

COMPUTER VISION SYSTEMS FOR THE ENHANCEMENT OF INDUSTRIAL ROBOTS FLEXIBILITY

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Abstract. *The new generation of industrial robots will have more flexibility in task implementation thanks to the advances in developing highly modular and reconfigurable manipulators. To achieve the full flexibility of such robots, in addition to the mechanical flexibility, it is necessary to achieve the flexibility in control. Precise automatic calibration of these manipulators is essential precondition for achieving this goal. Possibilities and limitations of implementation of vision systems for automatic calibration of highly modular and reconfigurable manipulators are presented in this paper.*

Key words: *Robot calibration, modular reconfigurable robot, computer vision, camera calibration*

1. INTRODUCTION

European strategic directions for robotic research are defined by projects EURON and CARE. Five key areas of robotic research and application are defined in these projects. The first key area refers to industrial robots which examines the main directions of development of advanced manufacturing systems. It is estimated that, as a result of market globalization, the existing trend of effectiveness of the flexibility of industrial production will continue. For this reason there will be a strong need for flexible manufacturing solutions that will provide a wide variety of products with short delivery time according to the principles of production just-in-time. Therefore, progress in this area is linked with the development industrial robots as the main element of advanced manufacturing systems.

Providing the above, it is clear that further increase of industrial robots flexibility will be one of the key areas of robotic research [1].

Vision systems have developed significantly over the last ten years and now have become standard automation components. They represent qualitative bounce in the area of metrology and sensing because they provide us with a remarkable amount of information

about our surroundings, without direct physical contact [2]. At the same time, vision systems are the most complex sensors [3].

Calibration of cameras is necessary first step in vision system using. Camera calibration is the process of determining the internal camera (geometric and optical) characteristics and the 3D position and orientation of the camera frame relative to a world coordinate system [2,4]. There are a number of techniques which only requires the camera to observe a planar pattern(s) shown at a few different orientations. Precise set points are placed on the calibration plain. Calibration process is automatically performed based on the correspondence between the positions of calibration points and the positions of their images [5,6].

If the camera calibration is performed then for every scene point in a world coordinate system it is possible to determine the position of its image point in image plain. This transformation is called perspective transformation. Inverse perspective transformation is very important for computer vision application in industrial automation. This transformation examines the problem of how to identify the point position in a world coordinate system based on the position of its image point for different camera positions or for several cameras at the same time.

Inverse perspective transformation and advances in processing and image analysis have a wide range of applications in industrial automation, and allow companies to achieve previously impossible levels of efficiency and productivity. Effective cooperation in the computer aided manufacturing depends on the recognition and perception of typical production environments as well as on the understanding of tasks in their context. Vision systems are the basis for scene analysis and interpretation, both in time and 3D space. Measurement of the dimensions of objects and parts in many industrial fields is very important, as the quality of the product depends especially on the reliability and precision of each object part. The use of vision-based metrology allows calculating a set of 3D point coordinates and/or estimate the dimension and pose of a known object. They enable industrial robots to perform different and complex tasks reliably and accurately [7,8].

In the past decade, the development of modular reconfigurable manipulators (MRM) was started in order to increase the flexibility of manufacturing systems [9]. MRM consists of modular joints and links. The next generation of MRM, additionally to joints and links includes flexible fixtures [10]. These manipulators still have limited use in manufacturing. For the massive introduction of modular robots in industrial production it is necessary that modular robots have modular control algorithms. To perform this task, modular robots should have the possibility of automatic geometry calibration of modular reconfigurable manipulators. Possibilities and limitations of calibration of highly modular and reconfigurable manipulators by vision systems are presented in this paper.

2. COMPUTER VISION

2.1. Camera Model

This section describes the camera model. Fig. 1 illustrates the basic geometry of the camera model. The camera performs transformation from the 3D projective space to the 2D projective space. The projection is carried by an optical ray originating (or reflected)

from a scene point P . The optical ray passes through the optical center O_c and hits the image plane at the point p .

Prior describing the perspective transformation, and camera model, let us define the basic coordinate systems. The coordinate frames are defined as follows:

$O_w X_w Y_w Z_w$ - world coordinate system (fixed reference system), where O_w represents the principal point. The world coordinate system is assigned in any convenient location.

$O_c X_c Y_c Z_c$ - camera centered coordinate system, where O_c represents the principal point on the optical center of the camera. The camera coordinate system is the reference system used for camera calibration, with the Z_c axis the same as the optical axis. $O_i X_i Y_i Z_i$ - image coordinate system, where O_i represents the intersection of the image plane with the optical axis. $X_i Y_i$ plane is parallel to $X_c Y_c$ plane.

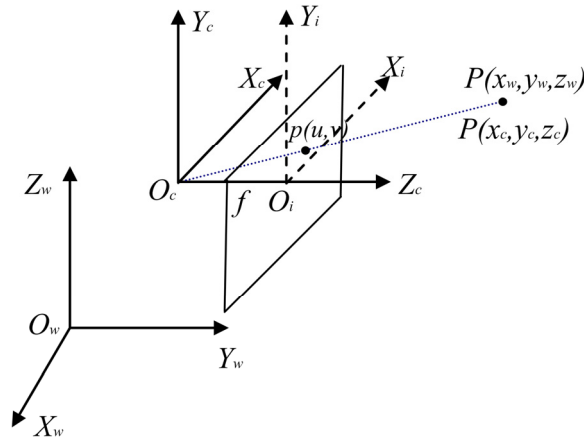


Fig. 1 The basic geometry of the camera model

Let (x_w, y_w, z_w) are the 3D coordinates of the object point P in the 3D world coordinate system, and (u, v) position of the corresponding pixel in the digitized image. A projection of the point P to the image point p may be represented by a 3×4 projection matrix (or camera matrix) $M [2,5]$:

$$p = K[R \ T]P = MP . \quad (1)$$

Matrix:

$$K = \begin{bmatrix} \alpha & 0 & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}$$

is called the internal (intrinsic) camera transformation matrix. Parameters α , β , u_0 and v_0 are so called internal distortion-free camera parameters.

R and T , a 3×3 orthogonal matrix representing the camera's orientation and a translation vector representing its position, are given by:

$$R = \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}, T = \begin{bmatrix} t_x \\ t_y \\ t_z \end{bmatrix},$$

respectively. The parameters $r_{11}, r_{12}, r_{13}, r_{21}, r_{22}, r_{23}, r_{31}, r_{32}, r_{33}, t_x, t_y, t_z$ are external (extrinsic) parameters and represent the camera's position referred to the world coordinate system.

Projection in an ideal imaging system is governed by the pin-hole model. Real optical system suffers from a number types of distortion. The first one is caused by real lens spherical surfaces and manifests itself by radial position error. Radial distortion causes an inward or outward displacement of a given image point from its ideal (distortion free) location. This type of distortion is mainly caused by flawed radial curvature curve of the lens elements. A negative radial displacement (a point is imaged at a distance from the principle point that is smaller than predicted by the distortion free model) of the image point is referred to as barrel distortion. A positive radial displacement (a point is imaged at a distance from point that is larger than the predicted by the distortion free model) of the image point is referred to as pin-cushion distortion. The displacement is increasing with distance from the optical axis. This type of distortion is strictly symmetric about the optical axis. Fig.2 illustrates the effect of radial distortion.

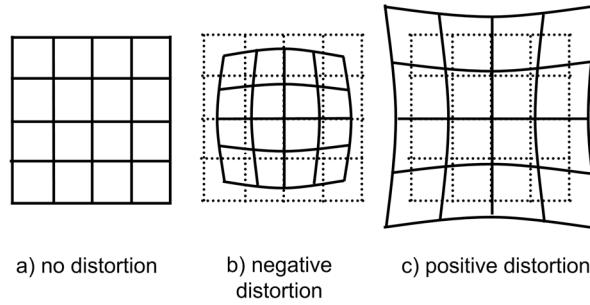


Fig. 2 Effect of radial distortion illustrated on a grid

The radial distortion of a perfectly centered lens is usually modeled using the equations:

$$\Delta x_r = x_i (k_1 r^2 + k_2 r^4 + \dots),$$

$$\Delta y_r = y_i (k_1 r^2 + k_2 r^4 + \dots),$$

where r is the radial distance from the principal point of the image plane, and k_1, k_2, \dots are coefficients of radial distortion. Only even powers of the distance r from the principal point occur, and typically only the first, or the first and the second terms in the power series are retained.

The real imaging systems also suffer from tangential distortion, which is at right angle to the vector from the center of the image. That type of distortion is generally caused by improper lens and camera assembly. Like radial distortion, tangential distortion grows with distance from the center of distortion and can be represented by equations:

$$\Delta x_t = -y_i(l_1 r^2 + l_2 r^4 + \dots),$$

$$\Delta y_t = x_i(l_1 r^2 + l_2 r^4 + \dots).$$

Fig. 3. illustrates the effect of tangential distortion. The reader is referred to [2,3,4] for more elaborated and more complicated lens models.

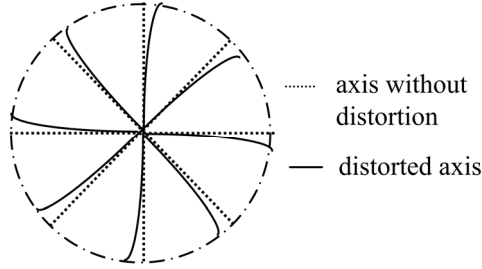


Fig. 3 Effect of tangential distortion

Note that one can express the distorted image coordinates as a power series using undistorted image coordinates as variables, or one can express undistorted image coordinates as a power series in the distorted image coordinates. The r in the above equations can be either based on actual image coordinates or distortion-free coordinates.

Bearing in mind the radial and tangential distortion, correspondence between distortion-free and distorted pixels image coordinates can be expressed by:

$$x_d = x_i + \Delta x_r + \Delta x_t,$$

$$y_d = y_i + \Delta y_r + \Delta y_t.$$

The parameters representing distortion of an image are: $k_1, k_2, \dots, l_1, l_2, \dots$. The distortion tends to be more noticeable with wide-angle lenses than telephoto lenses. Electro-optical systems typically have larger distortions than optical systems made of glass.

2.2. Camera Calibration

Camera calibration is considered as an important issue in computer vision applications. With the increasing need for higher accuracy measurement in computer vision, it has also attracted research effort in this subject. Task of camera calibration is to compute the camera projection matrix M from a set of image-scene point correspondences. By correspondences it means a set $\{(p_i, P_i)\}_{i=1}^m$ where p_i is a homogeneous vector representing image point and P_i is a homogeneous vector representing scene point, at the i^{th} step. Equation (1) gives an important result: the projection of a point P to an image point p by a camera is given by a linear mapping (in homogeneous coordinates):

$$p = MP.$$

The matrix M is non-square and thus the mapping is many-to-one. All scene points on a ray project to a single image point.

To compute M , it have to be solved the system of homogeneous linear equations

$$s_i p_i = MP_i ,$$

where s_i are scale factors.

Camera calibration is performed by observing a calibration object whose geometry in 3D space is known with very good precision. The calibration object usually consists of two or three planes orthogonal to each other. These approaches require an expensive calibration apparatus. Accurate planar targets are easier to make and maintain than three-dimensional targets. There is a number of techniques which only requires the camera to observe a planar pattern(s) shown at a few different orientation (Fig. 4). The calibration points are created by impressing a template of black squares (usually chess-board pattern) or dots on top of white planar surface (steel or even a hard book cover [5]). The corners of the squares are treated as a calibration points. Because the corners are always rounded, it is recommended to measure the coordinate of a number of points along the edges of the square away from the corners, and then extrapolate the edges to obtain position of the corners which lie on the intersection of adjacent edges.

Due to the high accuracy performance requirement for camera calibration, a sub-pixel estimator is desirable. It is a procedure that attempts to estimate the value of an attribute in the image to greater precision than that normally considered attainable within restrictions of the discretization. Since the CCD camera has relatively low resolutions, interest in a sub-pixel method arises when one applies CCD-based image systems to the computer integrated manufacturing [6].

Camera calibration entails solving for a large number of calibration parameters, resulting in the large scale nonlinear search. The efficient way of avoiding this large scale nonlinear search is to use two-stage technique, described in [2]. The methods of this type in the first stage use a closed-form solution for most of the calibration parameters, and in the second stage iterative solution for the other parameters.

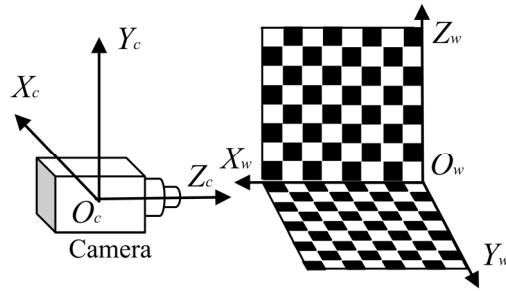


Fig. 4 Experimental setup for camera calibration using coplanar set of points.

In [4] a two-stage approach was adopted with some modification. In the first step, the calibration parameters are estimated using a closed-form solution based on a distortion-free camera model. In the second step, the parameters estimated in the first step are im-

proved iteratively through a nonlinear optimization, taking into account camera distortion. Since the algorithm that computes a closed-form solution is no iterative, it is fast, and solution is generally guaranteed. In the first step, only points near the optical axis are used. Consequently, the closed-form solution isn't affected very much by distortion and is good enough to be used as an initial guess for further optimization. If an approximate solution is given as an initial guess, the number of iterations can be significantly reduced, and the globally optimal solution can be reliably reached.

2.3. Stereo Vision

Calibration of one camera and knowledge of the coordinates of one image point allows us to determine a ray in space uniquely (back-projection of point). Given a homogeneous image point p , we want to find its original point P from the working space. This original point P is not given uniquely, but all points on a scene ray from image point p . Here, we will consider how to compute 3D scene point P from projections p_i in the several cameras, or projections p_i in one camera at different positions (different images are denoted by superscript i). Assume that m views are available, so that we have to solve linear system

$$s_i p_i = M_i P, \quad i=1, \dots, m.$$

This approach is known as triangulation (it can be interpreted in terms of similar triangles). Geometrically, it is a process of finding the common intersection of m rays given by back-projection of the image points by the cameras. In the reality, image points p_i are corrupted by noise, and the rays will not intersect and the system would have no solution. We might compute P as the scene point closest to all of the skew rays.

If two calibrated cameras observe the same scene point P , its 3D coordinates can be computed as the intersection of two of such rays. The epipolar geometry is a basis of a system with two cameras (principle of stereo vision). It is illustrated on Fig. 5. Let O_c^1, O_c^2 represents the optical centers of the first and second camera, respectively. The same consideration holds if one camera takes two images from two different locations. In that case O_c^1 represents optical center of the camera when the first image is obtained, and O_c^2 represents the optical center for the second image. p_1 and p_2 denote the images of the 3D point P . The base line is the line joining the camera centers O_c^1 and O_c^2 . The baseline intersects the image planes in the epipoles e_1 and e_2 . Alternatively, an epipole is the image of the optical center of one camera in the other camera. Any scene point P and the two corresponding rays from optical centers O_c^1 and O_c^2 define an epipolar plane. This plane intersects the image plane in the epipolar line. It means, an epipolar line is the projection of the ray in one camera into the other camera. Obviously, the ray $O_c^1 P$ represents all possible positions of P for the first image and is seen as the epipolar line l_2 in the second image. The point p_2 in the second image that corresponds to p_1 must thus lie on the epipolar line in the second image l_2 , and reverse. The fact that the positions of two corresponding image points are not arbitrary is known as the epipolar constraint. This is a very important statement for the stereo vision. The epipolar constraint reduces the dimensionality of the search space for a correspondence between p_1 and p_2 in the second image from 2D to 1D.

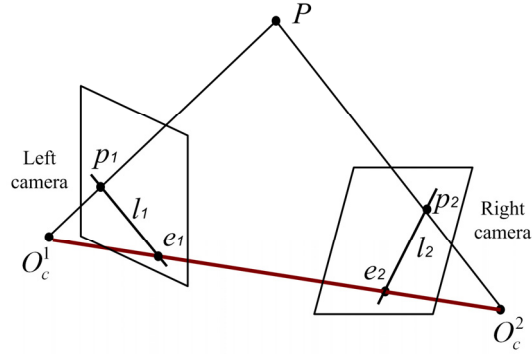


Fig. 5 The epipolar geometry

A special relative position of the stereo cameras is called rectified configuration. In this case image planes coincide and line $O_c^1 O_c^2$ is parallel to them, as shown in Fig. 6. The epipoles e_1 and e_2 go to infinity, and epipolar lines coincide with image rows, as a consequence. For the rectified configuration, if the internal calibration parameters of both cameras are equal, it implies that corresponding points can be sought in 1D space along image rows (epipolar lines).

The optical axes are parallel, which leads to the notion of disparity that is often used in stereo vision literature. Top view of two cameras stereo configuration with parallel optical axes is shown in Fig. 7. World coordinate system is parallel to cameras coordinate systems. The principal point O_w of the world coordinate system is assigned on the midway on the baseline. The coordinate z_w of point P represents its distance from the cameras ($z_w = 0$), and can be calculated from the disparity $d = u_1 - u_2$. Values $u_1 - u_2$ are measured at the same height (same rows of images). Noting that:

$$\frac{u_1}{f} = \frac{x_w + \frac{B}{2}}{z_w}, \quad \frac{u_2}{f} = \frac{x_w - \frac{B}{2}}{z_w},$$

we have:

$$z_w = \frac{Bf}{d}.$$

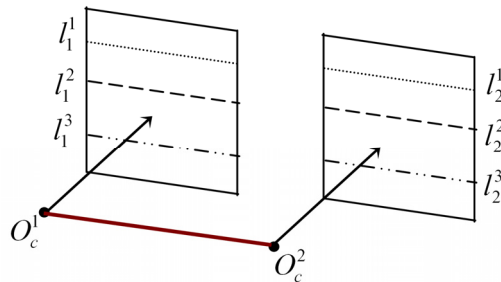


Fig. 6 The rectified configuration of two cameras

The remaining two coordinates of the 3D point P can be calculated from equations:

$$x_w = \frac{-B(u_1 + u_2)}{2d}, y = \frac{Bv_1}{d}.$$

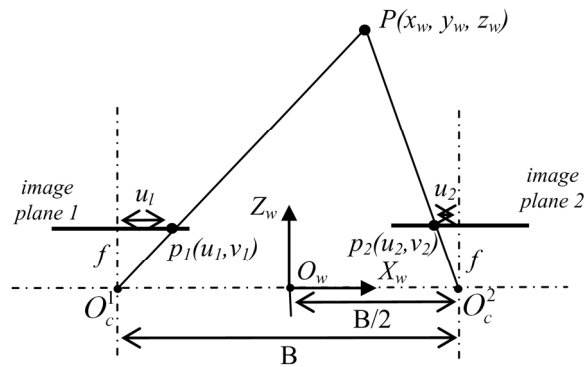


Fig. 7 Top view of two cameras with parallel optical axes rectified configuration

The position of the point P in the 3D scene can be calculated from the disparity d . It is a question, how the same point can be found in two images if the same scene is observed from two different viewpoints. The solution of this correspondence problem is a key step in any stereo vision. Automatic solution of the correspondence problem is under extensive exploration. Until now there is not solution in general case. The inherent ambiguity of the correspondence problem can in practical cases be reduced using several constrains. A vast list of references about this task can be found in the [3].

The geometric transformation that changes a general cameras configuration with non-parallel epipolar lines to the parallel ones is called image rectification. More deep explanation about computing the image rectification can be found out in [3].

3. ROBOT CALIBRATION

3.1. Manipulator Geometry Modeling

A high level of positioning accuracy is an essential requirement in a wide range of industrial robots applications. This accuracy is affected by geometric factors (geometrical parameters accuracy) and non-geometric factors (gear backlashes, encoder resolution, flexibility of links, thermal effects, etc.).

The error due to geometric factors accounted for 90% of the total error. A common approach is to calibrate the current geometric parameters and treat the non-geometric factors as a randomly distributed error. The calibration procedure is very important for robot programming using CAD systems where the simulated robot must reflect accuracy the real robot. During a manipulator control system design, and periodically in the course of task performing, manipulator geometry calibration is required [1,11].

The first step of manipulator calibration is concerned with a mathematical formulation that results in model which gives relation between the geometric parameters, the joint variables and end-effector position. Many researchers have been looking for the suitable kinematic models for robot calibration, since Richard Paul's book [12]. The most popular among them is the Denavit-Hartenberg (D-H) method. For this reason we will use this notation.

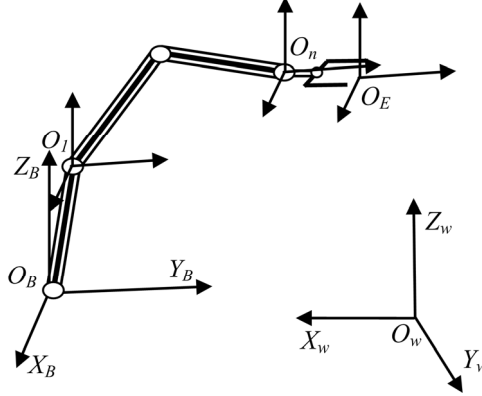


Fig. 8 Coordinate systems assignment for robot modeling

Prior description kinematic model let us define the basic coordinate systems as follows (Fig. 8.):

$O_B X_B Y_B Z_B$ – base coordinate system of the manipulator

$O_E X_E Y_E Z_E$ – end-effector (tool) coordinate system of the manipulator (we denote the origin O_E as the endpoint of the robot)

$O_i X_i Y_i Z_i$ ($i=1, n$) – coordinate system fixed to the i^{th} link ($O_n X_n Y_n Z_n$ – coordinate system fixed to the terminal link) of the manipulator.

The original D-H representation of a rigid link depends on geometric parameters. Four parameters a, d, α and θ denote manipulator link length, link offset, joint twist and joint angle, respectively. Composite 4×4 homogenous transformation matrix $A_{i-1,i}$ known as the D-H transformation matrix for adjacent coordinate system i and $i-1$, is:

$$A_{i-1,i} = \begin{bmatrix} \cos \theta_i & -\cos \alpha_i \sin \theta_i & \sin \alpha_i \sin \theta_i & a_i \cos \theta_i \\ \sin \theta_i & \cos \alpha_i \cos \theta_i & -\sin \alpha_i \cos \theta_i & a_i \sin \theta_i \\ 0 & \sin \alpha_i & \cos \alpha_i & d_i \\ 0 & 0 & 0 & 1 \end{bmatrix}.$$

The homogenous matrix $A_{B,i}$ which specifies the location of the i^{th} coordinate system with respect to the base coordinate system is the chain product of successive coordinate transformation matrices $A_{i-1,i}$, and expressed as:

$$A_{B,i} = A_{B,1} A_{1,2} \dots A_{i-1,i}.$$

Particularly, for $i=n$ we have $A_{B,n}$ matrix which specifies the position and orientation of the end-effector of the manipulator with respect to the base coordinate system. Matrix $A_{B,n}$ is a function of the $4n$ geometrical parameters which are constant for constant robot geometry, and n joint coordinates that change their value when manipulator moves.

Moreover, a robot is not intended to perform a single operation at the workcell, it has interchangeable different tools. In order to facilitate the programming of the task, it is more practical to have transformation matrix defining the tool coordinate system with respect to the terminal link coordinate system $A_{n,E}$.

Thus, the transformation matrix $A_{w,E}$ can be written as:

$$A_{w,E} = A_{w,B} A_{B,n} A_{n,E}.$$

Since the world coordinate system can be chosen arbitrarily by the user, six parameters are needed to locate the robot base relative to the world coordinate system. From independence to some manipulator parameters it follows that consecutive coordinate systems are represented at most by four independent parameters.

Since the end-effector coordinate system can be defined arbitrarily with respect to the terminal link coordinate system (O_n, X_n, Y_n, Z_n) , six parameters are needed to define the matrix $A_{n,E}$. If we extend the robot notation to the definition of the end-effector coordinate system, it follows that the end-effector coordinate system introduces four independent parameters. For more details the reader can refer to [1].

With above mentioned equations dependence between joint coordinates and geometrical parameters, and endpoint location of the tool can be written as:

$$\mathbf{X} = \mathbf{f}(\mathbf{q}, \mathbf{g}^0) \quad (2)$$

where x, q, g^0 denotes end-effector position vector expressed in the world coordinate system, vector of the joint variables, and vector of the geometric parameters, respectively. Dimension of the vector x is 6 if measurement can be made on the location and orientation of the end-effector. However, the most frequently only a location of the endpoint is measured, and therefore dimension of a vector x is 3. Dimension of the vector q is equivalent to the number of DOF for manipulator. Dimension of the vector g^0 is at most $4n+6$.

3.2. Geometric Parameters Estimation Based on the Differential Model

The calibration of the geometric parameters is based on estimating the parameters minimizing the difference between a function of the real robot variables and corresponding mathematical model. Many authors [11,13,14,15,16] presented open-loop methods that estimate the kinematic parameters of manipulators performing on the basis of joint coordinates and the Cartesian coordinates of the end-effector measurements. The joint encoders outputs readings are joint coordinates. It is assumed that there is a measuring device that can sense the position (sometime orientation) of an end-effector Cartesian coordinates.

A mobile closed kinematic chain method has been proposed that obviates the need for pose measurement by forming a manipulator into a mobile closed kinematic chain [17,18]. Self motion of the mobile closed chain places manipulator in a number of configurations and the kinematic parameters are determined from the joint position readings alone.

The calibration using the end-effector coordinates (open-loop method) is the most popular one. The model represented by equation (2) is nonlinear in \mathbf{g}^0 , and we must linearize it in order to apply linear estimators. The differential model provides the differential variation of the location of the end-effector as a function of the differential variation of the geometric parameters. The function to be minimized is the difference between the measured (\mathbf{x}) and calculated end-effector location (\mathbf{x}^m). Let $\Delta\mathbf{x}=\mathbf{x}-\mathbf{x}^m$, and $\Delta\mathbf{g}=\mathbf{g}^0-\mathbf{g}$ be the pose error vector of end-effector and geometric parameter error vector, respectively (\mathbf{g} – vector of geometric parameters estimation). From equation (2), the calibration model can be represented by the linear differential equation

$$\Delta\mathbf{x}=\mathbf{J}_g \Delta\mathbf{g} = \mathbf{x}-\mathbf{x}^m, \quad (3)$$

where:

\mathbf{g} is the ($p \times 1$) vector of geometric parameters estimation

$\Delta\mathbf{x}=\mathbf{x}-\mathbf{x}^m$ is the ($r \times 1$) pose error vector of end-effector

$\Delta\mathbf{g}=\mathbf{g}^0-\mathbf{g}$ is the geometric parameter error vector

\mathbf{J}_g is the ($r \times p$) sensitivity matrix relating the variation of the endpoint position with respect to the geometric parameters variation (calibration Jacobian matrix) [13,16].

To estimate $\Delta\mathbf{g}$ we apply equation (3) for a number of manipulator configurations. It gives the system of equations:

$$\Delta\mathbf{X}=\Phi \Delta\mathbf{g} +\mathbf{E} \quad (4)$$

where is:

$$\Delta\mathbf{X} = \begin{bmatrix} \Delta\mathbf{x}^1 \\ \Delta\mathbf{x}^2 \\ \vdots \\ \Delta\mathbf{x}^k \end{bmatrix}, \quad \Phi = \begin{bmatrix} \mathbf{J}_g^1(q^1, \mathbf{g}) \\ \mathbf{J}_g^2(q^2, \mathbf{g}) \\ \vdots \\ \mathbf{J}_g^k(q^k, \mathbf{g}) \end{bmatrix},$$

and \mathbf{E} is the error vector which includes the effect of unmodeled non-geometric parameters:

$$\mathbf{E} = \begin{bmatrix} e^1 \\ e^2 \\ \vdots \\ e^k \end{bmatrix}.$$

Equation (4) can be used to estimate iteratively the geometric parameters. This equation is solved to get the least-squares error solution to the current parameters estimate. The least-squares solution can be obtained from:

$$\Delta\mathbf{g}=(\Phi^T \Phi)^{-1} \Phi^T \Delta\mathbf{X}. \quad (5)$$

At the each iteration, geometric parameters are updated by adding $\Delta\mathbf{g}$ to the current value of \mathbf{g} :

$$\mathbf{g}=\mathbf{g}+\Delta\mathbf{g}. \quad (6)$$

By solving equations (5) and (6) alternately, the procedure is iterated until the Δg approaches zero.

Calibration a manipulator is an identification process, and hence, one should take a careful look at the identifiability of the model parameters [13,17]. A general method to determine these parameters have been proposed in [17]. Determination of the identifiable (base) geometric parameters is based on the rank of the matrix Φ . Some parameters of manipulator related to the locked passive joints may become unidentifiable in the calibration algorithm due to the mobility constraints. It reduces number of identifiable parameters in general for the closed-loop kinematic chain approach, compared with open-loop case.

As the measurement process is generally time consuming, the goal is to use set of manipulator configurations that use limited number of optimum points on the parameters estimation. Furthermore, goal is to minimize the effect of noise on the parameters estimation. The condition number of the matrix Φ gives a good estimate of the persistent excitation [1]. Therefore, much work was led on finding the so-called optimal excitation. The task of selecting the optimum manipulator configurations to be used during the calibration is discussed and solutions are proposed in [17-19]. It is worth noting that most of geometric calibration methods give an acceptable condition number using random configurations. The paper [20] presents an updating algorithm to reduce the complexity of computing and observability index for kinematic calibration of robots. An active calibration algorithm is developed to include an updating algorithm in the pose selection process.

4. ROBOT CALIBRATION USING COMPUTER VISION

Measurement of robot manipulator end-effector pose (i.e., position and orientation) in the reference coordinate system is unquestionably the most critical step towards a successful open-loop robot calibration. A variety of measurement techniques ranging from coordinate measuring machines, proximity measuring systems, theodolites, and laser tracking interferometer systems to inexpensive customized fixtures have been employed for calibration tasks. These systems are very expensive, tedious to use or with low working volume [15,21,22]. In general, the measurement system should be accurate, inexpensive and should be operated automatically. The goal is to minimize the calibration time and the robot unavailability.

To overcome the above limitations, advances in robot calibration allow the start using a computer vision to calibrate a robot. Compared to those mechanical measuring devices, the camera system is low cost, fast, automated, user-friendly, non-invasive and can provide high accuracy [23].

There are two types of setups for vision-based robot pose measurement [24]. The first one is to fix cameras in the robot environment so that the cameras can see a calibration fixture mounted on the robot end-effector while the robot changes its configuration [25]. The second typical setup is to mount a camera or a pair of cameras on the end-effector of the robot manipulator [26-30].

The stationary camera configuration requires the use of stereo system placed at fixed location. It is not possible compute 3D scene point P position from only one projection p , on the camera plane. The stereo system has to be placed in location that maintains neces-

sary field-of-view overlap. The proper camera position needs to be selected empirically. The stereo system must be calibrated before manipulator calibration. The manipulator is placed in a number of configurations. From pair of images the location (position and orientation) of the calibration board is computed for every configuration (Fig.9.). At the each configuration, geometric parameters are updated by adding Δg (calculated in accordance with equation (10)) to the current value of g .

If it is enough to measure only the end-effector pose (usually tool's tip) for robot calibration, then it is not necessary to use a calibration plate. Based on pair of images of manipulator tool 3D position of its tip is calculated. In this case, the main problem is automatic detection of points matching the manipulator's tip on both images.

This type of setups has two distinct advantages. First, it is non-invasive. The cameras are normally installed outside of the robot workspace, and need not be removed after robot calibration. Second, there is no need to identify the transformation from the camera to the end-effector, although this transformation is easy to compute in this case.

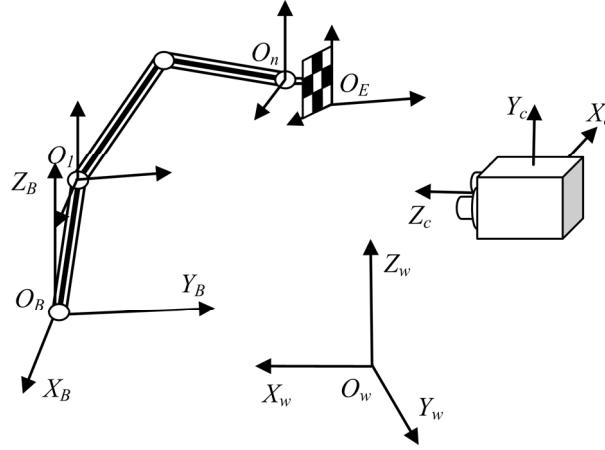


Fig. 9 A manipulator calibration using stationary camera configuration.

The major problem existing in all stationary camera setups is system accuracy. The accuracy improves with the decrease of distance between stereo system and object point. An approximated estimate of the errors in the point coordinates, for a simplified case is given by

$$e = d (\Delta l / f)$$

where e is the maximum 1D error in the point coordinates due to image quantization error, d is the distance from the point to the stereo system, Δl is the half of the 1D physical size of the image pixel.

In a case of stereo system with parallel optical axes one more problem exists. It is the small field of view by both cameras. In order to have larger scene area overlapped by the both cameras each camera have to be tilted towards the geometrical center line of the two cameras.

The moving camera approach (a camera on the end-effector) can resolve the conflict between high accuracy and large field-of-view of the cameras as the cameras only need to perform local measurements. The global information on the robot end-effector pose is provided by a stationary calibration fixture (Fig. 10.). In general, eye in hand robot calibration can be classified into two-step and one-step method.

Let us start with the two-step stereo camera setup case. The stereo cameras are rigidly fixed to the end-effector of the manipulator, as shown in Fig. 9. In the first step the stereo cameras are calibrated. After camera calibration (internal and external camera parameters are known), the 3D position of any object point (from its images) can be computed with the respect to the camera coordinate system. Since camera coordinate system is fixed with respect to the end effector coordinate system, it moves with the manipulator from one calibration configuration to another. On that way the position of cameras becomes known in world coordinate system at each manipulator configuration. Thus the homogenous transformation $A_{w,C}$ can be calculated for every configuration. For a known transformations $A_{w,B}$ and $A_{E,C}$ it follows: $A_{w,C}(q,g) = A_{w,B} A_{B,E}(q,g) A_{E,C}$. Thus the geometric parameters of the manipulator can be identified from the set of transformations $A_{w,C}(q,g)$.

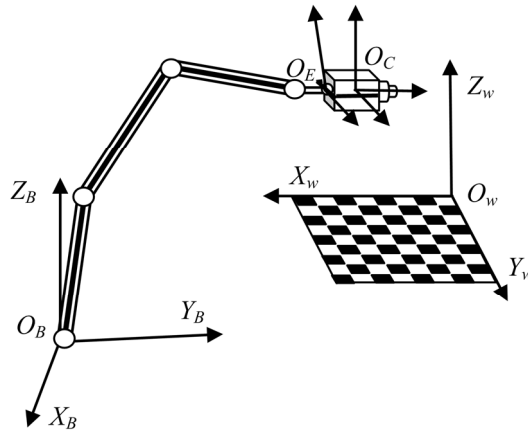


Fig. 10 A manipulator calibration with hand-mounted cameras.

In a monocular camera setup, a camera is rigidly fixed to the moving end-effector. In accordance with procedure presented in section 2.2 internal and external parameters of the camera are calculated by observing a planar target(s). In the next phase, the robot is moved from one configuration to another. The external camera parameters are calculated at each manipulator configuration, with the fixed value of internal parameters. It means that the position of the end-effector is computed for each manipulator configuration. The manipulator geometric parameters can be estimated using given that positions.

In a one-step method, both the camera parameters as well as manipulator geometric parameters are identified simultaneously. This method can be divided into stereo camera and monocular camera setup. The paper [23] focuses on the one-step method, and compares it with two-step method.

In the moving camera approach, as the cameras are mounted on the robot end-effector, this method is invasive. The second disadvantage of this method is that normally computes the position of the camera instead the end-effector. Thus a remaining task is to identify the transformation from the camera system to the tool system, which is a nontrivial task [26,29].

Moreover, a robot is not intended to perform a single operation at the workcell: it has interchangeable different tools. In order to facilitate the programming of the task, it is more practical to define coordinate system for each tool (tool coordinate system). It enhances robot flexibility. The paper [29] describes a technique for computing relative 3D position and orientation between the camera coordinate system and tool coordinate system in a moving camera approach.

Parallel manipulators are emerging in the industry. These manipulators have main property of having their end-effectors connected with several kinematic chains to their base, rather than one for the standard serial manipulators. This allows parallel manipulators to bear higher loads, at higher speed and often with a higher repeatability. However, the large number of links and passive joints often limits their performances in terms of accuracy. A kinematic calibration is thus needed. Even though, kinematic model of parallel manipulator is different to model of serial one, the calibration methods and procedures presented above for the serial manipulators can be used for the parallel manipulators [31].

5. ENHANCEMENT OF ROBOT FLEXIBILITY BY COMPUTER VISION

Conventional fixed-anatomy manipulators do not satisfy the requirements to adapt such a robot to variable tasks and environments. To respond to the rapid changes of product design, manufacturers need a more flexible fabrication system. In recent years, modular reconfigurable manipulators were developed to fulfill the requirements of the flexible production system. It is composed of interchangeable links and joint modules of various sizes and shapes. By reconfiguring the modules, different manipulators can be created so as to meet a variety of tasks requirements using standard mechanical and electrical interfaces. Serial and parallel modular reconfigurable manipulators are under development. New modular reconfigurable manipulators can be easily reassembled into a variety of configurations and different geometries.

To increase the flexibility of the robot system, the handling system is equipped with tool change system.

During the course of manufacturing processes it is necessary to fix, locate and position the work piece or product. This is referred to as fixturing. For a production system to be fully flexible, all of its components have to be flexible, including the fixtures. The reconfigurable fixtures have the ability to be changed (reconfigured), to suit different parts and products. The reconfigurable fixture sets the product interface point to correct position by the use of external measuring device. By the external measuring device it is possible position key features of the product to be constrained and build the fixture top-down instead of bottom-up. Several reconfigurable fixtures have been developed [10].

To reposition a fixture different approaches have been tested. It can be done manually, by actuators and using the robots.

The external measuring system adds cost. NC machine can be used for a measuring, but it is time consuming process, and the cycle time of manufacturing process need to allow for this operation.

For a more automated reconfiguration it is recommended to use robots for repositioning and computer vision system to measure the position of pick up interface that will hold the part. Furthermore, use robot and computer vision already present in the manufacturing opens up for an economically the best solution since it will not constitute an extra cost.

Machining setup verification is widely used before starting the actual machining operation. It is particularly time consuming in the case of high flexible manufacturing systems. The paper [7] presents a computer vision system to quickly verify the similarity between the actual setup and its digital model. That enables integration of CAD and CAM, and higher flexibility of manufacturing system.

6. CONCLUSION

Computer vision systems have developed significantly over the last ten years and now have become standard automation component.

Current trend and development of modular reconfigurable manipulators equipped with tool change system and reconfigurable fixtures enable mechanical flexibility enhancement. For the wider implementation of these mechanisms in the industry, it is necessary to achieve the flexibility in control. The use of computer vision-based metrology allows implementing flexible control algorithms to achieve flexible and effective manufacturing systems.

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POVEĆANJE FLEKSIBILNOSTI INDUSTRIJSKIH ROBOTA POMOĆU RAČUNARSKIH VIZUELNIH SISTEMA

Petar Marić

Nova generacija industrijskih robota će imati više fleksibilnosti u implementaciji zadataka zahvaljujući napretku u razvoju rekonfigurabilnih manipulatora sa većom modularnošću. Da bi se postigla potpuna fleksibilnost takvih robota, potrebno je postići fleksibilno upravljanje, pored mehaničke fleksibilnosti. Bitan preduslov za postizanje ovog cilja jeste precizna automatizovana kalibracija ovih manipulatora. U radu su prezentovane mogućnosti i ograničenja u primjeni vizuelnih sistema za automatizovanu kalibraciju rekonfigurabilnih manipulatora sa većom modularnošću.

Ključne reči: *kalibracija robota, modularni rekonfigurabilni roboti, računarski vid, kalibracija kamere*