

A Manipulator Control System for Creating Radiation Maps Using Mercuric Iodide (HgI₂) Detectors

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Abstract

In this paper we describe the development of a robotic system that uses Mercuric Iodide (HgI₂) sensors to create a map of radiation intensity in the environment. The sensors are mounted at the end-effector of a PUMA 560 manipulator. Data from these sensors is used to compute the radiation intensity. A control system is developed that moves the end-effector along constant intensity contours. The experiments use light sources (instead of radiation sources) and demonstrate the efficacy of such a system to create radiation maps.

1. Introduction

In this paper, we describe a system for measuring radiation using Mercuric Iodide detectors attached to a 6 DOF robotic arm. The goal of this system is to find a distribution of radioactive intensity in space. Generally an intensity map can, for example, be used for planning robot motions. By properly generating exploratory motions it is also possible to detect and characterize sources of radiation. Mercuric Iodide sensors are especially useful for this because they operate at room temperature. For a description of the characteristics of HgI₂ sensors the reader is referred to [22].

The simplest way to achieve our objective is to gather a lot of measurement points by scanning the sensor uniformly in a large space but this is time-consuming and not suitable for understanding the local characteristics of the space. To solve these problems, when looking into recent advanced robotics we can find some successful sensor-based robotic systems [1][2][3] realizing the specific task based on the sensor information. Especially visual servoing system in the area of active vision is a typical example [4][5][6]. The attempt to combine motion and perception is reasonable and important not only to increase the amount of spatial information but also to extract it selectively. With this view point we developed a measurement system to divide a space at a threshold value of radiation by introducing a tracking motion while making multiple measurement as the end-effector follows a virtual surface with a certain constant radiation intensity.

2. Problems for design of controller

We use a PUMA robot system in which a real time position control system is available for an input of a position displacement with the sampling time interval of 28ms. The radiation sensors are attached to the robot's end-effector. A block diagram for a sensory feed-back system is shown as Fig.1. In this system the tracking controller is given the reference sensor value, Y_d , and generates the differential motion command, δx_d , by comparing with the current sensor value, Y . We model the process from the robot motion to the change of the radiation intensity by describing the process as three sub-processes. The process, Pr_j , is a model of the kinematic relation between the robot motion and the potential displacement of the sensor location. If we regard this displacement as a motion of the sensor points, δr , on the most descendent (normal) direction of the potential space, the change of intensity, δI , for the sensor locations can be derived by multiplying

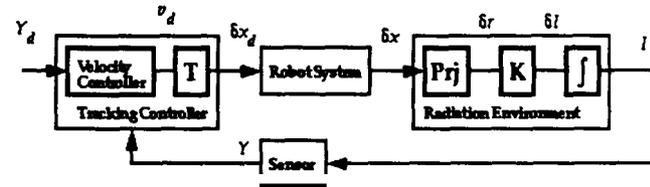


Fig.1 The tracking system for a radiation environment

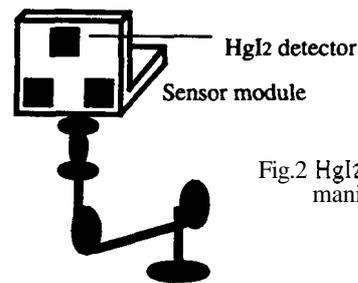


Fig.2 HgI₂ detectors attached to a 6DOF manipulator

with a coefficient, K . Therefore we define K shown as the second process in this diagram as:

$$K = \frac{\partial I}{\partial r}$$

We call this the normal derivative coefficient because the potential space has a virtual intensity surface with a specified intensity and the normal vector is coincident to the gradient. The third block is an integration process needed in a potential space.

The first problem for the controller design is concerned with the determination of radiation space. But initially we do not know the structure at all. How many radiation sources exist? What kind of shape do they have? Where are they located? We seem to need some assumptions for simplification and step by step approach. According to Fig.1, for the model based controller design we have to formulate the kinematic process, Pr_j , and estimate the derivative of intensity, K . However the above complexity of the radiation space almost reflects on the kinematic relation. We assume that the radiation sources can be treated as points because we are measuring the radiation far away from the source. Based on this, we first deal with the formulation for a single source and modify this simple model to apply to the more complicated case of multiple sources.

For the estimation of, K , we have to give an appropriate motion for the sensor in the most descendent (normal) direction in the space. But this is realized easily if we can get the virtual intensity surface mentioned before. Fortunately since we are using multiple sensors located on a plane (See Fig.2) we can make this sensor plane follow the virtual intensity surface by a simple control law. Actually we get the direction by a Bang-Bang controller with an additional damping condition before reaching the tracking position. And subsequently we give the straight line motion for the estimation. After determining the value of K , the control transits to the more sophisticated model-based

tracking control that we describe later.

The remaining problem is the design of the servo loop including the sensing process. The kinematic process is time-variant and non-linear. By assuming that the kinematic relation is constant around the tracking equilibrium point, it is possible to derive a time-invariant system and apply the conventional control law such as optimal regulator [9][10]. But in our case the objective of this tracking controller is to cover a relatively large space and the kinematic process may not be invariant. So we introduce a method to treat the non-linear time-variant process directly. We propose the control process including the inverse system of this kinematic process together with some classes of compensators. This controller is proved to be stable under some conditions of the robot system by using the passivity theorem. And the effectiveness is confirmed for a certain cost function.

In the following sections, we propose our method for estimating K , which is followed by the discussion of the design of the tracking controller. And finally we show some results of the experiment.

3. Controller Design

3.1. Estimation of K value

In the previous section, we defined K as the derivative of the radiation intensity. But to realize the control, we actually should know the derivative value of the sensing space obtained by projecting the real distribution of radiation intensity to that of a sensor value. This means that the space consisting of a sensor and a radiation environment is strongly influenced by the characteristics of the sensor used. Let us redefine K as a derivative of the sensor output, y .

Therefore, $K = \frac{\partial y}{\partial r}$ where r is a distance in the normal direction. In this case we have to maintain the relation between the sensor's axis of maximum sensitivity and this normal direction during measurement. If the control is executed to make the most sensitive direction of the sensor be oriented toward the radiation source, the data resulting is consistent with the normal direction, and would be useful. But this information of the whole space cannot be available in advance. So we have to build a proper model on the basis of the spatial knowledge of the radiation of the source.

Radiation is measured by the density of the flux of radiance[11][12]. Fig.3 shows the relation of a radioactive object and a sensor. A small area, dA , on the object radiates to the whole space and a part of that reaches the sensor, S . The intensity of radiant flux is represented as a rate passing through a unit solid angle of energy radiated from a unit area on the surface of the object. So defining the intensity of the surface radiance, L (watt)/(m².steradian), represents the differential flux received by the sensor, $d\Phi$ (warr)/m², as follows.

$$d\Phi = L \left(\pi \left(\frac{d}{2} \right)^2 \cos \alpha \times \frac{1}{r^2} \right) dA \cos \theta$$

where d , is a diameter of the

sensor's sensitive surface and r , is the distance between the position of, dA , and the sensor.

$$\text{And for whole object. } \Phi = \int_A d\Phi$$

But if the measurement point is far from the object, then $\cos \alpha \cong 1$, and the above equation becomes

$$\Phi \cong \pi L \left(\frac{d}{2} \right)^2 \int_A \frac{\cos \theta}{r^2} dA$$

So we can think of the integrated intensity as proportional to the whole solid angle of the object. And furthermore as the measurement point becomes distant, one may introduce a certain distance $z = r \cos \alpha$ which projects r to a line normal to the sensor that connects the measurement point and the sensor, z becomes approximately constant and we get

$$\Phi \cong \pi L \left(\frac{d}{2} \right)^2 \left(\int_A \cos \theta dA \right) / z^2$$

This approximation shows that the intensity is dominated by only the distance between the measurement point and the object represented by a point radiation source. In this report, when estimating K , we assume that this approximation holds in order to simplify the calculation. Therefore,

$$y \propto \frac{1}{r^2} \tag{1}$$

where, r is the distance to the radiation source measured in the normal direction on the virtual surface with a particular intensity. So,

$$K = \frac{\partial y}{\partial r} \propto -\frac{2}{r^3} \tag{2}$$

We estimate, K , by sampling a set of data for the position of the robot end effector and the sensor output during appropriate motion.

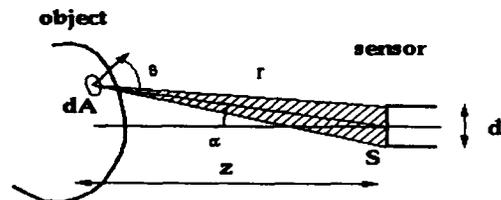


Fig.3 Relation of Radiation and sensor

To get a precise estimate we need many data points that are distributed in an appropriate range of the space since the data always include noise. But the measurement with motion has some constraints in its capability. The number of data is limited by the sampling rate. And data which exist in a broad space makes the estimation difficult because of it's non-linearity. So we have to determine the sampling specification according to the motion, the sensing capability and the computing power. For these reasons we derive a simple way of estimation as described in the following.

If we assume $r = rd$, $K = Kd$, at a tracking point, then, K , at any point on the path to the tracking point, is derived from equations. (1) and (2) as follows.

$$K = Kd \left(\frac{rd}{rd + \Delta r} \right)^3 \quad (3)$$

where $r = rd + A r$. Since we can assume $A r \ll rd$, and linearize equation (3) to obtain

$$K \cong Kd \left(1 - \frac{3}{rd} Ar \right) \quad (4)$$

The sensor output at the tracking point, yd can be represented as:

$$y = yd + \int_{r(td)}^{r(t)} K(t) dr = yd + \int_t^{td} K(t) v dt \quad (5)$$

where v is the partial velocity in the normal direction and t, td show the time at positions, r, rd , respectively. And on substituting equation (4) into (5), we get

$$y - yd = Kd (\Psi_1(t)) + \frac{3Kd}{rd} (\Psi_2(t)) \quad (6)$$

$$\text{Here, } \Psi_1(t) = \int_t^{td} v dt, \quad \Psi_2(t) = - \int_t^{td} (r - rd) v dt$$

We estimate, Kd , by using linear least squares from the measurement of, $y - yd$, $\Psi_1(t)$ and $\Psi_2(t)$.

The above equations can be represented in the discrete-time form as follows. If the position difference of two measurement points is defined as below,

$$\delta r^T = [\delta r_1, \delta r_2, \dots, \delta r_N], \quad \delta r_i = r(t_i) - r(t_{i-1}), \quad i = 1, \dots, N$$

Then, equation (6) can be represented as:

$$\Psi_1(t_i) = \sum_{k=i}^N \delta r_k, \quad \Psi_2(t_i) = - \sum_{k=i}^N \left(\sum_{j=i}^N \delta r_j \right) \delta r_k$$

On the other hand, we represent, y , as:

$$\bar{y}(t_i) = y(t_i) - y(t_d), \quad Y^T = [\bar{y}(t_1), \bar{y}(t_2), \dots, \bar{y}(t_N)]$$

and furthermore, define the matrices, Θ^T and Φ^T as:

$$\Theta^T = [\theta_1 \theta_2] = \left[Kd \quad \frac{3Kd}{rd} \right] \quad \Phi^T = \begin{bmatrix} \Psi_1(t_1) & \dots & \Psi_1(t_N) \\ \Psi_2(t_1) & \dots & \Psi_2(t_N) \end{bmatrix}$$

Then the estimation of Θ denoted by, $\hat{\Theta}$, becomes

$$e = (\Phi^T \Phi)^{-1} \Phi^T Y \quad (7)$$

Fig.4 shows the relation between the sensor position and the sensor output. Line (1) shows the filtered data of the sensor output sampled at 20 ms. Line (3) is derived by applying the radiation law (in eq.(1)) for the initial position, so that we can model the difference between the radiation space and sensor space as mentioned before. And line (2) is an approximation to the experimental data obtained by the logarithmic least square fit which assumes the measured values are described by the following equation.

$$\left(\frac{y}{y_0} \right) = \exp(b) \left(\frac{D-d}{D-d_0} \right)^a \quad (8)$$

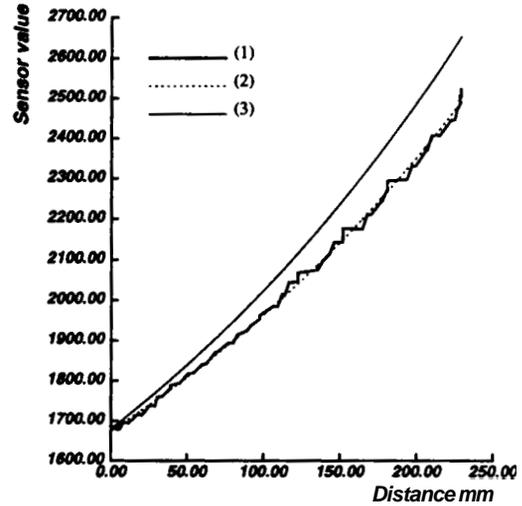


Fig.4 Filtered sensor signal

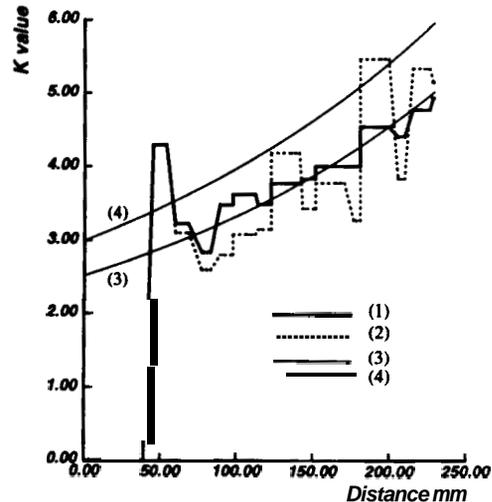


Fig.5 Result of the estimation of K

where y and d are the sensor value and the position, and y_0, d_0 are the initial values while a, b, D are constants which have the following values. $a = -1.389$. $b = -9.06 \times 10^{-5}$, $D = 920.1$.

Here the robot's end effector was driven at the maximum speed of 150 mm/s and the estimation was executed with a period of 100 ms. This estimation is based on the small number of data points distributed in a rather narrow range of space. where we set this range from 20 mm to 50 mm and obtain 20 data samplings.

Line (2) in Fig.5 shows the result of the estimation of K for the condition of the tracking motion with a single radiation source which is restricted to the specified direction. Here, we could lower the noise level of the data about 15 dB for the source by using a 2nd order linear filter. So the deviation of the filtered data can be estimated to be less than 1%. Nevertheless the estimation has a large error and looks unstable. We have to conclude this estimation is too sensitive. For making it robust, we developed an additional filtering technique which doesn't require much more computation and is shown next.

From equations (1) and (2) we get,

$$K = K_d (y/y_d)^3 \quad (9)$$

where K_d and y_d are the K value and the sensor output y at the different position which corresponds to the set of K, y . This equation shows the possibility of the prediction of K at a certain position from the estimation results at the other positions. If the distance between the data points are small this assumption may be appropriate. Based on this consideration, we constructed the following filter for the estimation of K .

$$K_{out}(t) = \frac{w(0)K(t) + \sum_{i=1}^N w(i)K_{out}(t-iT) \left(\frac{y(t)}{y(t-iT)}\right)^3}{\sum_{i=0}^N w(i)} \quad (10)$$

where K_{out} is output of the filter and w is a weight for the reliability of data and T is the sampling period. Line (1) in Fig.5 shows the filtered estimate for $N = 4$. We can effectively improve the estimation by this filter. If we could regard line (3), which is the derivative function derived from the logarithmic least square (line (2) in Fig.3). as the true value, the deviation of the estimation becomes less than 5%. Line (4) corresponds to line (3) in Fig.4. The accuracy of the estimation is sufficient for our controller design. When more accuracy is required, we could use equation (8) but we have to give up the advantage of this on-line estimation because of the limitation of the on-board computers. Because the radiation space in the real site, with scattered radiation sources, looks complex, there is no guarantee of getting a good estimate like the example with a single radiation source. However, the method we have developed is applicable to the more complicated situation due to the restricted range for the estimation where the non-linearity is not dominant.

3.2. A Tracking Controller

We can simplify the design of the controller if we build a precise model of the process between robot motion and sensor reaction. But this situation depends on the radioactive space. To show this reason-

ing, we at first consider the simple case of the tracking motion around a single source that can be regarded as a point. In this case the virtual surface to be tracked would be a spherical surface and we can get the kinematic relation between the robot end effector motion and the change of the radioactive intensity.

So let us design the controller with the premise that the modeling of the kinematics in radioactive space is possible. The first diagram in Fig.6 shows the block diagram of the target system and controller. As mentioned before the robot system receives the differential position signal from the tracking controller and drives the position servo system of the robot, Gr, which generate the motion x and dx . The matrix, B , represents the process from the motion to the intensity, I . In general the controller uses the signal of the state of the robot system as well as the sensor output. These signals are important to improve the performance of the whole system. But since our strategy of designing simply make us remove this, consequently we propose the tracking controller shown in the middle diagram. The controller has the functional process of B besides compensators, $C1, C2$ and generates the velocity command, v_d , to output the differential positioning command, Δx_m , by multiplying it with the sampling period, T , of the robot controller. The introduction of B , is reasonable because one of this design problems is the kinematic optimization of generating the correcting signal when the sensors fail to follow the tracking surface. But the design is not sufficient when taking into account the dynamics of the system. Here we might need additional compensation to improve the whole system performance. So we introduce the compensators while designing the controller as the function of B .

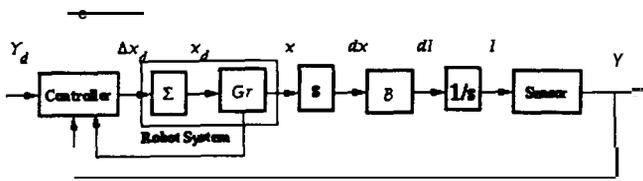
If the dynamics of the sensing process can be neglected (therefore $I \propto Y$) and the discrete process, $\sum \Delta x_d T$, can be replaced by continuous integration, the representation of the system can be simplified as shown in the third diagram. Here, G_j , is a joint-based transfer matrix and, J , is the Jacobian matrix of the robot. Therefore, $Gr = JG_j J^{-1}$. We can analyze the system if we could determine the transfer functions for each input. However the transfer functions are time-varying and complicated by the interaction between robot joints. Therefore the deterministic design is quite difficult. To simplify this problem, most sensor based systems neglect the robot dynamics under the assumption that the sensor feedback loop is slow compared with that of the robot controller.

Under the condition we select the next controller for the sensor-based system.

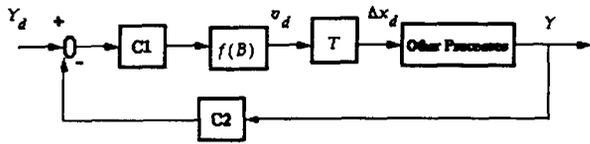
[[Proposed Controller]] Selecting the matrix, $f(B)$ which satisfies $Bf(B) = I$ and set a positive real, $C2$, and a strictly positive real, $C1$, as the compensators.

Because the controller gives the simple structure for compensators if the transfer matrix G_j . can be assumed a diagonal matrix with similar positive real transfer functions. And if the transfer functions are completely equal the system becomes BIBO stable by the Passivity theorem [18]. But this selection is still intuitive and we need to guarantee the effectiveness.

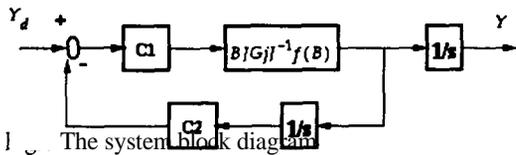
For the effectiveness of our controller we can find a good answer in the work described next provided that they don't take account of the robot dynamics. Papanikolopoulos [6][7] introduced the cost function to derive the control law for a non-linear, multi-variable, time-varying visual servoing system which is equivalent to our system when formulating the relation between the robot motion and the optical flow in the image of the camera installed on the robot end effector. Our controller is one solution for the optimal criteria proposed in their work.



Tracking Controller



Simplified System



The system block diagram

The system is generally represented in the discrete state-space form as follows.

$$x(k+1) = x(k) + B(k)u(k) \quad (11)$$

where, x , is the sensor state value and, u , is the motion input. And, B , shows the kinematic relation between the robot motion and the changing rate of the sensor state values. Here is the cost function.

$$J(k+1) = \Delta x(k+1)^T Q \Delta x(k+1) - u(k)^T R u(k) \quad (12)$$

$$\Delta x(k) = x(k) - x_D(k)$$

where, x_D , is the sensor reference and, Q , R , are the positive matrices. And the control law to minimize the cost function is as follows.

$$u(k) = -(B^T(k)QB(k) + R)^{-1}B^T(k)Q[x(k) - x_D(k+1)]$$

The matrix, R , is a penalty for the limitation of the available magnitude of the input. So if the error is relatively small this is not necessary. And when, Q , is a diagonal matrix with equivalent terms, the feedback gain for the tracking error become proportional to the pseudoinverse $(B^T B)^{-1} B^T$ of the matrix B if the matrix, $B \in R^{m \times n}$, $m > n$, and the matrix, $B^T B$, is non-singular. This is coincident to our intuitive selection. But this is limited to the application for the specified class of the matrix B . To extend this analysis to the general case we propose the next control law.

$$u(k) = -(B^T(k)QB(k) + R)^{\Pi} B^T(k)Q[x(k) - x_D(k+1)] \quad (13)$$

where, Π , is the operator of the pseudoinverse. Here if we again assume $R = 0$, $Q = qI$ (I is unit matrix, q is a constant), we get the next control law.

$$\begin{aligned} u(k) &= -(B^T B)^{\Pi} B^T q^2 [x(k) - x_D(k+1)] \\ &= -B^{\Pi} q^2 [x(k) - x_D(k+1)] \end{aligned} \quad (14)$$

This result shows that we select the pseudoinverse of the process, B , as a control process, $f(B)$. And when $B \in R^{m \times n}$, $m \leq n$ and $B^T B$ is non-singular, because $B^{\Pi} = B^T (BB^T)^{-1}$,

$$Bf(B) = BB^T (BB^T)^{-1} = I \in R^{n \times n} \geq 0 \quad (15)$$

Therefore we can confirm the effectiveness of our controller minimizing the error together with its stability. Next, we'll apply this control scheme to our tracking controller based on a simple model.

3.2.1. A model for a single source

We need a minimum of 3 DOF of the motion to realize the tracking motion in a certain position on the virtual surface, because we are assuming the target is stationary. The redundant DOF essentially should be used for optimization of the motion. We need 2 DOF independently to position the sensors on the surface to get the spatial information. And if the sensors need to be oriented we need one more. We formulate the tracking model assuming that 3 DOF of motion are reserved for scanning and only 3 DOF are available for tracking.

Let us assume the three sensors are tracking a spherical surface in the sensor coordinates system shown in Fig.7, we can get the kinematic relation between the robot motion velocity u and the changing rates of the distances, r_i , from the center of the sphere to sensor, i .

$$\dot{r} = \begin{bmatrix} \frac{-(c_x - p2_x)}{r_2} & \frac{-(c_y - p2_y)}{r_2} & \frac{-c_z}{r_2} & \frac{-p2_y c_z}{r_2} & \frac{p2_x c_z}{r_2} & \frac{p2_y c_x - p2_x c_y}{r_2} \\ \frac{-(c_x - p3_x)}{r_3} & \frac{-(c_y - p3_y)}{r_3} & \frac{-c_z}{r_3} & \frac{-p3_y c_z}{r_3} & \frac{p3_x c_z}{r_3} & \frac{p3_y c_x - p3_x c_y}{r_3} \end{bmatrix} u \quad (16)$$

$$\text{Here, } \dot{r} = [\dot{r}_1 \ \dot{r}_2 \ \dot{r}_3]^T, \quad u = [v_x \ v_y \ v_z \ \omega_x \ \omega_y \ \omega_z]^T$$

where the points $(p2_x, p2_y, p2_z)$, $(p3_x, p3_y, p3_z)$ show the sensor positions but because the sensors are located on the x-y plane while one sensor is located at the origin, $p2_z = p3_z = 0$. And the position of the radioactive source is represented as (c_x, c_y, c_z) in the sensor coordinates.

So, the motion causes the change of the sensor signal $Y = [y_1, y_2, y_3]^T$. We define the error signal for the reference y_D as:

$$e = [y_D - y_1, y_D - y_2, y_D - y_3]^T$$

Furthermore, from the previous assumption of the radiation space,

$$\dot{e} = K\dot{r}, \quad \text{and} \quad \frac{1}{T_i} = -\frac{K}{2y_i} \quad (i = 1, 2, 3)$$

Therefore,

$$\frac{K^2}{2} \begin{bmatrix} \frac{c_x}{y_1} & \frac{c_y}{y_1} & \frac{c_z}{y_1} & 0 & 0 & 0 \\ \frac{c_x - p2_x}{y_2} & \frac{c_y - p2_y}{y_2} & \frac{c_z}{y_2} & \frac{p2_y c_z}{y_2} & \frac{-p2_x c_z}{y_2} & \frac{p2_x c_y - p2_y c_x}{y_2} \\ \frac{c_x - p3_x}{y_3} & \frac{c_y - p3_y}{y_3} & \frac{c_z}{y_3} & \frac{p3_y c_z}{y_3} & \frac{-p3_x c_z}{y_3} & \frac{p3_x c_y - p3_y c_x}{y_3} \end{bmatrix} u = \frac{B}{T} e \quad (17)$$

Here, we can get the representation of non-linear, time-varying system equivalent to eq.(17). So we can propose the following simple control law.

$$u(k) = \zeta B(k)^{\Pi} e(k) \quad (18)$$

where, ζ , is an appropriate coefficient and, $1/\zeta$, is equivalent to a time constant for the system response. And, k , represents a time, kT .

Next, we derive the tracking controller for 3 DOE As mentioned before we need to modify this to realize the scanning motion in the

arbitrary tangent direction. At first we neglect rotation ω_z because we keep the direction on scanning. So the tracking motion has to be done by the 3 DOF of v_z, ω_x, ω_y , while absorbing the effect of the scanning motion. This situation can be represented as follows.

$$\begin{bmatrix} \dot{e} \\ v_x \\ v_y \end{bmatrix} = \begin{bmatrix} 1 & 0 & \begin{bmatrix} B_1 \\ \emptyset \end{bmatrix} & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ v_z \\ \omega_x \\ \omega_y \end{bmatrix} = \frac{B_2}{T} u' \quad (19)$$

where B_1 is the matrix which is obtained by removing the 6th column from B in equation (17). The matrix B_2 is always non-singular. Therefore we can get the following control law.

$$u(k) = \zeta B_2^{-1} e(k) \quad (20)$$

Fig.8 shows the structure of the whole system. The scanning planner generates the pattern of scanning velocity corresponding to the reference area on the virtual surface. And in the experiment we generate square wave like patterns with a constant acceleration on starting and stopping.

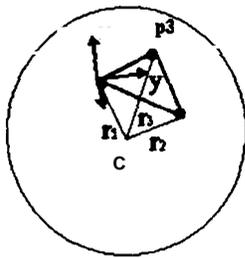


Fig.7
Sensor coordinates on a sphere

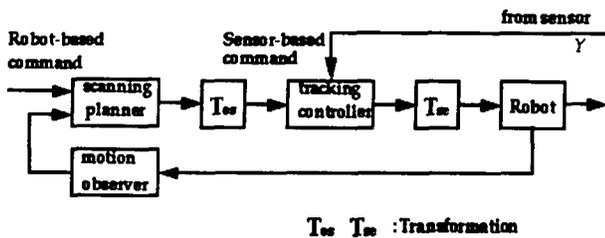


Fig.8 The tracking controller and the scanning planner

4. Experiment

We conducted some experiments to confirm the performance of our tracking system in a radioactive space. First we describe the experimental hardware.

Fig.9 shows the configuration of the Mercuric Iodide sensors[24]. As mentioned before we use three sensors and located them on the sensor module in a position which forms an imaginary equilateral triangle which has 2.5 in. length of each side. And the sensor module is attached to the final link of the 6 DOF manipulator, a PUMA 560. The sensor signals are magnified by an amplifier installed in the sensor module. This is connected to the VME bus on which the real-time operating system of the CHIMERA II [12][13] is installed to give an effective environment for developing the control software.

The control algorithm is executed by Ironics M68020 on-board computers. Since our control law is so simple that we can realize it by a single board of this computer. The cycle period of the robot control is 14 ms, that of the parameter estimator is 100 ms, and that of measuring the sensor output and calculating the robot kinematics is 20 ms.

Next we show the setting of the experiment. The first experiment is for the process of getting the K value and establishing a tracking motion around a single radioactive source. In this experiment we prepared a light source using an ordinary electric lamp as a radiation source. And instead of the Mercuric Iodide detector we use a photodiode (SFH205 by Siemens) which is sensitive in an infrared band. This setting is convenient to conduct the experiment under an ordinary illuminative environment. We already showed the result in Fig.4. Here, we set the sensor about 1 m away from a 40 w light bulb with frosted glass. Because of the fluctuation of the power the control gain, ζ , must be up to 5. But the tracking performance is enough for a relatively slow scanning motion up to the speed of 50 mm/s.

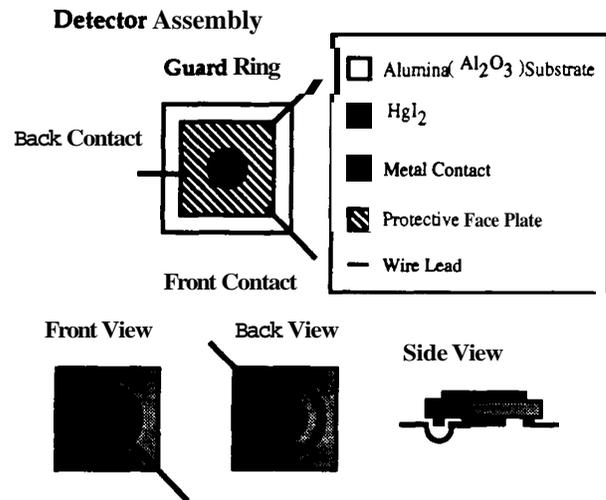


Fig.9 Configuration of the Mercuric Iodide Detector

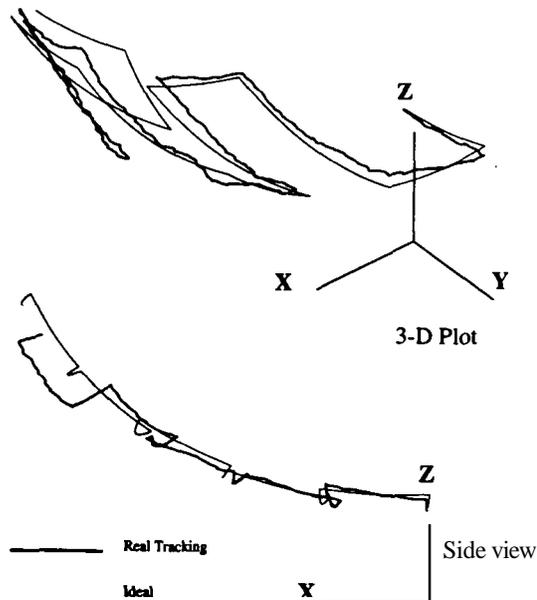


Fig. 10 Trajectory of a square wave like scanning motion

Fig. 10 shows the result of scanning around a single light source (90 watt bulb) while keeping the distance of a bulb 370 mm. In this experiment we are using the Mercuric Iodide sensor in a dark room. This sensor is not so sensitive for the incandescent lamp with relatively long wavelength but it can be seen that the robot tracked the spherical surface well. The difference between the real trajectory and the ideal which is assumed to be on a sphere surface, is considered to be due to that the actual radiation is more complicated physically under some influence of reflection and the shape of the radiation source. Here, the length of the coordinate axis lines in the figure corresponds to 100 mm.

5. Summary

A system for measuring radiation intensity by using three radiation detectors attached to a robot manipulator is proposed in this paper. This technique is based on the model-based tracking controller proposed. An effective mapping of radiation intensity can be realized by getting some local information such as the distances to radiation sources and the surface of the contour with constant intensity in the radiation space. Tracking motion accompanied by some appropriate scanning motion can give the capability. Therefore we provide the formulation for the controller assuming the kinematics model can be described as a tracking around a point like radiation source. And we confirm the effectiveness and stability of this controller by theoretical and experimental approaches. Especially the system using HgI₂ radiation detectors and PUMA 560 manipulator can demonstrate the successful result as well as its practical feasibility. Finally to accomplish the mapping by using a robot in a real site, we might need other techniques such as an optimal design and control of the manipulator to maintain the manipulability for a tracking space and a vision system to monitor the specified environment for safety. But these techniques have been accessed to be applied.

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