2014 IEEE International Conference on Robotics & Automation (ICRA)
Hong Kong Convention and Exhibition Center
May 31 - June 7, 2014. Hong Kong, China

Active Calibration and Its Applications on Micro-operating Platform with Multiple Manipulators

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Abstract— **The microscope has characteristics of a planar vision with small view field and small view depth. For micro operation systems with multiple manipulators, the handling of irregular objects may lead to a nonorthogonal microscopic system, which needs to focus on clear viewing interested features, and it may also hardly locate the exact position and posture of the robot arms. In view of these, this paper proposes an active calibration method to compute image Jacobian matrix, which maps from the relative motion of the manipulators to the image coordination changes in the microscopes. We also investigate the applications in micro operator positioning, tracking for distributed systems, and movement optimization in micro-assembly. Experiments are carried out on a micro-assembly platform equipped with three microscopes and six robot arms, and the results validate the effectiveness of the proposed method.**

I. INTRODUCTION

In recent years, micro-operation and micro-assembly have been widely investigated [1], [2], which can greatly increase the manufacturing quality and facilitate assembly with high precision. Wason [3] used multiple coordinated probes for micro-assembly with automated vision-guided. He developed the capabilities required for construction of 3D structure using only planar micro fabricated parts. Rabenorosoa [4] used a two-sensing-fingers gripper to grasp planar microparts and analyzed the lateral contact force which was estimated less than 3mN. In Ref. [5], a hybrid micro-assembly technique was reported to combine a robotic micro-manipulator and a water droplet self-alignment.

Microscopic vision is the most important sensing for micro-operation and attracts concerns in the community of micro-operation. Chen [6] analyzed the characteristics of macro and micro computer visions and proposed a fast auto-focus algorithm based on depth from defocus. Our previous work [7] analyzed the characteristics of monocular microscope and the sensitive DoFs of the microscopic vision system. A class of miniature vision sensors was proposed and analyzed that enabled a wide field-of-view within a small form through a refractive optical design [8].

For microscopic vision, calibration is very important to acquire the basic knowledge of how to control the manipulator precisely. For monocular and stereo microscopes, different methods were applied in calibration. Pattern-based [9] and motion-based [10] approaches are usually used for monocular microscope. Cheah [11] presented a simple vision based setpoint controller with adaptation to uncertainty in depth information. In Ref. [10], broyden method was used to estimate the image Jacobian matrix representing the relation between the variations of image coordinates and Cartesian planar coordinates. The two microscopic vision systems were orthogonal in order to have three dimensional information of the object. In our previous work, an active calibration method was used to acquire monocular microscopic Jacobian matrix and applied on assembly of micro-pipe and micro-sphere [7]. To calibrate stereo microscope, Wang [12] estimated the main parameters and rectification parameters of an imaging model using the symmetry and the differences between the two optical paths of stereo microscopic vision system. In Refs. [13], [14], a three dimensional positioning problem was handled via considering the object model or the position of the microscopic vision. Lee [15] experimentally determined the Jacobian matrix by adding constant translational motions to the actuators and acquiring the corresponding displacements on the image plane.

To assemble or manipulate complex components requires multiple robot arms with different grippers to work simultaneously in the small clear view of the microscopic vision system. This may lead to placing some robot arms in positions or postures that can not be exactly measured, and therefore affect the precision of the micro-operation. To handle irregular components under the supervision of the microscopes may enforce to locate microscopes where the interested features can be clearly viewed, and this commonly results in a nonorthogonal microscopic vision system. In these issues, how to precisely control the micro motion using microscopic vision feedback is very important.

This paper uses an active approach to calibrate Jacobian matrix to acquire the relationship between the relative motion of the manipulators and the image coordination changes in the microscopic vision system. This method allows any placement of robot arms and microscopes, and provides high precision and fast response. We apply it to micro manipulator positioning, tracking for distributed systems, and motion optimization in micro-assembly. To validate the effectiveness of the proposed method, we conduct experiments on a micro-assembly platform. This mechanism has a nonorthogonal vision system incorporating three microscopes and six robot arms, whose locations are not measured.

The rest of the paper is organized as follows. Section II presents the active calibration method for a nonorthogonal microscopic vision system and multiple robot arms whose location are hardly measured. In Section III, applications are addressed in the positioning, tracking of distributed systems, and motion optimization. Experiments are carried out in the

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next section on our micro-assembly platform. The paper is concluded in Section IV.

II. Active Calibration

Compared with traditional vision system, microscope has different characteristics which can be concluded as: 1) small view depth, which may be at the levels of ten to hundred microns; 2) small view field, which is determined by the magnification factor of the microscope lens and the size of the camera's sensing area; 3) neglectable lens distortion; 4) planar vision; 5) adjusting platform to have clear images.

In view of the microscope characteristics, for a platform with multiple manipulators designed to operate irregular and complex objects of micro size, the microscopes need to be placed at positions to be able to clearly observe interested features. This usually leads to a nonorthogonal vision system. For irregular object assembly, the robot arms may situate in postures that can hardly be exactly measured. We need a general method to map from the image plane of each microscope to the Cartesian movement of each manipulator. For any point, which is in the clear view area of the studied microscope, in the end-effector of any manipulator, the relative movements in Cartesian space have only a scale to their position changes in the eye of the microscope. The relation is

$$\begin{bmatrix} \Delta u_i \\ \Delta v_i \\ \Delta \phi_i \end{bmatrix} = {}^i\boldsymbol{J}_j \begin{bmatrix} \Delta x_j \\ \Delta y_j \\ \Delta z_j \\ \Delta \alpha_j \\ \Delta \beta_j \\ \Delta \gamma_j \end{bmatrix}, \tag{1}$$

where $[\Delta x_j, \Delta y_j, \Delta z_j, \Delta \alpha_j, \Delta \beta_j, \Delta \gamma_j]^{\mathrm{T}}$ is the relative movement of the j^{th} manipulator, $[\Delta u_i, \Delta v_i, \Delta \phi_i]^{\mathrm{T}}$ is the image coordination change in the i^{th} microscope, $[\Delta u_i, \Delta v_i]^{\mathrm{T}}$ is the coordination change of point features and $\Delta \phi_i$ represents the angle change of line features, ${}^i\boldsymbol{J}_j \in \mathbb{R}^{3\times 6}$ is the image Jacobian matrix of the j^{th} manipulator in the i^{th} microscope.

Since microscope has very small view depth and small view field, pattern-based calibration method which is widely used in traditional vision system can not be suitable. Here we use active calibration method. To solve the Jacobian matrix in the above equation, the least square method is applied.

$${}^i\boldsymbol{J}_j = \boldsymbol{A}_i \boldsymbol{B}_j^{\mathrm{T}} (\boldsymbol{B}_j \boldsymbol{B}_j^{\mathrm{T}})^{-1}, \tag{2}$$

where

$$\boldsymbol{A}_i = \begin{bmatrix} \Delta u_{i1} & \Delta u_{i2} & \cdots & \Delta u_{in} \\ \Delta v_{i1} & \Delta v_{i2} & \cdots & \Delta v_{in} \\ \Delta \phi_{i1} & \Delta \phi_{i2} & \cdots & \Delta \phi_{in} \end{bmatrix},$$

$$\boldsymbol{B}_j = \begin{bmatrix} \Delta x_{j1} & \Delta x_{j2} & \cdots & \Delta x_{jn} \\ \Delta y_{j1} & \Delta y_{j2} & \cdots & \Delta y_{jn} \\ \Delta z_{j1} & \Delta z_{j2} & \cdots & \Delta z_{jn} \\ \Delta \alpha_{j1} & \Delta \alpha_{j2} & \cdots & \Delta \alpha_{jn} \\ \Delta \beta_{j1} & \Delta \beta_{j2} & \cdots & \Delta \beta_{jn} \\ \Delta \gamma_{j1} & \Delta \gamma_{j2} & \cdots & \Delta \gamma_{jn} \end{bmatrix},$$

$[\Delta x_{jk}, \Delta y_{jk}, \Delta z_{kj}, \Delta \alpha_{kj}, \Delta \beta_{kj}, \Delta \gamma_{jk}]^{\mathrm{T}}$ is the 3D movement vector of the j^{th} arm in the k^{th} step, $[\Delta u_{ik}, \Delta v_{ik}, \Delta \phi_{ik}]^{\mathrm{T}}$ represents the image coordination change in the i^{th} vision system in the k^{th} step, n is the total trials. Equation (2) has solution if and only if matrix $\boldsymbol{B}$ is full rank; and since the matrix $\boldsymbol{B}$ is a $6 \times n$ matrix, the sufficient and necessary condition to compute the Jacobian is $n \geq 6$, i.e., the active motions include at least six steps. More recorded motions can improve the calibration accuracy. The hand-eye calibration is also achieved by applying action calibration.

A microscope is only sensitive to three DoFs: two translational motion in a plane vertical to the camera lens and one rotational movement around the axis parallel to the camera lens. So two cameras are at least required to determine the exact motion without multiple solutions. Using the Jacobian matrix, we can compute the corresponding manipulator motion given the required tasks in each individual camera. For the j^{th} arm, the expected manipulator movement is

$$\begin{bmatrix} \Delta x_j \\ \Delta y_j \\ \Delta z_j \\ \Delta \alpha_j \\ \Delta \beta_j \\ \Delta \gamma_j \end{bmatrix} = \begin{bmatrix} {}^1\boldsymbol{J}_j \\ \vdots \\ {}^m\boldsymbol{J}_j \end{bmatrix}^{\dagger} \begin{bmatrix} \Delta u_1 \\ \Delta v_1 \\ \Delta \phi_1 \\ \vdots \\ \Delta u_m \\ \Delta v_m \\ \Delta \phi_m \end{bmatrix}, \tag{3}$$

where $\boldsymbol{J}_j = [{}^1\boldsymbol{J}_j^{\mathrm{T}}, \cdots, {}^m\boldsymbol{J}_j^{\mathrm{T}}]^{\mathrm{T}}$ is the Jacobian matrix mapping the j^{th} robot arm motion to the image coordination changes in the microscopic vision system, † means the pseudo-inverse, and m is the number of microscopes. In practical application, we can pick a part of specific features and form a simplified equation, which is addressed in an experiment example.

III. Applications

A. Positioning for Platform with Multiple Micro Operators

After computing the Jacobian matrix of each robot manipulator, we can directly use it to micro-operation. The control system block diagram is shown in Fig. 1, which is separated by the microscopic vision system and manipulator control blocks. The vision system observes each manipulator, finds interested features, and feedbacks the feature locations and postures. With the expected states of each manipulator, the

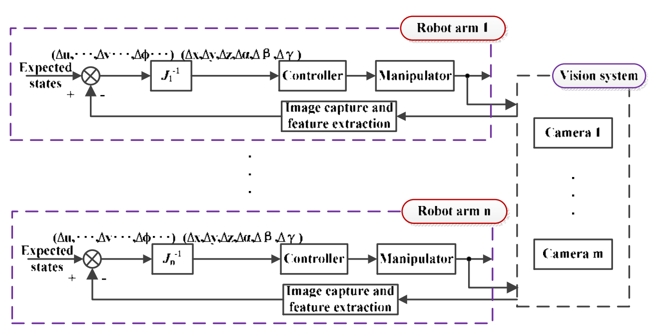


Fig. 1. Control diagram using Jacobian for multiple robot arm.

desired image coordination changes can be computed, which are then multiplied with the corresponding pseudo-inverse Jacobian matrix to acquire the expected motor movements. These results can be fed into Controller to drive motors. The controller is added for specific reasons: robust controllers to make the moving robust, adaptive controllers to adapt the environment, and commonly used time invariant PID controller to eliminate overshooting, etc.

B. Tracking

For distributed robot systems, the motion of each manipulator is determined by its own controller, not by a central controller, and each subsystem has communications. If one manipulator is expected to follow another one and the only information got from outside is the leader's motion command of the next time step, the follower has to compute how to move in order to catch up with the leader while still in the clear view of the microscopic vision system. We can determine the relationship between manipulators under the clear vision of the i^{th} microscope.

$$\begin{bmatrix} \Delta x_k \\ \Delta y_k \\ \Delta z_k \\ \Delta\alpha_k \\ \Delta\beta_k \\ \Delta\gamma_k \end{bmatrix} = ({}^i\boldsymbol{J}_k^T {}^i\boldsymbol{J}_k)^{-1} {}^i\boldsymbol{J}_k^T {}^i\boldsymbol{J}_j \begin{bmatrix} \Delta x_j \\ \Delta y_j \\ \Delta z_j \\ \Delta\alpha_j \\ \Delta\beta_j \\ \Delta\gamma_j \end{bmatrix}, \tag{4}$$

where $[\Delta x_k, \Delta y_k, \Delta z_k, \Delta\alpha_k, \Delta\beta_k, \Delta\gamma_k]^{\mathrm{T}}$ is the k^{th} manipulator movements, $[\Delta x_j, \Delta y_j, \Delta z_j, \Delta\alpha_j, \Delta\beta_j, \Delta\gamma_j]^{\mathrm{T}}$ is the j^{th} manipulator movements, ${}^i\boldsymbol{J}_k$ and ${}^i\boldsymbol{J}_j$ are the image Jacobian matrices of the k^{th} and j^{th} manipulators in the i^{th} microscopic vision system. As discussed earlier, to acquire unique solutions needs vision feedback information from two or more microscopes. The Jacobian matrix in the above equation needs to be calibrated in an appropriate microscopic vision system. If the system is reduced to three dimensional translation, two microscopes at least is required. Specific controllers can also be added in order to deal with possible overshooting and detection errors.

C. Movement optimization

To manipulate two or more components, e.g., micro-assembly, the traditional way is to manually design a trajectory for each manipulator, which executes its own command to reach the desired state. But this is definitely not optimal, for several reasons: 1) since some robot arms are not parallel to the vision systems, the end effectors have different effort in moving to keep the features still in the small clear view area of the microscopic vision system; 2) usually the components are irregular, and some arms are easy to drive and energy-saving, while others are on the contrary. In some cases, some manipulators easily move out of the clear view of the microscopic vision system. All these rise difficulties to manually tune the relative motion parameters. By using optimization and incorporating Jacobian matrix is a useful way to help the manipulator to determine where to go and in what posture. This also improves the intelligence of the micro-assembly.

We present a simple example to illustrate what this means, as shown in Fig. 2. In the clear view of the microscope k, two end effectors are initialized with certain angles and the distance is $[\Delta P_i, \Delta P_j]$ pixels. The optimized state is the position that two objects are very close and vertical in this camera's eye. In order to generate the expected trajectory, at least two microscope feedback should be used. We pick n coordination changes in the microscopic vision system as the image state, and the mapping relation between manipulators and cameras is

$$\begin{bmatrix} \Delta x_i \\ \Delta y_i \\ \Delta z_i \\ \Delta\alpha_i \\ \Delta\beta_i \\ \Delta\gamma_i \end{bmatrix} = {}^v\boldsymbol{J}_i^{\dagger} \begin{bmatrix} \Delta P_1 \\ \Delta P_2 \\ \vdots \\ \Delta P_n \end{bmatrix}, \tag{5}$$

where $[\Delta P_1, \Delta P_1, \cdots, \Delta P_n]^{\mathrm{T}}$ is the image coordination change we pick from the vision system, and this vector corresponds to the expected changes in camera's eyes. n is the total number of the expected image coordination change, and when n is larger than the manipulator's DoFs, redundant information is provided, which may lead to precision problem. ${}^v\boldsymbol{J}_i$ is the Jacobian matrix mapping the relative movement of manipulator i to the picked feature changes in the vision system.

To simplify the computation, we use an example of assembling two components. For more parts handling, this method can also be applied. We define ΔP_i^1 as the i^{th} feature change of the first component, and ΔP_i^2 as of the second one. The following equation separates the expected feature coordination changes,

$$\begin{aligned} |\Delta P_1^1 - \Delta P_1^2| &= \Delta P_1, \\ &\vdots \\ |\Delta P_n^1 - \Delta P_n^2| &= \Delta P_n. \end{aligned} \tag{6}$$

This equation also addresses the motion relationship between the executing manipulators. We use the expected image coordination change of one object as the optimization variable,

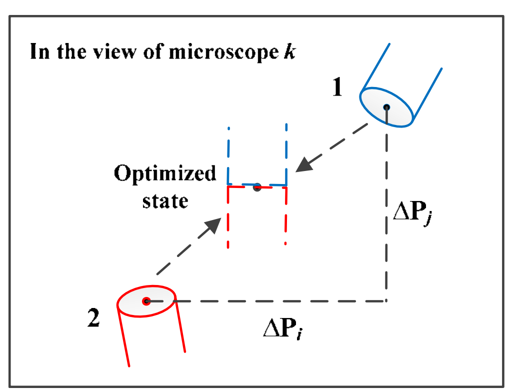
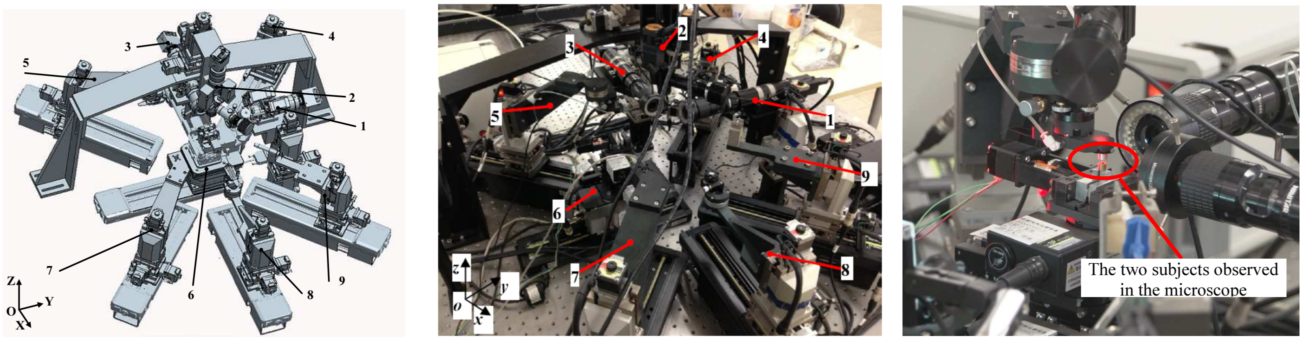


Fig. 2. Optimization process description.



(a) schematic model (b) platform (c) subject location

Fig. 3. The platform model for complex components assembly. 1-3 are microscopic vision systems, and 4-9 are robot arms.

and the above equation can compute the desired change of the other object.

We define $\mathbf{P} = [P_1, P_2, \cdots, P_n]^{\mathrm{T}}$, which is the position and posture of interested features in corresponding cameras, and define the clear area of the microscopic vision system as $\mathbf{V}$, which is the intersection set of the clear view area of each microscope. Since each feature we picked should be clearly viewed, the constraint for optimization is then set as $\mathbf{P} \in \mathbf{V}$, i.e. features never move out of the clear view of microscopes. For the state slips out during optimization, a big punishment is added into the cost function.

We define $\Delta \mathbf{X}_i = [\Delta x_i, \Delta y_i, \Delta z_i, \Delta \alpha_i, \Delta \beta_i, \Delta \gamma_i]^{\mathrm{T}}$, which is the relative movement of manipulator i, and define the optimization criterion as a weighted sum squared on each motor movement,

$$L = \Delta \mathbf{X}_1^{\mathrm{T}} \mathbf{R} \Delta \mathbf{X}_1 + \Delta \mathbf{X}_2^{\mathrm{T}} \mathbf{Q} \Delta \mathbf{X}_2, \tag{7}$$

where $\mathbf{R} \in \mathbb{R}^{6\times6}$ and $\mathbf{Q} \in \mathbb{R}^{6\times6}$ are the weight matrices. The desired motion for each manipulator can then be optimized by employing appropriate optimization tools.

IV. EXPERIMENTS

A. Platform System

The platform model is shown in Fig. 3. This machine has 6 robot arms and 3 microscopic vision systems, and has 34 DoFs totally. In the figure, the optic axes of the camera 1, 2, and 3 are parallel with y-axis, z-axis, and x-axis, individually. But the cameras are not strictly orthogonal; they can also be placed at certain position so that interested features are in their clear view. Each microscopic vision system has 3D micro translational DoFs, which can actively follow the motion of interested features and increase the clear view area of the microscope. The six robot arms are all equipped with a macro translational rail, so they can share the small micro working space without interference. The arm 6 has a z-axis translational DoF and three rotational DoFs; and the other arms all have three micro translational DoFs. The arms 4, 5, and 8 have equipped with micro-force sensors and a rotational mechanism to manually adjust the end effector's posture. The macro motion axes of the arm 6 and 8 are approximately parallel with y-axis and x-axis, and the other arms are just placed in order to facilitate assembly in the micro space, according to the irregular objects they grip. We have designed six manipulators in this platform in order to facilitate assembling several subjects simultaneously.

B. Jacobian Results

We use the arm 5 as an example to testify the usefulness of the proposed method. This arm has three micro translational DoFs and horizontal cameras are used to form a microscopic vision system. The equation (1) is then simplified as

$$\begin{bmatrix} \Delta u_i \\ \Delta v_i \end{bmatrix} = {}^{i}\boldsymbol{J}_5 \begin{bmatrix} \Delta x_5 \\ \Delta y_5 \\ \Delta z_5 \end{bmatrix}, \tag{8}$$

where $[u_i, v_i]^{\mathrm{T}}$ is the image coordination in the horizontal cameras, $i = 3$ means in the view of the camera 3 which is along x-axis and $i = 1$ is of the camera 1 which is parallel with y-axis,$[x_5, y_5, z_5]^{\mathrm{T}}$ is the position vector of the manipulator 5.

In this example, the equation (2) has solution if and only if $\mathrm{R}(\mathbf{B}) = 3$, i.e, at least three steps of active motions of the 5^{th} manipulator are required. This manipulator is actuated for 6 steps and the image coordination change of an interested feature are recorded in each camera. Moving in the view area of the camera 3, we have

$${}^{3}\mathbf{B}_5 = \begin{bmatrix} 1000 & -1000 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1000 & -1000 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1000 & -1000 \end{bmatrix} \mu m,$$

$${}^{3}\mathbf{A}_5 = \begin{bmatrix} 223.1 & -223.0 & -225.8 & 225.7 & 8.2 & -8.2 \\ 7.4 & -7.4 & -4.5 & 4.5 & -318.2 & 319.1 \end{bmatrix} pixels.$$

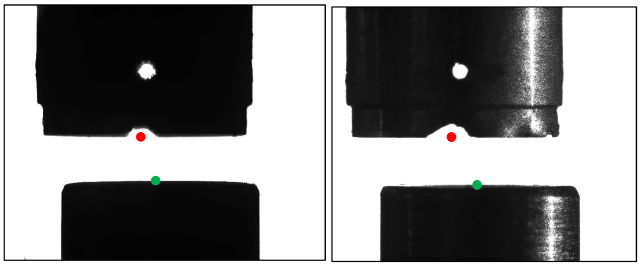
The Jacobian matrix of the manipulator 5 in the camera 3 is then calculated as

$${}^{3}\boldsymbol{J}_5 = \begin{bmatrix} 0.2230 & -0.2258 & 0.0082 \\ 0.0074 & -0.0045 & -0.3187 \end{bmatrix}.$$

Applying the same method results in the Jacobian matrix of the manipulator 5 in the camera 1

$${}^{1}\boldsymbol{J}_5 = \begin{bmatrix} -0.2301 & -0.2116 & -0.0033 \\ 0.0046 & -0.0049 & -0.3157 \end{bmatrix}.$$

The manipulator has three DoFs while two cameras feedback four image coordination changes. Since the image size of the two cameras is different, redundant feedback



(a) in camera 1 (b) in camera 3

Fig. 4. The initial and desired states of the component gripped by the manipulator 5.

information may result in incorrect positioning. According to the characteristics of the platform, we only feedback three observed states in this experiment, removing the vertical change in the camera 3. The feedback state becomes $[\Delta u_1, \Delta v_1, \Delta u_3]^{\mathrm{T}}$, and the corresponding Jacobian matrix is

$$\boldsymbol{J}_5 = \begin{bmatrix} -0.2301 & -0.2116 & -0.0033 \\ 0.0046 & -0.0049 & -0.3157 \\ 0.2230 & -0.2258 & 0.0082 \end{bmatrix}.$$

To testify the effectiveness of the Jacobian method, we propose an example of alignment which is very common in assembly. As shown in Fig. 4, the upper object is attached to the gripper of the manipulator 5, while the lower one is fixed on the end effector of the robot arm 4. Figs. 4(a) and 4(b) reflect the initial state of the end effector 5 (the red point is the center of the upper object), and the desired state (100 pixels higher than the current center position of the lower object) in the horizontal cameras. We use Jacobian matrix to compute the expected motion and pick a PI controller to drive motors. The results are shown in Fig. 5: the first step moves the distance about $[316, -496, 329]^{\mathrm{T}}$ pixels with the error of $[-4, 4.7, -25]^{\mathrm{T}}$ pixels deviated from the expected state. Starting from the second step, the errors of all the picked features in the two cameras are less than 0.1 pixels, in this example 0.5μm. The error ratio compared with the moving distance is less than 0.04. This demonstrates that the proposed method of using image Jacobian matrix has good precision.

C. Tracking

As an example, we use the manipulator 5 to track end effector 4's motion in the clear view of the horizontal cameras. Since these two manipulators both have three translational DoFs, the equation 4 is then simplified as

$$\begin{bmatrix} \Delta x_5 \\ \Delta y_5 \\ \Delta z_5 \end{bmatrix} = (\boldsymbol{J}_5^T \boldsymbol{J}_5)^{-1} \boldsymbol{J}_5^T \boldsymbol{J}_4 \begin{bmatrix} \Delta x_4 \\ \Delta y_4 \\ \Delta z_4 \end{bmatrix}. \tag{9}$$

We can also compute the Jacobian matrix of the manipulator 4 in the clear view of the cameras 1 and 3 by taking 6 steps,

$$\boldsymbol{J}_4 = \begin{bmatrix} -0.221 & -0.223 & 0.006 \\ -0.0025 & 0.0055 & 0.3165 \\ -0.23 & 0.2235 & -0.0085 \end{bmatrix}.$$

In this experiment, the manipulator 4 is actuated to move in the distance of $[-445.2, 1.2, 312.4]^{\mathrm{T}}$ motor pulse, whose image is still in the clear view of the horizontal cameras, and send this motion command to the manipulator 5. The control system of this manipulator can calculate the motion that is needed to follow the manipulator 4's movement, by using equation (9). After taking this step, the tracking error is $[3.1, -4.4, 3.2]^{\mathrm{T}}$ pixels, and the error ratio compared with the moving distance is less than 0.04.

D. Motion Optimization

We also use the manipulators 4 and 5 to test the effectiveness of motion optimization. Since the manipulators only have translational DoFs, this optimization is reduced to a three dimensional problem. Suppose that the end effector 4 is on the upper-left side of 5, and the image distance measured in the horizontal cameras is $\Delta \mathrm{P} = [100, 100, 100]^{\mathrm{T}}$ pixels. Set the motion of the manipulator 4, $\Delta \mathrm{P}^1$, as the optimization variables, and the other manipulator's motion is restricted by equation 6. We set the weight matrix as $\mathbf{R} = \mathbf{Q} = \mathbf{I}_{3\times 3}$ in order to investigate the effect of robot arm's placement on image motion in microscope. SNOPT [16] is a general purpose system for constrained optimization, using sequential quadratic programming (SQP). We use it to find the optimal motion planning in this example.

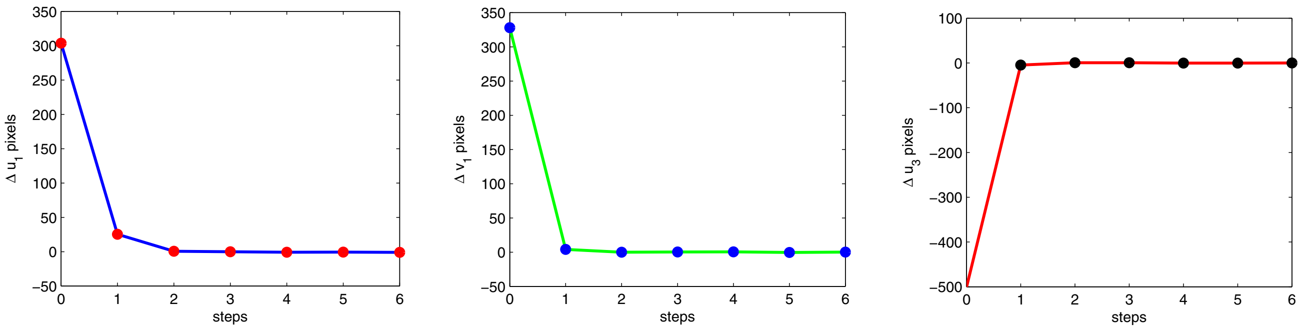
TABLE I

THE OPTIMIZED CHANGES OF MANIPULATORS AS $\mathbf{Q} = \mathbf{I}_{3\times 3}$.

Manipulator 4	image change	$[51.4, 50.1, 51.6]^{\mathrm{T}}$ pixels
	motor movement	$[-229.2, 0.8, 156.4]^{\mathrm{T}}$ pulses
Manipulator 5	image change	$[48.6, 49.9, 48.4]^{\mathrm{T}}$ pixels
	motor movement	$[3.5, 223.5, 154.7]^{\mathrm{T}}$ pulses

The optimized image coordination changes and motor movements of each manipulator are displayed in Table I, which show the difference of robot arm placement and its effect. Since the two manipulators are placed in positions that are almost symmetric along x-axis and on the same horizon plane, the optimal results for the two manipulators are almost equal (We can also explain this by comparing the elements of Jacobian matrix of each manipulator). But for the robot arms with different angles in the vision system, the results will be different.

The weight matrix can be set different, for the cases that some manipulators have difficulties in moving one or more of their motors, or the operator hopes to drive some manipulators as less as possible because of their delicate end effectors, or some end effectors may easily go out of the clear view of the vision system. In this example, we wish the manipulator 5 to move less, especially upward motion. So the weight matrix is set as $\mathbf{R} = \mathbf{I}_{3\times 3}$ and $\mathbf{Q} = diag(5, 5, 10)$. The optimized results are changed to Table II. We can see that the manipulator 5's motion is much less, especially motion along the z-axis.



(a) Δu_1 (b) Δv_1 (c) Δu_3

Fig. 5. The image coordination error from the expected position.

TABLE II
THE OPTIMIZED RESULTS OF MANIPULATORS AS $\mathbf{Q} = diag(5,5,10)$.

Manipulator 4	image change	$[84.2, 90.8, 84]^{\mathrm{T}}$ pixels
	motor movement	$[-374.4, 1.2, 283.8]^{\mathrm{T}}$ pulses
Manipulator 5	image change	$[15.8, 9.2, 16]^{\mathrm{T}}$ pixels
	motor movement	$[1.2, 73.1, 28.1]^{\mathrm{T}}$ pulses

V. CONCLUSIONS

This paper proposes an active calibration method for micro operation systems equipped with multiple robot manipulators. The Jacobian matrix maps the relative movements of manipulators to the image coordination changes in the microscopic vision system. This method is especially suitable for operating irregular objects, since the robot arms and microscopes have to be located to clearly view the interested features. We also investigate its applications in positioning, tracking, and motion optimization. Experiments are carried out on a micro-assembly platform equipped with three microscopes and six robot arms.

ACKNOWLEDGMENT

This work is supported by the Program for National Nature Science Foundation of China (61305115, 61227804).

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