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Sensing Planning of Calibration Measurements for Intelligent Robots

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1. Introduction

1.1 Overview of the problem

Improvement of the accuracy and performance of robot systems implies both external sensors and intelligence in the robot controller. Sensors enable a robot to observe its environment and, using its intelligence, a robot can process the observed data and make decisions and changes to control its movements and other operations. The term *intelligent robotics*, or *sensor-based robotics*, is used for an approach of this kind. Such a robot system includes a manipulator (arm), a controller, internal and external sensors and software for controlling the whole system. The principal motions of the robot are controlled using a closed loop control system. For this to be successful, the bandwidth of the internal sensors has to be much greater than that of the actuators of the joints. Usually the external sensors are still much less accurate than the internal sensors of the robot. The types of sensors that the robot uses for observing its environment include vision, laser-range, ultrasonic or touch sensors. The availability, resolution and quality of data varies between different sensors, and it is important when designing a robot system to consider what its requirements will be. The combining of information from several measurements or sensors is called *sensor fusion*. Industrial robots have high repeatable accuracy but they suffer from high absolute accuracy (Mooring et. al. 1991). To improve absolute accuracy, the kinematic parameters, typically Denavit – Hartenberg (DH) parameters or related variants can be calibrated more efficiently, or the robot can be equipped with external sensors to observe the robot's environment and provide feedback information to correct robot motions. With improved kinematic calibration the robot's global absolute accuracy is improved. While using external sensors the local absolute accuracy is brought to the accuracy level of the external sensors. The latter can also be called workcell calibration. For kinematic calibration several methods have been developed to fulfil the requirements of several applications. There are two main approaches for calibration (Gatla et. al. 2007): open loop and closed loop. Open loop methods use special equipment such as coordinate measuring machines or laser sensors to measure position and orientation of the robot end-effector. These methods are relatively expensive and time-consuming. The best accuracy will be achieved when using these machines as Visual Servoing tools where they guide the end-effector of the robot on-line (Blank et. al. 2007). Closed loop methods use robot joint measurements and end-effector state to form closed loop equations for calculating the calibration parameters. The state of the end effector can be

physically constrained, e.g., to follow a plane, or it can be measured with a sensor. These methods are more flexible but are more sensitive to quality of set of samples.

External sensors, like vision and laser sensors have been used extensively for a long time; the first visual guidance was demonstrated already in the 70's and 80's, e.g., carrying out simple assembly tasks by visual feedback in a look-and-move manner (Shirai & Inoue, 1971). Later on even heavy duty machinery have been equipped with multiple sensors to automatically carry out simple material handling applications (Vähä et. al. 1994). The challenge in using external sensor is to utilize the information from external sensors as efficiently as possible.

Simulation and off-line programming offer a flexible approach for using a robot system efficiently. Nowadays product design is based on CAD models, which are used also for simulation and off-line programming purposes. When the robot is working, new robot paths and programs can be designed and generated with off-line programming tools, but there is still a gap between the simulation model and an actual robot system, even if the dynamic properties of the robot are modelled in the simulation model. This gap can be bridged with calibration methods, like using sensor observations from the environment so that motions are corrected according to the sensor information. This kind of interaction improves the flexibility of the robot system and makes it more cost-effective in small lot sizes as well.

Sensing planning is becoming an important part of a flexible robot system. It has been shown, that even for simple objects the spatial relation between the measured object and the observing sensor can have a substantial impact on the final locating accuracy (Järviluoma & Heikkilä 1995). Sensing planning as its best includes a method for selecting optimal set of target features for measurements. The approach presented in this chapter, i.e., the purpose of the sensing planning is to generate optimal measurements for the robot, using accuracy or low level of spatial uncertainties as the optimality criterion. These measurements are needed e.g. in the calibration of the robot work cell. First implementations of such planning systems into industrial applications are now becoming a reality (Sallinen et. al. 2006).

This chapter presents a synthesis method for sensing planning based on minimization of a posteriori error covariance matrix and eigenvalues in it. Minimization means here manipulation of the terms in the Jacobian and related weight matrices to achieve low level of spatial uncertainties. Sensing planning is supported by CAD models from which planning algorithms are composed depending on the forms of the surfaces. The chapter includes an example of sensing planning for a range sensor – taken from industry – to illustrate the principles, results and impacts.

1.2 State-of-the-art

Methods for sensing planning presented in the literature can be divided into two main types: generate-and-test and synthesis (Tarabanis et. al. 1995). In addition to these, there are also other sensing planning types, including expert systems and sensor simulation systems (Tarabanis et. al. 1995). The quality of the measured data is very important in cases where only a sparse set of samples is measured using, e.g., a point-by-point sampling system or when the available data is very noisy. Third case for careful planning is for situations where there is only very limited time to carry out measurements such as real-time systems. Examples of systems yielding a sparse set of data include the Coordinate Measuring Machine (CMM) (Prieto et. al. 2001), which obtains only a few samples, or a robot system with a tactile sensor. Also, compared with vision systems, the amount of data achieved

using a point laser rangefinder or an ultrasound sensor is much smaller, unless they are scanning sensors. Several real-time systems have to process measurement data very fast and there quality of the data improves reliability significantly.

Parameters that a sensing planning system produces can vary (see figure 1). In the case of a vision system they can be the set of target features, the measurement pose or poses and optical settings of the sensor, and in some cases the pose of an illuminator (Heikkilä et. al. 1988, Tarabanis et. al. 1995). The method presented here focuses on calculating the pose of the sensor. The optical settings include those for internal parameters including visibility, field of view, focus, magnification or pixel resolution and perspective distortion. The illumination parameters include illuminability, the dynamic range of the sensor and contrast (Tarabanis et. al. 1995).

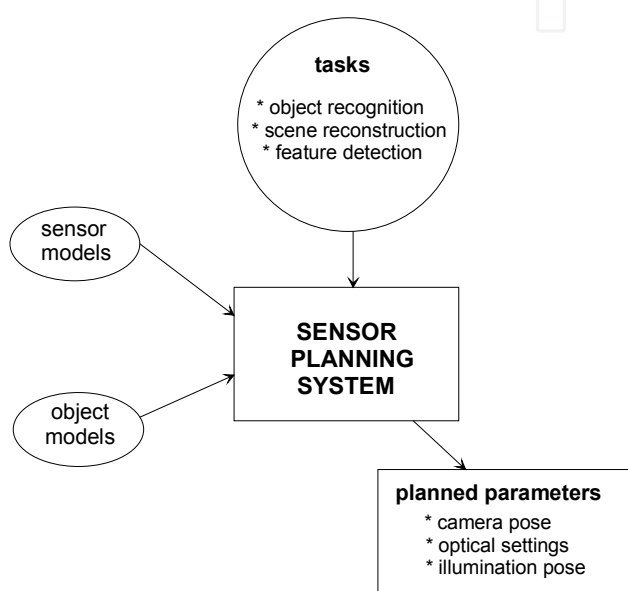


Figure 1. Sensing planning for computer vision (adapted from Tarabanis et. al. 1995)

In the object recognition that precedes the planning phase in general sensing planning systems, the object information is extracted from CAD models. The required parameters or other geometric information for sensing planning will be selected automatically or manually from the CAD models. This selection is based on Verification Vision Approach assuming that shape and form of the objects is known beforehand (Shirai 1987).

In the following chapters, pose estimation methods and related sensing planning for work object localization are described. In addition, some further analysis is done for the criteria used in the sensing planning. Finally, an example for work object localization with automatic sensing planning is described, followed by a discussion and conclusions.

2. Work object localization

In the robot-based manufacturing work cells, the work objects are fixed in the robot's working environment with fastening devices, like fixtures or jigs. These devices can be calibrated separately into the robot coordinate system. However, the attachment of the work object may not be accurate and even the main dimensions of the work object may be inaccurate, especially when considering cast work objects in foundries (Sallinen et. al. 2001). Geometric relationships with coordinate frames and transformations of the measuring

system are illustrated in figure 2. In this case the sensor is attached to the robot TCP and the work object is presented in robot coordinate frame.

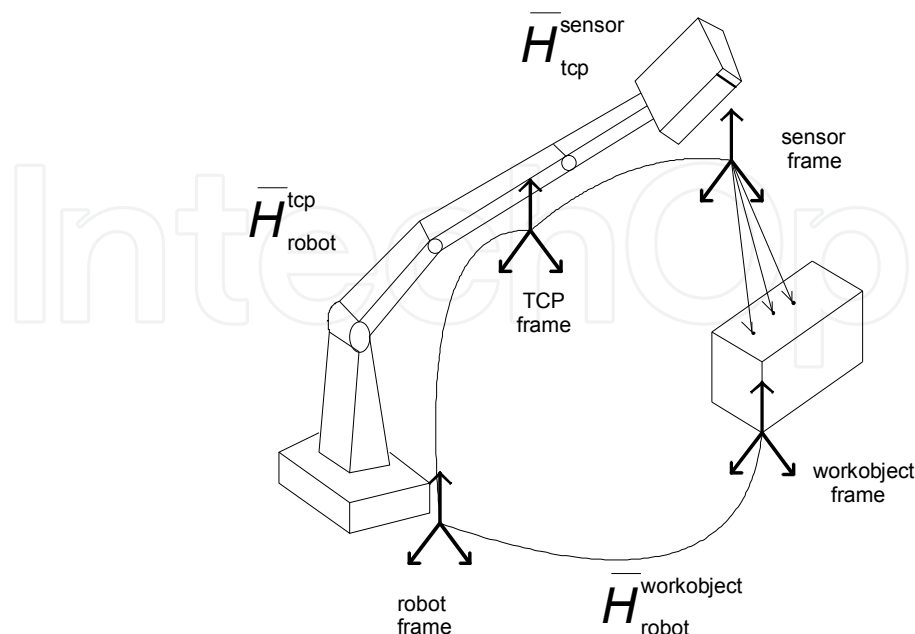


Figure 2. Coordinate frames and transformations for the work object localization

2.1 Estimation of the work object model parameters

In the work object pose estimation, the 3D point in sensor frame is transferred first into the robot wrist frame, then to the robot base frame and finally to the work object frame, where an error function is calculated for fitting the measurements to the object model. The idea is to fit the points measured from the object surface into reference model of the work object. All the points are transformed to the work object coordinate frame, see figure 2. As a reference information a CAD model of the work object is used.

We define the work object surface parameters by surface normal \bar{n} and the shortest distance from the work object coordinate origin d . To minimize the distance between the reference model and measured points, we need an error function. The error function for a point in the surface of the work object is now defined as

$$\bar{e}_{PtoS} = \bar{n} \cdot \bar{p} - d \quad (1)$$

where

\bar{e}_{PtoS} is the error function from point to surface

\bar{p} is the measured point

\bar{n} is the surface normal vector

d is the shortest distance from surface to the work object origin

We define the pose of the work object as $\bar{m}_{workobject} = [x \ y \ z \ \phi_x \ \phi_y \ \phi_z]$, which includes three translation and three rotation parameter (xyz euler angles). The corrections for estimated parameters are defined as additional transformations following the nominal one. The pose parameter (translations and rotations) values are updated in an iterative manner

using linear models for the error functions. Linearization of the equation (1) gives the following partial derivatives for the work object pose parameters using the chain rule:

$$\frac{\partial \bar{e}_{PtoS}}{\partial \bar{m}_{workobject}} = \frac{\partial \bar{e}_{PtoS}}{\partial \bar{p}_p} \frac{\partial \bar{p}_p}{\partial \bar{m}_{workobject}} \quad (2)$$

Equation (2) can be written in matrix form as

$$\bar{J}_m^e = \frac{\partial \bar{p}_{PtoS}}{\partial \bar{m}_{workobject}} = \begin{bmatrix} n_x & n_y & n_z \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 & p_{z,c} & -p_{y,c} \\ 0 & 1 & 0 & -p_{z,c} & 0 & p_{x,c} \\ 0 & 0 & 1 & p_{y,c} & -p_{x,c} & 0 \end{bmatrix} \quad (3)$$

where

\bar{J}_m^e is the Jacobian matrix

n_x , n_y and n_z are the components of the surface normal vector.

$p_{x,c}$, $p_{y,c}$ and $p_{z,c}$ are the coordinates of the point in reference model.

Each sample (a point) on the surface produces a row into the compound work object localization Jacobian matrix. The Jacobian matrix, equation (3), is then used for the computation of correction increments for the work object localization, i.e., for the pose parameters:

$$\Delta \bar{m}_{workobject} = - \left(\bar{J}_m^e{}^T \bar{Q}^{-1} \bar{J}_m^e \right)^{-1} \bar{J}_m^e{}^T \bar{Q}^{-1} \bar{e}_{PtoS} \quad (4)$$

where

$\Delta \bar{m}_{workobject}$ is an incremental correction transformation for the work object pose,

\bar{Q} is error covariance of the measurements \bar{e}_{PtoS} ,

\bar{J}_m^e are jacobians, equation (3)

\bar{e}_{PtoS} is the error vector containing the error values, cf. equation (1)

In each iteration step we get a correction vector $\Delta \bar{m}_{workobject}$ and the estimated parameters are updated using the correction vector $\Delta \bar{m}_{workobject}$. Computation of corrections using equation 4 is repeated until corrections become close to zero.

2.2 Weight matrices for the workobject localization

We are calculating the matrices to weight more certain measurements more than uncertain ones and call here these as weight matrices. In this case the error covariances become somewhat more complicated. Work object localization includes errors coming from the robot joint control and range sensor measurements. In addition to this, work object localization is affected by the error of the sensor hand-eye calibration.

The Jacobian for the measurements can be written as follows:

$$\bar{J}_h^e = \frac{\partial \bar{e}_{PtoS}}{\partial \bar{h}} = \begin{bmatrix} \frac{\partial \bar{e}_{PtoS}}{\partial \bar{h}_{TCP}} & \frac{\partial \bar{e}_{PtoS}}{\partial \bar{h}_{S,TCP}} \end{bmatrix} \quad (5)$$

where

$\frac{\partial \bar{e}_{PtoS}}{\partial \bar{h}_{TCP}}$ is the partial derivative of the error function with robot TCP parameters

$\frac{\partial \bar{e}_{PtoS}}{\partial \bar{h}_{S,TCP}}$ is the partial derivative of the error function with sensor in robot TCP

The error function that is used to derive equation (5) is the one presented in equation (1).

The Jacobian of the robot pose parameters $\partial \bar{e} / \partial \bar{h}_{TCP}$ can be written then as follows:

$$\bar{J}_{TCP}^e = \frac{\partial \bar{e}}{\partial \bar{p}_s} \frac{\partial \bar{p}_s}{\partial \bar{h}_{TCP}} \quad (6)$$

For the Jacobian for the parameters of the sensor hand eye calibration we get

$$\bar{J}_{hS,TCP}^e = \frac{\partial \bar{e}}{\partial \bar{h}_{S,TCP}} = \frac{\partial \bar{e}}{\partial \bar{p}} \frac{\partial \bar{p}}{\partial \bar{h}_{S,TCP}} \quad (7)$$

where

$$\frac{\partial \bar{e}}{\partial \bar{h}_{S,TCP}} = \begin{bmatrix} n_x & n_y & n_z \end{bmatrix} \bar{V}_P^T \bar{V}_R \begin{bmatrix} 1 & 0 & 0 & 0 & p_z & -p_y \\ 0 & 1 & 0 & -p_z & 0 & p_x \\ 0 & 0 & 1 & p_y & -p_x & 0 \end{bmatrix} \quad (8)$$

The covariance for the actual measurement is then an extension of the one in the sensor calibration:

$$\bar{R} = \begin{bmatrix} \bar{R}_{\Delta TCP,W} & \bar{0} \\ \bar{0} & \bar{R}_{\Delta S,TCP} \end{bmatrix} \quad (9)$$

where

$\bar{R}_{\Delta TCP,W}$ is the noise matrix of the robot TCP

$\bar{R}_{\Delta S,TCP}$ is the noise matrix between sensor origin and robot TCP

The covariance matrix \bar{Q} for the measurements \bar{J}_m^e is then

$$\bar{Q} = \bar{J}_h^e \bar{R} \bar{J}_h^{eT} \quad (10)$$

which is finally used in the estimator, see equation 4.

In the case of the work object localization, the estimated parameters $\bar{m}_{e,w-o}$ are $\bar{m}_{e,w-o} = [x \ y \ z \ \phi_x \ \phi_y \ \phi_z]$. The form of the partial derivative is close to equation (5), but due to a different error function the error derivative for the error covariance of the measuring calibration is written as

$$\frac{\partial \bar{e}_{PtoS}}{\partial \bar{h}_{S,TCP}} = \begin{bmatrix} n_x & n_y & n_z \end{bmatrix} \bar{V}_P^T \bar{V}_R \begin{bmatrix} 1 & 0 & 0 & 0 & p_z & -p_y \\ 0 & 1 & 0 & -p_z & 0 & p_x \\ 0 & 0 & 1 & p_y & -p_x & 0 \end{bmatrix} \quad (11)$$

where

$\begin{bmatrix} n_x & n_y & n_z \end{bmatrix}$ is the partial derivative of the error function with respect to the point in the sensor frame, i.e. $\partial \bar{e} / \partial \bar{p}_s$.

The effect of the sensor calibration error, the partial derivatives of the error function with respect to parameters of the sensor calibration can be written as follows:

$$\frac{\partial \bar{e}_{PtoS}}{\partial h_{s,TCP}} = \begin{bmatrix} n_x & n_y & n_z \end{bmatrix} \bar{V}_P^T \bar{V}_R \bar{V}_T \begin{bmatrix} 1 & 0 & 0 & 0 & p_z & -p_y \\ 0 & 1 & 0 & -p_z & 0 & p_x \\ 0 & 0 & 1 & p_y & -p_x & 0 \end{bmatrix} \quad (12)$$

The equation (12) has been used to calculate weight matrices for the calculation of covariances in the case of work object location estimation. In addition to that, the robot joint uncertainty (noise in the joints propagated in to TCP pose uncertainty) has been taken into consideration.

3. Planning of the measurements

This chapter presents a new synthesis method for sensing planning based on minimization of a posteriori error covariance matrix and eigenvalues of it. The method is based on multiplication of the Jacobian matrix by the weight matrix, and minimization means here manipulation of the terms in the Jacobian and weight matrices to achieve a low level of spatial uncertainties. The minimization of error covariance matrix and effect of signal-to-noise ratio is illustrated in simulations, where the location of the measurement points in the surface of the work object affects to the pose uncertainties. This is because composition of equations is made intuitively from the equations composed for parameter estimation. The Jacobian and weight matrices may belong to any phase of the calibration of the robot system, and planning is carried out for each phase separately. The work is relying on the work done by Nakamura & Xu in (Nakamura & Xu 1989) and mathematical background for the work is in principal component analysis (PCA) introduced in (Hotelling 1933).

3.1 Error covariance matrix and SNR

The earlier reported methods for sensing planning using a posteriori error covariance matrices as evaluation criteria are suitable for many cases, but they have following shortcomings: Borgli & Caglioti (Borgli & Caglioti 1998) used the method only in a 2D case and based it on the calculation of range distances between a robot and a surface. This kind of criteria formation is not possible in hand-eye calibration, for instance, because the solution space is more complicated. Nilsson et. al. (Nilsson et. al. 1996) also used geometric distances and the respective uncertainties as criteria for sensing planning. These methods were designed for mobile robots and are more suitable for purposes in which there are usually 3 degrees of freedom and the minimization criteria can be composed based on simple geometric features of the environment. Condition number is also a criteria for evaluating uncertainties. Geometrical interpretation of condition number is a ratio of largest and smallest dimension of the uncertainty ellipsoid. This has been studied in (Motta & McMaster 1997) and (Zhao & Wang 2007). In most of the cases this gives a relatively good solution but if the criteria will be optimized, it leads to a situation where uncertainty ellipsoid is flat. It means uncertainties are very small in one direction and very large in other

direction respectively. Nahvi presents a new observability index called Noise Amplification Index which is a ratio of maximum singular value to condition number of the measurement matrix (Nahvi & Hollenbach 1996). We use this criteria also for evaluating our sensing planning method later in chapter 6. First versions of sensing planning for Hand-eye calibration presented here were presented in (Sallinen & Heikkilä 2003).

The planning is focused on selecting reference features in the measurement pose. The poses are assumed to be given, and optimization considers selecting the features that will be measured. The goal is to minimize the uncertainties in an estimated pose and the selection of measurements that especially affect the rotation uncertainties is considered. As will be illustrated later, the estimation of translation parameters is not so sensitive to quality of measurements as the estimation of the orientation parameters of the pose. Here the minimization and maximization of matrices means selecting of values for parameters in matrix rows and columns. The goal of the selection is to achieve low level of uncertainties in terms of eigenvalues of the error covariance matrix. To simplify the evaluation of uncertainty criteria, multiplication and sum of all eigenvalues is used which is illustrated in simulations further in this chapter.

2.2 Computation of the covariance

The method presented here is based on minimizing a posteriori error covariance of the estimated parameters when using Bayesian-form modelling of the spatial uncertainties. This means that the sensor has to be placed in such poses that the noise in the estimated parameters will be minimized. In addition to noise, there are a lot of unmodelled error sources which cannot be adjusted.

The error covariance matrix \bar{P} of the estimated parameters can be calculated as follows:

$$\bar{P} = (\bar{J}^T \bar{Q}^{-1} \bar{J})^{-1} \quad (13)$$

where

\bar{J} is the Jacobian matrix for estimating the model parameters

\bar{Q} is the weight matrix of the measurements

The error covariance matrix \bar{P} consists of the product of the Jacobian matrix \bar{J} and the weight matrix \bar{Q} . According to equation (13), the minimization leads to a situation in which \bar{J} has to be maximized and \bar{Q} has to be minimized. These matrices share the same parameters, however, so that minimization of \bar{P} is not so straightforward. It may be carried out in two ways: by measuring optimal points for localization, i.e. each row in the Jacobian matrix will give a large amount of information and there are only a few rows, or else the number of rows in the Jacobian matrix can be increased but each row will give only a little information.

The control parameters of the sensing planning system presented here are parameters of the Jacobian matrix \bar{J} and weight matrix \bar{Q} . These may include (x,y,z) point values of a calibration plate frame in hand-eye calibration, range of measurement in the sensor frame, point values on the work object surface or the orientation of the TCP of the robot, for example.

3.3 Computation of the criteria

When planning the set of measurements, the parameters to be estimated have to be considered first. The partial derivatives of the error function with respect to the estimated parameters comprise the parameters that affect the spatial uncertainties of the estimated parameters. The error function is the same as that used in parameter estimation, e.g. estimation of the pose of the work object. Estimation of rotation parameters requires at least a pair of points, which leads to a situation in which the distance between these points is maximized in order to achieve a high signal to noise ratio (SNR) and this is formulated as a max problem. Based on these parameters, the set of samples will be generated by selecting the maximum values of the composed parameters, taking into consideration the constraints of the parameter space. Thus the equation to be maximized for generating a set of samples based on a Jacobian matrix is the following:

$$\vec{\Psi}_j = \partial \vec{e} / \partial \vec{m} \quad (14)$$

where

\vec{e} is the error function

\vec{m} are the estimated parameters

The boundary values for (14) are usually set by the dimensions of the parameter space. It means the control parameters have to be manipulated to maximize the distance between the measurement points, i.e. sequential lines of Jacobian matrix. Signs of control parameters do not need to be considered because covariance matrix P includes multiplication of Jacobian matrix $\vec{J}^T \vec{J}$ and the result is always positive. The number of solution spaces depends on the amount of parameters in a Jacobian row. In the example above, there are two parameters and it will give two different point pairs: $(x \approx 0, y \approx c)$ and $(x \approx c, y \approx 0)$.

In general case, the Jacobian matrix $\partial \vec{e} / \partial \vec{m}$ determines the control parameters and may include position and orientation parameters from the world frame or work object frame as well as the sensor range or other internal or external parameters of the sensor. The composed position parameters from the partial derivative $\partial \vec{e} / \partial \vec{m}$ are maximized by selecting their largest possible values.

The idea is following the ideas presented by Lowe (Lowe 1985) where a small rotation around different axes can be projected as a small translation in a perpendicular axis. Using this principle, the set of samples is generated by maximizing the distances between the points.

2.4 Effect of the weight matrix

The weight matrix \vec{Q} also has to be studied when considering the optimal positions and orientation. The weight matrix consists of partial derivatives of the error function with respect to the measurements \vec{K} and their noise matrix, as follows:

$$\vec{Q} = \vec{K} \vec{R} \vec{K}^T \quad (15)$$

where

\vec{K} is a matrix consisting of partial derivatives of the error function with respect to the input parameters

\vec{R} is a matrix consisting of the noise affecting the input parameters

If the noise matrix \vec{R} is assumed to be constant, then the goal will be to minimize the weight matrix \vec{K} , which can be written in partial derivative form:

$$\vec{K} = \partial e / \partial \vec{m}_{input} \quad (16)$$

where

e is the error function

\vec{m}_{input} is the vector containing the measurement parameters

As in the case of computation of the criteria, the error function depends on the type of surface form and the measurement parameters of the robot system. E.g., the plane surface is a part of cube or plane -formed calibration plane for hand-eye calibration. The partial derivatives for the weight matrix can be written:

$$\vec{\Psi}_K = \partial e / \partial \vec{m}_{input} \quad (17)$$

Optimizing both equations (14) and (17) is not so simple, due to the interdependence of the parameters between the equations. Of the two, equation (14) has the larger effect on the estimation process, due to the duplicate terms in the Jacobian matrix \vec{J} compared with the weight matrix \vec{Q} in (13). The effect of equation (15) becomes noticeable when the noise of the input parameters is not linear.

Minimization of weight matrix \vec{Q} is similar with maximizing the Jacobian matrix \vec{J} . In the case of weight matrix, also the point pairs of sequential rows are selected and distance between them are minimized. The weight matrix includes multiplication of matrices \vec{K} such that sign does not have to be considered ($\vec{K}\vec{K}^T$).

When forming the total measurement matrix $\vec{\Psi}$, the information obtained from both the Jacobian measurement matrix $\vec{\Psi}_J$ and the weight measurement matrix $\vec{\Psi}_K$ has to be considered.

4. Properties of the planning criterion

Here we verify the planning criterion by simulating measurements and evaluating results by two different methods. The selection of measurement points in sensing planning i.e. maximizing the distances between the points is shown here to illustrate the effect of given criteria for spatial uncertainties of the localized cube. The result of the sensing planning is verified by distributing the measurement points around the three sides of the work object and analyzing the spatial uncertainties of a corner point of the localized cube. The points included equal noise. Throughout this simulation, the criteria of selection of the measurement points are maximum distances from each others. The criteria used for evaluating the uncertainties were product of eigenvalues of error covariance matrix, sum of eigenvalues of error covariance matrix and volume of the uncertainty ellipsoid. In all the three different cases, two pairs of points from each surface was measured. The placing of the points to the surfaces was done similarly in each side: all the possible location variations of measurement points were calculated. The parameter that uncertainties were related to was a distance between measurement points on each surface. The criterion for selecting the pair of points is two distances that give the largest total distance. These two largest distances were

summed together and total distance becomes then a sum of distances between two point pairs in each surface.

Figure 3 illustrates the uncertainties of a point in the calibrated cube frame when the measurement points are distributed around the three sides of the cube. In all the figures 3-5 the highest uncertainties are cut off to improve the illustration of the curves. From the figure 3 it can be seen that when the distance between the points on the surface of each side increases, the uncertainties of pose of the cube decreases. The trend of the curve seems to be that uncertainties are decreased dramatically first and after that, decrease is more stable.

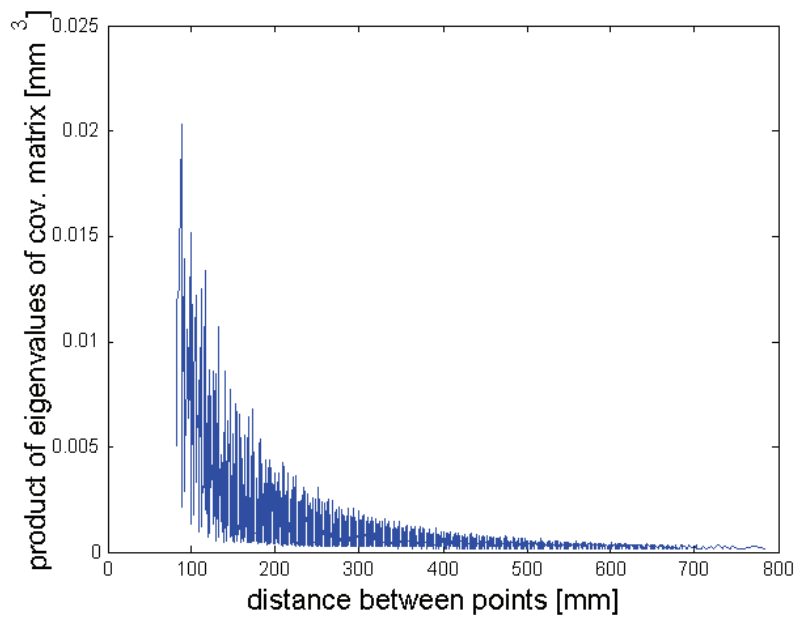


Figure 3. Product of eigenvalues of error covariance matrix vs. distance between the measurement points

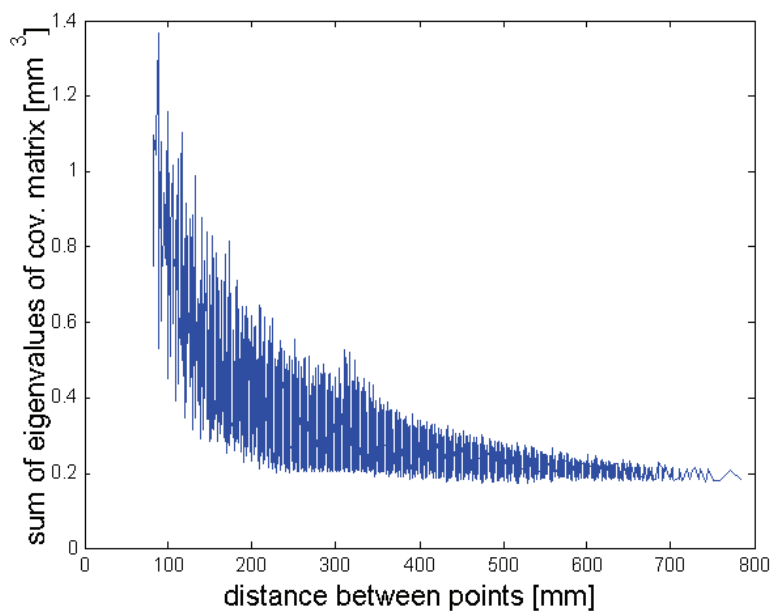


Figure 4. Sum of eigenvalues of error covariance matrix vs. distance between the measurement points

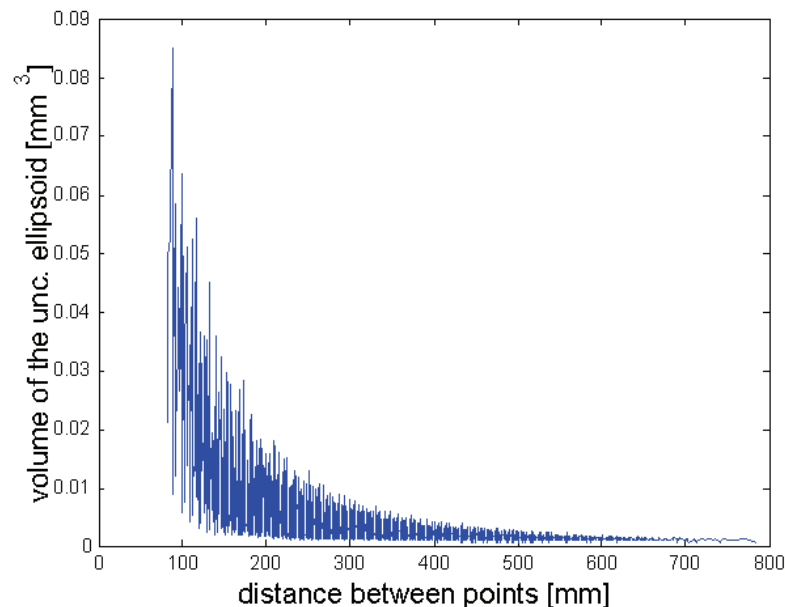


Figure 5. Volume of the uncertainty vs. distance between the measurement points

In the figure 4, sum of the eigenvalues of the error covariance matrix with respect to distance between the points is presented. As in the case of product of eigenvalues, the trend is that uncertainties are decreasing, though here not such fast.

In the last case, figure 5, volume of the uncertainty ellipsoid is illustrated for different distances between the points. Curve is close to product of eigenvalues, i.e. the curve is decreasing rather fast.

All the three different cases illustrated the same behaviour between uncertainties of the localized cube and distance between the measurement points. Here one criteria of uncertainties in simulations has been selected to simplify the interpretation of results, i.e. product on sum of eigenvalues, not single eigenvalues. This kind of method is suitable because usually the goal is to minimize all uncertainties of the system, not only within one direction.

The principle of using distances between measurement points can be generalized into other forms of set of points. The set of points may form a feature the distances of which will be considered. Here an example of localizing of a cube using three points forming a triangle in each surface is illustrated. The goal is to decrease uncertainties and the distance of points is calculated as a circle of triangle formed by the three measurement points. The uncertainties are illustrated in a same way as in case of two point pairs, product and sum of eigenvalues and the volume of the uncertainty ellipsoid.

However, if the number of points increases, the complexity of computing distances becomes higher and one has to be careful when calculating the distances.

The problem involved in planning the reference features illustrated in this chapter is that planning is based on the assumption that the feature contains very few or no spatial uncertainties. This means that the requirement for successful measurement is that the deviation between the nominal location of the pose of the work object, for example, and its actual location should be smaller than in the selection of details for the reference features. If the deviation is larger, there is a possibility that the robot will measure false features or even

ones lying beyond the work object. The proposed planning method is illustrated in an example of work object localization.

5. Example: Planning of the measurements for workobject localization

We will consider here equations for planning the measurements required to localize a cubic work object. Of the six plane surfaces constituting the cube, three are measured for localization of the pose. The sensing planning starts out from the parameters to be estimated, i.e. the pose of the work object.

The pose of the work object is determined using three translation values and three orientation values:

$$\vec{m}_{cube} = [x \quad y \quad z \quad \phi_x \quad \phi_y \quad \phi_z] \quad (18)$$

The measurement points are planned for each of the three plane surfaces, in order to minimize uncertainties in all six pose parameters. Each surface is determined using translation from the origin to the surface and two orientation values of the surface. The surfaces are termed here the x-plane, y-plane and z-plane, referring to normal directions in the world coordinate frame. Error functions for localizing the cube in the world frame can then be written for the sides as follows: the error function for the measurement point on the x-plane surface is $e_x = x$, for the measurement point on the y-plane surface $e_y = y$, and for the measurement point on the z-plane surface $e_z = z$. These error functions are used to compose the parameters for sensing planning. The Jacobian matrix for estimating the pose parameters of the work object for the measurements $1 \dots n$ for three different surfaces can be written as (19).

The goal of the planning is to find measurements points (x,y,z) for each pair of rows in (19) such that they will give an optimum or close to optimum amount of information for parameter estimation.

$$\frac{\partial \vec{e}}{\partial \vec{m}_{cube}} = \begin{bmatrix} 1 & 0 & 0 & 0 & -z_{x,1} & y_{x,1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & 0 & 0 & 0 & -z_{x,n} & y_{x,n} \\ 0 & 1 & 0 & -z_{y,1} & 0 & x_{y,1} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 1 & 0 & -z_{y,n} & 0 & x_{y,n} \\ 0 & 0 & 1 & -y_{z,1} & x_{z,1} & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 1 & -y_{z,n} & x_{z,n} & 0 \end{bmatrix} \quad (19)$$

where

$(x_1 \dots x_n, y_1 \dots y_n, z_1 \dots z_n)$ are the measurements of the parameters (x,y,z) between $1 \dots n$ for x, y and z surfaces

n is the number of measurements

To find the parameters to be maximized in each pair of rows in Jacobian matrix, the partial derivative of the error function with respect to the parameters to be estimated for the plane surface in the direction x can be written as (20). The whole pose includes 6 pose parameters, but each surface (here the x -plane) gives information only on three parameters and also information on these parameters for the Jacobian matrix, i.e. one translation and two orientation parameters.

$$\frac{\partial \vec{e}_x}{\partial \vec{m}_{cube,x}} = \begin{bmatrix} \frac{\partial e}{\partial x} & \frac{\partial e}{\partial \phi_y} & \frac{\partial e}{\partial \phi_z} \end{bmatrix} \quad (20)$$

The partial derivative of the error function with respect to the estimated pose parameter x is 1. The control parameters are then obtained from partial derivatives of the error function with respect to the orientation parameters, equation (18), when the constraints of the model are $0 \dots n$ and $n + 1 \dots n + n$, as follows:

$$\vec{\Psi}_{i=0}^{i=n} = \max \{ (y_1, z_1), (y_2, z_2) \dots (y_{n-1}, z_{n-1}), (y_n, z_n) \}_{cube,x} \quad (21)$$

$$\vec{\Psi}_{i=0}^{i=n} = \max \{ (x_1, z_1), (x_2, z_2) \dots (x_{n-1}, z_{n-1}), (x_n, z_n) \}_{cube,y} \quad (22)$$

$$\vec{\Psi}_{i=0}^{i=n} = \max \{ (x_1, y_1), (x_2, y_2) \dots (x_{n-1}, y_{n-1}), (x_n, y_n) \}_{cube,z} \quad (23)$$

The minimization and maximization (21), (22) and (23) all contain the same parameters, so that the result of planning is that measurements will be minimized and maximized in these directions and the uncertainties in the pose of the work object will be minimized.

The criteria to be considered are the weight matrix of the error covariance matrix and computation of the parameters which affect the uncertainties in the estimated parameters, i.e. matrix $\vec{\Psi}_K$. This means that the weight matrix \vec{K} has to be minimized, which is done by minimizing its parameters in a pair of rows. When locating the work object, as in the case of calculating the matrix $\vec{\Psi}_J$, each surface has to be considered separately, because weights for the surfaces are different. The input to the system is a measurement point p :

$$p = \begin{bmatrix} p_x & p_y & p_z \end{bmatrix}.$$

The weight matrix is composed by calculating the partial derivatives of an error function $e_x = x$ with respect to the input parameters. For the plane in the direction x , the weight matrix can be computed as follows:

$$\frac{\partial e_x}{\partial p} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \quad (24)$$

The weight matrices for the plane surfaces in the directions y and z can be written in a similar way, where the error functions are $e_y = y$ and $e_z = z$. As illustrated above, the weight matrices are constant in all directions. It can be written for $1 \dots n$ measurements for all in one matrix:

$$\vec{K}_{cube} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ \vdots & \vdots & \vdots \\ 1_n & 0 & 0 \\ 0 & 1_n & 0 \\ 0 & 0 & 1_n \end{bmatrix} \quad (25)$$

The above example means that only the translation parameters of the measurement affect the uncertainties in the estimated parameters, and the measurement poses can be planned based on information from the Jacobian matrix $\tilde{\Psi}_J$. This is because only the uncertainty attached to the measurement points in the work object coordinate frame was considered. The output of the sensing planning algorithm is a total measurement matrix $\tilde{\Psi}$ which is a combination of the measurement matrix $\tilde{\Psi}_J$ and the measurement matrix $\tilde{\Psi}_K$.

The total number of features composed using sensing planning is 12. Depending on the requirements of the spatial uncertainties of the location of the work object, the measurement points are constantly distributed around these features.

6. Experimental tests in laboratory

6.1 Calculation of a pose of a cube

To test the sensing planning algorithm when estimating full 6 DOF pose, we run a test where we measured points from three sides of a cube. The marks were positioned around the cube using the PUMA 650 industrial robot with 6 degrees of freedom and all the points was generated off-line. The camera system we used was CCD stereo camera system, developed by Tomita et. al. More information about the camera system, see (Tomita et. al. 1998) and for test case (Sallinen 2002).

6.2 Results from the actual tests

The different set of samples was generated in a following way: planned set of samples means the sample set generated using the sensing planning method proposed in this chapter. Random set of samples is a set of points randomly selected from the surfaces of the cube and pattern is constantly selected points from three side of the cube. The noise level and the number of points (8 in each side) is same in all the set of samples. The table 1 illustrates the results from the pose estimation of a cube.

Results in the table 1 illustrates the goodness of the selection of the set of samples when using the proposed sensing planning method. In the table, eigenvalues of the pattern set is close to planned, but still worse than that. The remarkable improvement between pattern and planned compared with random and planned is the orientation of the eigenvectors. When using planning algorithm, the eigenvectors points almost towards to coordinate axis of the estimated cube. In the case of pattern eigenvectors are a little bit rotated and in the case of random, they point random directions. When the eigenvectors point to direction of axis, the eigenvalues are usually close to each other. This means the uncertainty ellipsoid has a form of a sphere.

Set of sample	Eigenvalue λ_1 [mm]	Eigenvalue λ_2 [mm]	Eigenvalue λ_3 [mm]	Eigenvectors
Planned	0.0381	0.0439	0.0339	0.9651 0.1782 0.1919 0.1577 -0.9805 0.1173 -0.2090 0.0830 0.9744
Random	0.0510	0.0402	0.0722	-0.7292 0.6107 -0.3086 0.6607 0.7457 -0.0856 -0.1778 0.2663 0.9473
Pattern	0.0493	0.0408	0.0453	-0.9369 0.3494 0.0133 0.2193 0.6168 -0.7560 0.2723 0.7054 0.6545

Table 1. Results from estimation of a cube

Compared to our previous studies, the optimal location of set of samples is more important than the noise level or the number of samples. When we have a good set of samples, the eigenvectors are not rotated and in that way eigenvalues are easier to control (e.g. changing the noise level or increasing the number of samples). In addition to eigenvalues, we calculated condition number, noise amplification indexes and volumes of the uncertainty ellipsoid for cube estimation. For more information about Noise Amplification Index, see (Nahvi & Hollenbach 1996). Table 2 illustrates the results:

Set of sample	Condition Number	Noise Amp. Index	Vol. Of Uncertainty Ellipsoid
Planned	565	$0.470 \cdot 10^6$	$2.3760 \cdot 10^{-4}$
Random	1721	$1.424 \cdot 10^6$	$6.1957 \cdot 10^{-4}$
Pattern	813	$0.594 \cdot 10^6$	$3.8159 \cdot 10^{-4}$

Table 2. Condition number, Noise amplification indexes and volume of uncertainty ellipsoid for different set of samples

Results in the table above show the efficiency of the proposed sensing planning method. As in the case of eigenvalues, pattern –form set of samples is better than random but not such good as planned. According to results, even the scale between different evaluation criteria seem to be close to each other.

7. Industrial application

The calibration and sensing planning algorithms were implemented in an industrial application to test the operation in foundry environment. The application consists of planning the localization measurements and localization of the work object. A touch sensor was selected as the measuring device because it is working well in harsh environments and

is easy to use. Disadvantages include speed of measuring and sparse amount of measured data.

The target for sensor feedback was to localize a sand mould for robotized milling. It was done by six measurements made on its front surface. The measuring system was built in a demonstration robot cell at the foundry, Finland, see figure 6.



Figure 6. Actual robot system

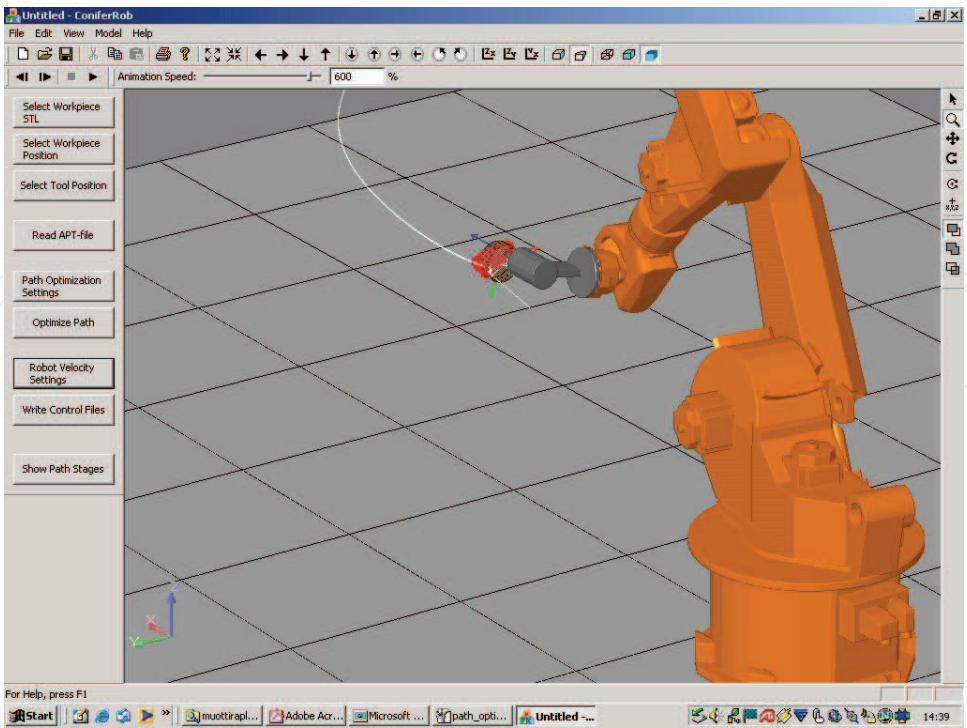


Figure 7. Sensing planning in the off-line programming software

The measuring system was implemented into a commercial robot off-line programming system which includes an easy-to-use graphical interface to facilitate use, see Figure 7. Software is distributed by Simtech Systems Ltd (Simtech 2008).

The planning and measuring system operated well in the foundry application. When measuring took time, it was very useful for operator to get verification that there are enough measurement points. Calibration was also successful in every case during the test period.

8. Discussion

Goal of the work was to achieve a flexible robot-based manufacturing work cell. A lot of work can be done off-line before executing the job with the actual robot. This preparatory work involves planning the measurements, simulating them and computing the related spatial uncertainties. The final goal for sensing planning is analysis of the results and a decision to increase the number of measurements or begin executing the job with the actual robot. The planning system uses initial CAD information obtained from the work cell, including the robot model and work object models, but is also able to adjust itself to changing conditions which are not all programmed beforehand. This adjustment is based on sensor observations on the environment and can be carried out on-line. The results of this chapter represent a system which is operating in the way described here. The system has been verified with point simulations, laboratory tests with a robot and a camera system and finally in industrial application. All phases show the goodness of the developed sensing planning method.

9. Conclusions

In this chapter we have presented a novel method for sensing planning which relies on modelling of the spatial uncertainties using covariance and trying to minimize criterion related to the error covariance matrix. The planning method can be used for generating an optimal or close to optimal measurements for robot and work cell calibration. When the behaviour of the spatial uncertainties in parameter estimation is known, the error covariance matrix can be used as a planning criterion and the results can be interpreted either as values or geometrically. The selection of set of points is based on minimizing the error covariance matrix and it leads to a situation where distances between measurement points are maximized. The reliability of the criteria is illustrated with simulations where pose uncertainties compared with distance between the measurement points. There is not such a close connection between uncertainty analysis and sensing planning in the literature as is proposed in this chapter, and as a result the new method of sensing planning is very flexible and easy to implement in conjunction with other planning operations than work object localization, e.g. hand-eye calibration or estimation of the model parameters for a surface.

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In this book we have grouped contributions in 28 chapters from several authors all around the world on the several aspects and challenges of research and applications of robots with the aim to show the recent advances and problems that still need to be considered for future improvements of robot success in worldwide frames. Each chapter addresses a specific area of modeling, design, and application of robots but with an eye to give an integrated view of what make a robot a unique modern system for many different uses and future potential applications. Main attention has been focused on design issues as thought challenging for improving capabilities and further possibilities of robots for new and old applications, as seen from today technologies and research programs. Thus, great attention has been addressed to control aspects that are strongly evolving also as function of the improvements in robot modeling, sensors, servo-power systems, and informatics. But even other aspects are considered as of fundamental challenge both in design and use of robots with improved performance and capabilities, like for example kinematic design, dynamics, vision integration.

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