control stops immediately when this failure happens.

This scheme should be performed at the observation level of the joint servo control. This level occurs before the sensor observation are converted into the joint position and velocity. The technique must be implemented in the real time robot control. The program which calculates the present algorithm includes 6 multiplications, 7 divisions and 19 additions. The computation load is small enough to apply the technique in real time.

3. SENSOR MODELING

It would be useful to be able to also use the motor data to estimate joint state. The motor voltage V_m is given by the sum of the back emf and the armature voltage in the dc motor.

$$V_m = I_a R_a + \nu K_b, \tag{3.1}$$

where, I_a, R_a, ν and K_b are armature current, armature resistance, angular velocity and back emf constant of the motor, respectively. In the equation it is assumed that the inductance effect can be ignored. If the motor voltage and the armature current are sensed or known, the angular velocity can be estimated from Equation (3.1). Therefore, the motor voltage is an independent information source for the joint velocity.

Figure 2 shows the actual observation of motor data where the velocity is estimated by using Equation (3.1). When constant armature current is applied, the estimated velocity dose not have a lot of noise (Fig. 2(a)). But, unfortunately, if the armature current is changed to control the velocity, the noise becomes much larger (Fig.2 (b)). The inductance term, which is proportional to the armature–current change, makes a major contribution to the noise during the control. We are thus unable to use the motor data as an information source.

In this paper, we employ an encoder and a tachometer for each joint to estimate position and velocity and to detect sensor failute. The system is simplest among the multi–sensor system described, also these sensors are popular in commercial robots. The encoder and the tachometer have the following noises and error parameters:

a. Quantizing noise of both the encoder and A/D converter

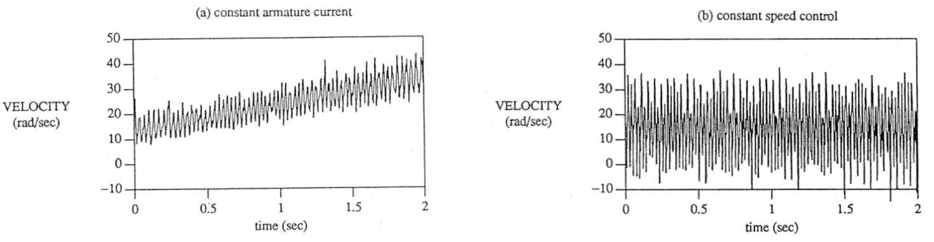

Fig. 2 Motor data

b. Ripple noise due to the commutation of the tachometer or motor

c. Error in differentiation or integration to derive both position and velocity.

More than one of these noise sources is mixed up in each sensor source. The contributions of noise to the sensors is listed in Table 2.

Table 2: Contribution of noises in the observation

sensor	information	noise
encoder	position	$r_{qe}{}^{p}$
	velocity	$r_{qe}{}^{v} + r_{diff}$
tachometer	position	$r_{rip}{}^{p} + r_{integ} + r_{qad}{}^{p}$
	velocity	$r_{rip}{}^{v} + r_{qad}{}^{v}$

r_{qe} : quantizing noise of encoder

r_{qad} : quantizing noise of A/D converter

r_{rip} : ripple noise of tachometer or motor

r_{diff} : errors by first derivative

r_{integ} : error by integration

3.1. Quantizing Noise

Digital data has truncation errors. The accuracy is determined by the quantization size, q . The probability density function for quantizing noise is uniform in the range $0 \leq r \leq q$. In general, the uniform probability density function can be written as follows:

$$f(\mathrm{r}) = \begin{cases} 1/(a-b) & \text{if } a \leq r \leq b \\ 0 & \text{if } r < a \text{ or } r > b \end{cases} \tag{3.2}$$

The probability density models of quantizing noise for an encoder and an A/D converter are listed in Table 3. The q_e and q_{ad} are the quantization sizes of the encoder and the A/D converter. Since the A/D converter produces, as output, a voltage, the noise is divided by the back emf constant K_b to estimate the velocity from the observed voltage.

Table 3: Uniform distribution functions for noises

$f(r)$	$\frac{1}{b-a}$	a	b
$f(r_{qe})$	$\frac{1}{q_e}$	0	q_e
$f(r_{qad}{}^{v})$	$\frac{K_b}{q_{ad}}$	0	$\frac{q_{ad}}{K_b}$

The mean and variance are calculated by the following manner for the uniform distribution.

$$u_q = E[r] = \int_{-\infty}^{\infty} \xi f_r(\xi)\, d\xi = \frac{a+b}{2}, \tag{3.3}$$

and

$$R_q = E[(r-u_q)^2] = \int_{-\infty}^{\infty} (\xi - u_q)^2 f_r(\xi) d\xi = \frac{(b-a)^2}{12}. \tag{3.4}$$

The mean and variance of the noise in the data which is modified by differentiation or integration can be obtained from those of the original noise. If the original noise was uncorrelated and has the same mean, u_o, the same variance, R_o, the means and variances of modified noise is as follows:

$$u_d \approx E\left[\frac{z(n)-z(n-1)}{h}\right] = \frac{1}{h}(u_0 - u_0) = 0 \tag{3.5}$$

$$R_d \approx E[(z(n)-u_d)^2] = E\left[\left(\frac{z(n)-z(n-1)}{h}\right)^2\right] = \frac{2}{h^2} R_o \tag{3.6}$$

$$u_i \approx E\left[\sum_{i=1}^{n} \frac{z(i)+(i-1)}{2} h\right] = nhu_o \tag{3.7}$$

$$R_i \approx E[(\int zdt - u_i)^2] = E\left[\left(\sum_{i=1}^{n} \frac{z(i)+z(i-1)}{2} h - nhu_o\right)^2\right] = n\frac{h^2}{2} R_o \tag{3.8}$$

The mean and variance for each noise are listed in Table 4.

Table 4: Mean and variance for error source

noise	model	
source	mean	variance
r_{qe}^{p}	$\frac{q_e}{2}$	$\frac{q_e^2}{12}$
r_{qe}^{v}	0	$\frac{q_e^2}{6h^2}$
r_{qad}^{p}	$n\frac{q_{ad}h}{2K_b}$	$n\frac{q_{ad}^2 h^2}{24K_b^2}$
r_{qad}^{v}	$\frac{q_{ad}}{2K_b}$	$\frac{q_{ad}^2}{12K_b^2}$
r_{rip}^{p}	0	$0.0571 \times (Ah)^2 n$
r_{rip}^{v}	0	$0.1142 \times A^2$
r_{diff}	0	$(30h)^2$
r_{integ}	0	$(1.7h^3 n)^2$

3.2. Ripple noise

In the observed data of the tachometer, there is a ripple noise. The noise could be modeled as follows:

$$r_{rip}{}^{\nu} = A \mid \sin(\omega t) \mid - \frac{A}{2} \tag{3.9}$$

The amplitude, A, is proportional to velocity until certain velocity. Over the velocity the amplitude is constant.

$$A = \begin{cases} K_a \mid \nu \mid & \text{if } \mid \nu \mid < \nu_{rip} \\ K_a \nu_{rip} & \text{if } \mid \nu \mid \geq \nu_{rip} \end{cases}$$

$$\omega = K_{ome} \mid \nu \mid$$

Since the probability density distribution of ripple noise is not simple, the mean u_{ripp} and the variance R_{rip} were simulated by using the noise function, Equation. (3.9). From the result it could be estimated by

$$u_{rip} = 0 \tag{3.10.a}$$

$$R_{rip}{}^{\nu} = 0.1142 \times A^2. \tag{3.10.b}$$

3.3. Errors in Differentiation and Integration

A first backward difference of the encoder observation data is employed to calculate the velocity.

$$z^{\nu}(n) \approx \frac{z^{p}(n) - z^{p}(n-1)}{h} \tag{3.11}$$

where, h is time period between two samplings. While, in order to compute the position from the velocity data we need to integrate as follows.

$$z^{p}(nh) \approx \sum_{i=1}^{n} \frac{z^{\nu}(i) + z^{\nu}(i-1)}{2} h \tag{3.12}$$

There are truncation errors in both Equations (3.11) and (3.12). The errors are obtained by the following equations.

$$r_{diff} = \frac{z^{p\prime\prime}(\xi)}{2} h \tag{3.13}$$

$$r_{integ} = -\frac{z^{\nu\prime\prime}(\xi)}{12} h^3 n \tag{3.14}$$

where, ξ is a value that lies somewhere between $i-1$ and i. Therefore, these errors depend on the acceleration and the jerk. If we assume a cubic function as the trajectory,

$$x(t) = a_0 + a_1 t + a_2 t^2 + a_3 t^3, \tag{3.15}$$

the acceleration and the jerk are as follows:

$$x^{p''} = 2a_2+6a_3 t$$
$$x^{\nu\,''} = 6a_3$$

The parameters a_2 and a_3 are computed as follows:

$$a_2 = \frac{3}{t_f^2} x_f$$
$$a_3 = -\frac{2}{t_f^3} x_f$$

where, t_f and x_f are the moving time and distance. those errors can be modeled as random variables with Gaussian probability density functions. In order to detrtmine the variance, we assume 2(*sec*) and 80(*rad*) for the t_f and x_f, respectively. The maximum absolute value of the acceleration is 120 (rad^2/sec^2). We use half of the maximum value as the standered deviation. While, the standard deviation of the jerk is 20 (rad^3/sec^3). The variances for errors in the differentiation and the integration are shown in Table 4.

4. EXAMPLE AND SIMULATION

To check the model we built a test system which consists of an encoder, a tachometer and a motor. The values of the parameters of the experimental test system are tabulated in Table 5. The resolution of A/D converter is 12 bits for ± 10V. The values of the amplitude and frequency of the ripple noise are evaluated from the experimenral data. The example velocity data obtained from the test system are shown in Fig. 3 and 4. There are quantizing and ripple noises in Fig. 3 and 4, respectively, such as described in the sensor model. The statistical values of noises are listed in Table 6. The values are calculated by using values of parameters denoted in Table 5. According to Table 2, the mean and variance of noise in each sensor observation are computed with the values of each noise (Table 7).

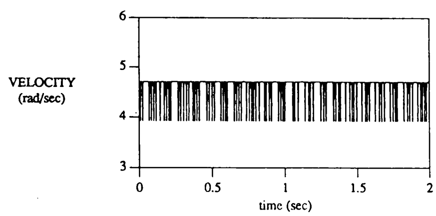

Fig. 3 Encoder data

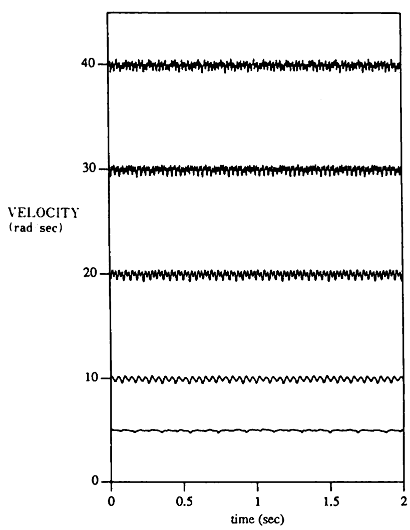

Fig. 4 Tachometer data

Table 5: Value of the coefficients	
q_e	$\frac{2\pi}{2000}(rad)$
h	$4\times10^{-3}(sec)$
q_{ad}	$4.88\times10^{-3}(V)$
K_b	$0.20(V/rad/s)$
A	$0.12v\ (v<20),\ 2.4\ (v>20)$
K_{ome}	$7(1/rad)$

Table 6: Mean and variance of noise source		
noise	estimated value	
source	mean	variance
$r_{qe}{}^{p}$	1.6×10^{-3}	8.2×10^{-7}
$r_{qe}{}^{v}$	0	0.1
$r_{qad}{}^{p}$	$4.9\times10^{-5}n$	$4.0\times10^{-10}n$
$r_{qad}{}^{v}$	1.2×10^{-2}	5.0×10^{-5}
$r_{rip}{}^{p}$	0	$1.3\times10^{-8}\times v^2 n\ (v<20)$ $5.3\times10^{-6}n\ (v\geq20)$
$r_{rip}{}^{v}$	0	$1.6\times10^{-3}\times v^2\ (v<20)$ $0.66\ (v\geq20)$
r_{diff}	0	1.4×10^{-2}
r_{integ}	0	$1.2\times10^{-14}n^2$

Table 7: Statistics of noises for each sensor			
sensor	information	mean	variance
encoder	position	1.6×10^{-3}	8.2×10^{-7}
	velocity	0	0.114
tachometer	position	$4.9\times10^{-5}\times n$	$(1.3\times10^{-8}\times v^2+4.1\times10^{-10})\times n$ $+1.2\times10^{-14}n^2\ (v<20)$ $(5.3\times10^{-6}+4.1\times10^{-10})\times n$ $+1.2\times10^{-14}n^2\ (v>20)$
	velocity	1.2×10^{-2}	$1.6\times10^{-3}\times v^2+5.0\times10^{-5}$ $0.66+5.0\times10^{-5}\ (v>20)$

In calculating the velocity it is not true that the tachometer information source is more precise over entire range than the velocity information calculated from encoder data. In the position information, the encoder data are not always more accurate than that from tachometer. The variance changes for the encoder as a function of velocity (Fig. 5); the noise of encoder is independent on the velocity. On the other hand, the tachometer data become more noisy as velocity increases. Therefore, in the high velocity range the encoder data has smaller variance than that of the tachometer. There exists the same situation in position observation. As we can see from Table 7, the position data evaluated from the tachometer has smaller variance than that of the encoder at low speed and in the small number range of integration cycles. In conclusion it can be seen that it is important to combine the both encoder and tachometer information sources to accurately estimate joint state. The present technique described in Section 2 is useful to combine the multi–sensor information sources with optimal weights.

The simulation was performed by using the values of parameter in Table 7 to verify the present technique. The cubic function denoted in Equation (3.15) was used as a command trajectory for control. The actual trajectory is calculated by adding the control error to the command path (Fig. 6(a)), where the control error is modeled as a sinusoidal curve (Fig. 6(b)).

$$r_c{}^p = 0.05 sin\ (10\pi t) \tag{3.16}$$

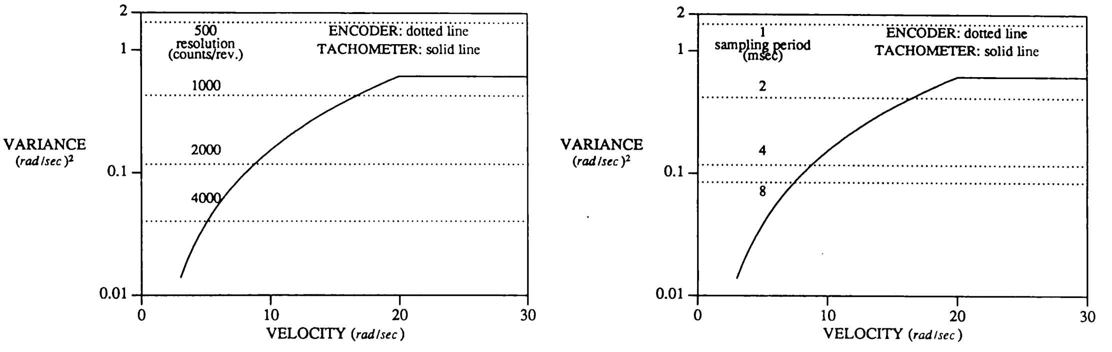

Fig. 5 Variance Change in Velocity

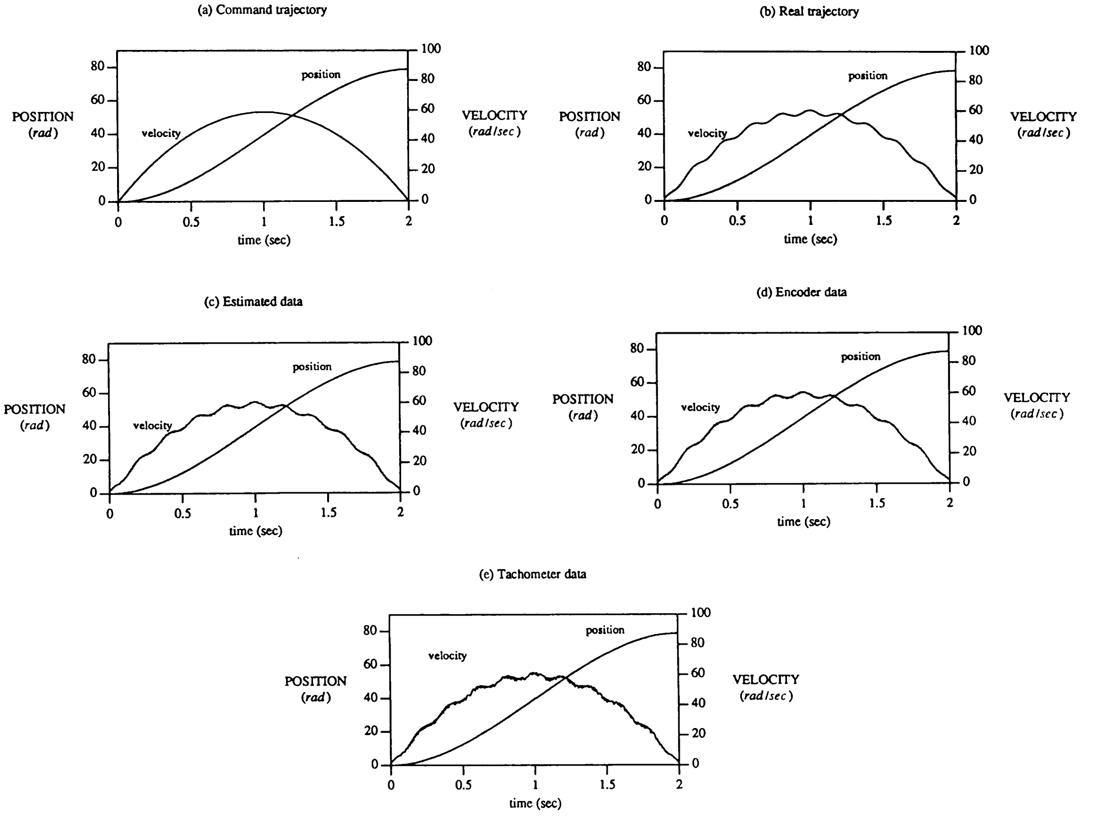

Fig. 6 Integration of Multi-Sensor Information

The variances of control error are 2.5×10^{-3} and 2.4 in position and velocity, respectively. The data are shown in actuator space, i.e., the value of angle is that of the motor shaft. The simulated results of sensor observation are shown in Fig. 6(d) and (e). We can find that the estimator (Fig. 6(c)) provides a clean information source over the entire range of velocities.

The simulations for sensor failures are shown in Fig 7 and 8. The real trajectory used here is

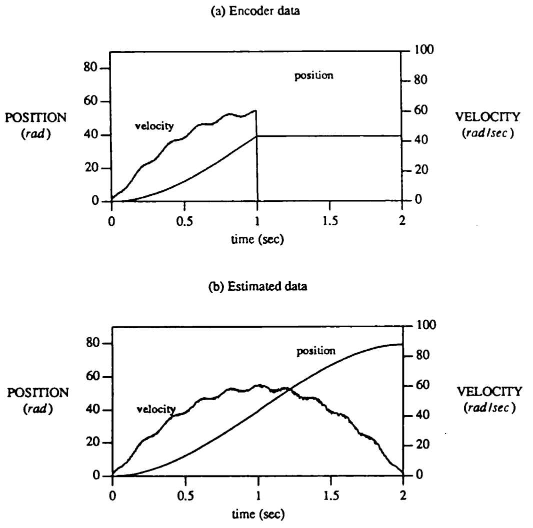

Fig. 7 Encoder Failure Simulation

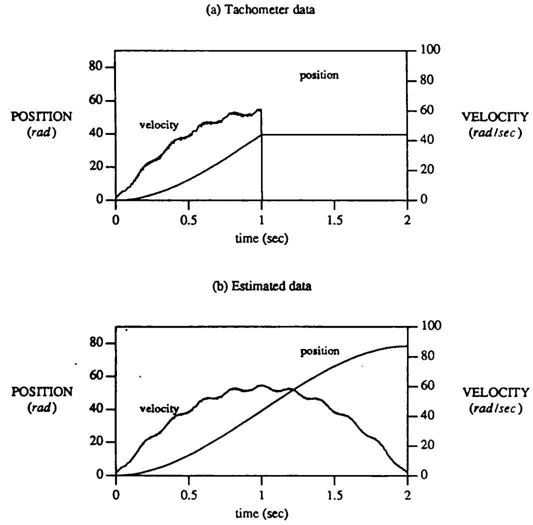

Fig. 8 Tachometer Failure Simulation

the same as that in Fig.6(b). The failures happen at 1 second. The cross–checking test finds the failure and then the information is ignored from the estimation. In this point there is no time delay. If the time delay is included, the estimated data will become very bad, bacause the velocity change due to the encoder failure is a large. The figure shows that after the failure happens the estimator follows the real path in both cases of encoder and tachometer failures.

5. CONCLUSIONS

A method which integrates the joint sensor information sources was proposed with the evidence of validity by simulation. The technique combines an estimator and a crosschecking hypothesis test for redundant multi–sensor information based on Fisher static model. The method provides for the efficient use of multi–sensor system to estimate precise joint state without introducing any time delay and also detection of a spurious sensor information source. In addition it can check any control failure by the hypothesis test. Therefore the scheme is useful for the precise and robust robot control. It is easy to extend this technique to the other joint sensors such as a resolver, potentiometer, etc.

In order to get complete information of joint status, the acceleration and the torque are important. The acceleration can be obtained by the differentiation from velocity data. Unfortunately this data is even more noisy than the control error. Therefore we did not consider the information in this paper. To get the clean information for acceleration, we will need either a high resolution encoder or an acceleration sensor. While, the torque information is also related with the velocity and the acceleration in the dynamic equation of the motor. By using a torque sensor we can get in addition to the force information more exact data for joint angle, velocity and acceleration. Consequently, the technique could be used for robust force feedback control.

ACKNOWLEDGMENTS

The authors would like to thank Dr. M. Mintz for his helpful suggestion and discussion. And also we thank Mr. F. Fuma for making the test system.

REFERENCE

[1] T. Suehiro and K. Takase: "*A Manipulation System Based on Direct–Computational Task–Coordinate Servoing*", Second Int. Symp. Robotics Research, pp 34–41. 1984.

[2] P. Allen and R. Bajcsy: "*Two Sensors are Better Then One: Example of Vision and Touch*", Third Int. Symp. Robotics Research, pp 48–53, 1985.

[3] H. F. Durrant–Whyte: "*Consistent Integration and Propagation of Disparate Sensor Observations*", IEEE Int. Conf. Robotics and Automation, pp 1464–1469, 1986.

[4] H. F. Durrant–Whyte: "*Integration, Coordination and Control of Multi–Sensor Robot Systems*", Ph. D. Thesis in Systems Engineering, Univ. Pennsylvania, August 1985.

[5] F. C. Schweppe: "*Uncertain Dynamic Systems*", Prentice–Hall Inc., 1973.