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Environment Model Calibration Using Range Data

Eimei Oyama
Mechanical Engineering Laboratory
Namiki 1-2, Tsukuba Science City,
Ibaraki 305 Japan

Susumu Tachi
RCAST, The University of Tokyo
Komaba 4-6-1, Meguro,
Tokyo 153 Japan

Abstract:

In order to control a remote robot, supervisory control using virtual environment is proposed. The environment model for the virtual environment was constructed from the design data of the real environment. However, there are usually modeling errors in the environment model. The modeling errors must be continuously calibrated. In environments with poor visibility, the ordinary visual sensor is not useful. Thus range sensors that can work in such environments are necessary. A hybrid environment display system using both the image made from the range data and the virtual image made from the environment model is proposed. For the comparison between the measured range and the environment model, the position error and the orientation error of the robot must be estimated. A new method for the parameter estimation from the range data using least squares method with a robust estimation technique, Tukey's Biweight method, is proposed. In order to test the proposed method, numerical experiments were conducted and the performance of the method was confirmed.

Keywords:Virtual Environment, Range Sensor , Nonlinear Least Squares Method, Robust Estimation

1 INTRODUCTION

In order to conduct operations in poor visibility environments, supervisory control using virtual environment which simulates the real environment was proposed[1]. The environment model for the virtual environment was constructed from the design data of the real environment. However, there are usually modeling errors in the environment model. When using virtual reality for controlling slave robots, the modeling errors must be continuously calibrated. In environments with poor visibility, the ordinary visual sensor is not useful. Thus range sensors that can work in such environments are necessary. Although the environment model can directly be constructed from the range data, the precision of the range data is relatively low. Furthermore, the lack of color information sometimes critically affects the operator's recognition performance.

In this paper, a hybrid display system using both the image made from the range data and the virtual image made from the environment model is proposed. The virtual image should be displayed for the operator in parts of the image where the environment model is more reliable than the measured range image. The measured range image based should be displayed for the operator in parts of the image where the measured range image is more reliable than the model.

Before comparison of the measured range and the expected range, the position error and the orientation error of the slave robot and those of the objects in the environment model should be estimated. A new method for the parameter error estimation technique using the range data is proposed. This method solves the measurement equation after the detection of the correspondences between the measured 3D vertexes, lines, and planes by range sensor and those of the object model in the environment model. If the assumed correspondences between the range data and the object model is correct, the parameter errors can be calculated easily. Though the computation for such measurement equation is easy, finding true correspondence is a difficult task. The assumed correspondences usually include some wrong correspondences. The proposed method solves the measurement equation by using a nonlinear least squares method with robust estimation technique, Tukey's Biweight method[7]. If most parts of the correspondences detected are accurate, true values of the unknown parameters can be obtained. This method can also be used for the detection of the wrong correspondences. In order to test the proposed method, numerical experiments were conducted and the performance of the method was partially confirmed.

2 HYBRID ENVIRONMENT DISPLAY

2.1 Operation in poor visibility environment using virtual environment

Tele-existence is an advanced type of teleoperation system that enables a human operator to perform remote manipulation tasks dexterously with the feeling that he or she exists in the remote anthropomorphic robot operating in a remote environment [2].

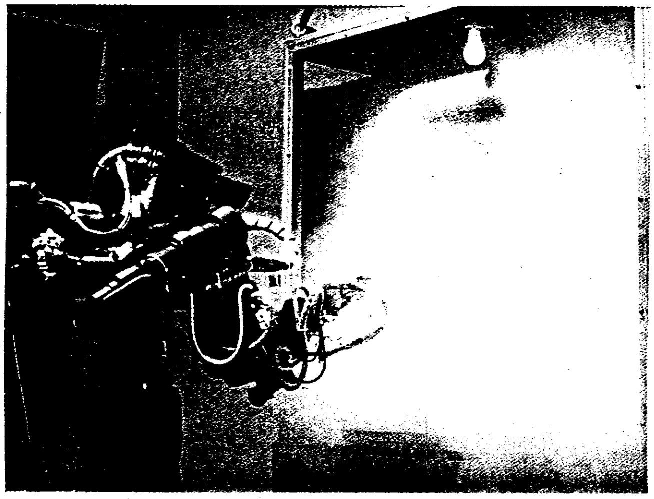

Figure 1 Operation in poor visibility environment

Supervisory control using the virtual environment generated by computer graphics was proposed and developed for the remote robot control [1]. The extended tele-existence system using virtual reality technology for the extension of human functions has been proposed [2][3]. Figure 1 shows an experimental robot operation in poor visibility environment. Figure 2 shows the virtual environment used in the operation. This system can provide the supervisory control using a virtual environment with the sense of reality. When using the virtual environment to control a slave robot, modeling errors in the environment model becomes critical. The environment model used in the virtual environment has been constructed from the design data of the environment. However, there are usually errors in the environment model. In particular, a contact task is difficult when the virtual environment does not accurately correspond to the real environment. When using virtual reality for controlling slave robots, the modeling errors must be continuously calibrated using external sensory information.

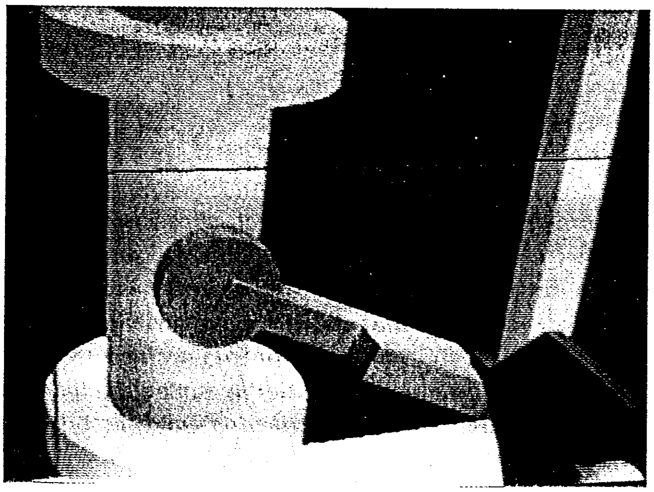

Figure 2 virtual environment

2.2 Range sensor

An ultrasonic array sensor, with following specifications, have already been developed[4]. Its detected range is 2 m. Its range resolution is under 1 cm. Its maximum angle of field of view is 60 degrees. Its direction resolution is 1.5 degrees. An active laser scanner, with following specifications, has been developed[5]. Its detected range is from 3 m to 30 m. Its range resolution is under 10 cm. The maximum angle of field of view is 8 degrees. Its direction resolution is less than 0.03 degree.

2.3 Hybrid environment display

The virtual image should be displayed for the operator in parts of the image where the environment model is more reliable than the measured range image. The measured range image should be displayed for the operator in parts of the image where the measured range image is more reliable than the model. If the error between the measured range and the expected range from the environment model is within the expected measurement error, the reliability of the model is high. If the error is larger than the expected measurement error, the reliability of the model is low.

Consider the coordinate system (x, y, z), where z is the depth direction. Let the measured range be $z_{real}(x, y)$, the calculated range from the environment model be $z_{model}(x, y)$, and the standard deviation of the measurement error of the range sensor be σ.

$$|z_{real}(x, y) - z_{model}(x, y)| > \alpha\sigma \qquad (1)$$

where α is an appropriate factor. In our system, α is 3. Although the range sensor is not so precise, but it is based on the real environment. Therefore α is set to relatively small. If the above condition is fulfilled, the environment model is not reliable near the point $(x, y, z_{model}(x, y))$ and the range data $z_{real}(x, y)$ is converted to the display image for the operator instead of the virtual environment.

2.4 Effects of parameter errors

There usually exist errors in parameters used for the calculation of the model of range data. For example, the position and the orientation of the robot carrying the range sensor usually has errors. In such a case, the condition (1) is not reliable and the standard deviation σ must be modified as follows. Let the unknown parameter vector be q and the measurement model of the range $z_{model}(x, y)$ be $h(x, y, q)$. The measured range $z_{real}(x, y)$ is approximated by the sum of the true measurement model $h(x, y, q)$ and the noise vector ω. The measurement equation can be defined as follows.

$$z_{real}(x, y) = h(x, y, q) + \omega \qquad (2)$$

Let the noise vector ω be Gaussian and its standard deviation is σ. Let the error vector of the unknown parameter vector be e_q and the covariance matrix of the error vector P. Then,

$$P = E(e_q {e_q}^T) \qquad (3)$$

Let the standard deviation of the measured range z be σ'. σ' can be estimated as follows:

$$\sigma' = \sqrt{HPH^T + \sigma^2} \qquad (4)$$

where H is Jacobian of the measurement model $h(x, y, q)$. The condition (1) is modified as

$$|z_{real}(x, y) - z_{model}(x, y)| > \alpha\sigma' \qquad (5)$$

2.5 Environment model calibration

After the detection of the parts of the image which have large differences between the measured range data and the calculated data, the environment model is corrected. Objects of the environment model which makes large differences are removed and the new object models made from the range data are included.

3 UNKNOWN PARAMETER ESTIMATION

Before the comparison between the real range data and the expected range data generated from the environment model, the position and the orientation of the robot carrying the range sensor must be estimated as precisely as possible. For this purpose, the method used in our system is illustrated in this section.

3.1 Unknown parameter estimation procedure

The unknown parameter estimation is conducted according to following procedures.

(1) Acquisition of range data
The range data of the real environment is acquired by using an appropriate range sensor.

(2) Extraction of basic elements of range image
The basic elements of the range image are extracted from the measured range data using image processing techniques. For example, vertexes, lines and planes are included in the elements.

(3) Initial correspondence detection
The correspondences between elements (vertexes, lines, planes) extracted from the measured range data and elements which comprise the environment model are detected (See 3.2). This procedure is carried out according to the calculated likelihood of the element.

(4) Solving measurement equation
Based on the extracted correspondence, a measurement equation is defined. It is solved by using linear or nonlinear least squares method. The initial correspondences usually include wrong correspondences. The robust estimation technique (See 3.4) is used for the estimation.

(5) Comparison between measured range and calculated range
According to the condition (5), the measured range and the calculated range are compared. The correspondences between most of the measured elements and most of the calculated elements from the model are detected.

3.2 Initial correspondence detection

The central problem of unknown parameter estimation is the detection of the correct correspondence between the measured range data and the environment model. The range data consists of many elements, such as vertexes, lines, and planes. The environment model also has such elements.

There are many characteristic values about the i-th element. For example, each extracted line has a length and an angle between two planes which construct the line itself. The vector u_{mi} is defined by such characteristic values about the i-th element of the model. The vector u_{rj} is also defined by such characteristic values about the j-th element of the real range data. By using the appropriate threshold γ, a candidate of the correspondence are selected. The (i,j) component of matrix C, which represents correspondence between the i-th element of the model and the j-th element of the range data, is calculated as follows:

$$C_{ij} = \begin{cases} 1 & e_{uji} < \gamma \\ 0 & \text{otherwise} \end{cases}$$

$$e_{uij} = |u_{mi} - u_{rj}| \tag{6}$$

But these detected correspondences usually contain the wrong correspondences. True solution cannot be obtained using conventional nonlinear least squares methods.

Linear estimation techniques can be used for the detection of the wrong correspondences. For example, if the correspondences of two straight lines between the range data and the model are detected, the position and the orientation can be calculated. Its result is good for first approximation of the parameters. But it is not enough for the comparison of the range data and the model. The comparison based on a sufficient number of correspondences has greater reliability. Therefore, a new estimation method based on the many correspondences is necessary.

3.3 Nonlinear Least squares method

When using a larger number of measurement values than numbers of estimated parameters, the nonlinear least square method is usually used. Let the known parameter vector be p, the unknown parameter vector be x and the measurement model be $f(p,x)$. The measurement vector y is the sum of the true measurement model $f(p,x)$ and the noise vector ω. The measurement equation can be defined as follows.

$$y = f(p,x) + \omega \tag{7}$$

Let the noise vector ω be Gaussian and the weight matrix W be the inverse matrix of the covariance matrix of the noise vector.

$$W = E(\omega\omega^T)^{-1} \tag{8}$$

The value of the unknown parameter vector x can be estimated by minimizing the following evaluation function:

$$S = (y - f(p,x))^T W (y - f(p,x)) \tag{9}$$

This equation can be solved by randomly searching for the initial value of x and by using the nonlinear least squares methods such as Marquardt's method [6].

When k is the number of iterations, this method improves the estimated value $x(k)$ iteratively as follows:

$$x(k+1) = x(k) + \Delta x(k) \tag{10}$$

$$\Delta x(k) = K(p, x(k))(y - f(p, x(k))) \tag{11}$$

$$\begin{aligned} K(p,x) &= (A(p,x)^T W A(p,x) + \lambda I)^{-1} \\ &\quad A(p,x)^T W \end{aligned} \tag{12}$$

$$A(p,x) = \frac{\partial h(p,x)}{\partial x} \tag{13}$$

$A(p,x)$ is the Jacobian of the measurement model $f(p,x)$. λ is a non-negative parameter adjusted to suit the degree of nonlinearity. If there is observability of the measurement equation (7), $x(k)$ converges to a correct solution by using randomly searching the initial value of the unknown parameter vector $x(0)$. Though the Marquardt method requires the Jacobian of the measurement model, the Jacobian can be easily obtained through numerical differentiation.

3.4 Robust Estimation Technique

In order to obtain true solution using data which includes wrong correspondences, an method using robust estimation technique is proposed. The value of the unknown parameter vector x can be estimated by minimizing evaluation function (9). W in the evaluation function is the diagonal weight matrix defined as

$$W_{ii} = 1/\sigma_i^2 \tag{14}$$

where σ_i is the standard deviation of the i-th component of the measurement value vector y. Tukey's Biweight estimation method changes the weight W_{ii} according to the normalized measurement error v_i defined as

$$v_i = \frac{y_i - h_i(p,x)}{\sigma_i} \tag{15}$$

The weight W_{ii} is modified as

$$W'_{ii} = \begin{cases} W_{ii}(1 - (\frac{v_i}{c})^2)^2 & |v_i| < c \\ 0 & \text{otherwise} \end{cases}$$

where c is a parameter for cut-off. When v_i is large, the corresponding weight W_{ii} become small and the effect of the bad data become small. According to Tukey's proposal, c is calculated as

$$c = \zeta median\{|v_i|\} \tag{16}$$

The factor ζ is set to 3 in our system.

3.5 Estimation Procedure

The total estimation procedure of our system is as follows.

(1) Correspondences detection
Based on the initial values of the parameters, the new correspondences are detected. The nearest element j of the range data from element i of calculated range data is selected and the new correspondence C_{ij} is defined.

(2) Nonlinear least squares estimation
Using nonlinear least squares method based on the weight matrix W, the parameters are estimated.

(3) Weight matrix modification
Using the robust estimation techniques, the weight matrix are modified according to the equation (3.4).

(4) Checking correspondences
Let the weight of k-th component of the measurement vector y be W_{kk}. if W_{kk} become nearly equal 0, the correspondence C_{ij} corresponding y_k, are set to 0 and the weights of all components of y based on C_{ij} are set to 0.

(5) Iteration
Repeat (2) to (3) until the change of estimated parameters become enough small.

If good estimation cannot be obtained, the random search of the initial values is started and above procedures are repeated.

4 SIMULATION

In order to test the proposed method, numerical experiments were conducted and the performance of the method was partially confirmed.

4.1 Robust estimation

In order to check the proposed robust estimation techniques (see 3.4), numerical experiments are conducted. The problem is the estimation of the position and the orientation of a brick. Its width is 3,its depth is 4, and its height is 5. The position (x, y, z) and the orientation (ϕ, θ, ψ) of the brick are generated using random generators. A brick has 8 vertexes. The positions of all vertexes of the brick are measured. The standard deviation of each component of measurement vector is 0.01. The position and the orientation are estimated using robust nonlinear least square methods base on the correspondences between vertexes which includes wrong correspondences. The correspondence between a vertex of the measured brick and a vertex of the model is defined by using a matrix C(see 3.2). C_{ij} is set to 1 at the probability of 50 (%) and is made 0 at the probability of 50 (%). C_{ii} represents true correspondence at the probability of 50 (%). C_{ij} includes many wrong correspondences. 1000 trials are conducted in order to check the method. By using the estimation procedure(see 3.5), estimation succeeded in 973 trials. Most wrong correspondences are detected in the iteration process of the estimation procedure. The mean number of iteration of the nonlinear least squares method is 50.5 times. But usually 1.8 times initial value search is necessary. The standard deviation of the error of the estimated position vector is 0.01 and the standard deviation of the error of the estimated orientation vector is 0.012 (rad).

4.2 Position and Orientation Estimation from Range Data

In this simulation, the measurement model of range data is defined as

$$z_{real}(x, y) = \int\int z(x+u, y+v)dudv + \omega \tag{17}$$

where $z(x, y)$ is the real range data. In this simulation, the calculation of the range data is simplified. Its maximum angle of field of view is considered 50 degrees. This range data is approximated by digital images $I_r(i, j)$ which have 512 x 512 pixels. The graphics computer generating virtual environments usually has z buffer system for the hidden plane elimination.

The z value of the z buffer is almost the same as the range data. Therefore, it is used for the simulated range data.

$$I_r(ix, iy) = \sum_{j=-N}^{N} \sum_{i=-N}^{N} I_z(ix + i, iy + j) + \omega \quad (18)$$

In this simulation, N is 10 and the standard deviation of ω is 5.0 cm. The range data $I_z(i,j)$ is calculated using z values in z buffer. The system extracts vertexes, lines, and planes from the simulated range image $I_r(i,j)$.

Figure 3 shows the superimposed image of the extracted lines and the results of the robust estimation by nonlinear estimation technique.

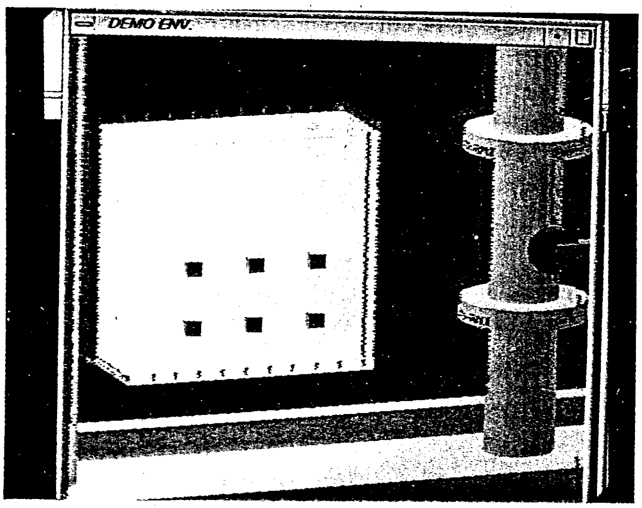

Figure 3 Estimation result

A total of 36 lines are extracted from the simulated range data. And the 21 correspondences between two large straight lines are used for the robust nonlinear least squares estimation. Finally correct 7 correspondences are selected and almost correct position and orientation are obtained. 100 estimation trials are conducted. The standard deviation of the error of the estimated position vector is 0.03 (m) and the standard deviation of the error of the estimated orientation vector is 0.034 (rad).

5 CONCLUSION

In order to conduct operations in poor visibility environments, a hybrid environment display system using both the image made from the range data and the virtual image made from the environment model is proposed. In order to compare the range image and the virtual image, a new method for the parameter error estimation using least square method with Tukey's Biweight method is proposed. In order to test the proposed estimation method, numerical experiments were conducted and the performance of the method was confirmed. The examination of the method using real data is the problem to be solved in the future.

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