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Uncalibrated Vision-Based Control for Optical Manipulation of Microscopic Particles

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Vision is a useful information for manipulation tasks since it provides a large spectrum of details about the environment. The visual feedback information can be used to guarantee the manipulation accuracy and improve robustness to uncertainty. In this paper, a vision-based adaptive control method is proposed for micromanipulation using optical tweezers. A general model of robotic manipulator is introduced in the optical tweezers system so that the movement of the laser beam is controlled by vision-based closed-loop robotic manipulation techniques. A new adaptive Jacobian controller is proposed for the regulation problem in presence of camera calibration errors. The stability of the closed-loop system is analyzed with consideration of the dynamics of both the particle and the robotic manipulator. Simulations are presented to illustrate the performance of the proposed method.

1. Introduction

Microscopic optics and cameras are commonly used in micromanipulation or biomanipulation workstations since they provide a large spectrum of visual details and information. The visual feedback guarantees the accuracy of micromanipulation and improves robustness to uncertainty. A variety of vision-based manipulation systems have been developed for diverse micromanipulation tasks, such as force measurement,¹ cell injection,² and microassembly of MEMS devices.³

Optical tweezers⁴ are one of the most useful micromanipulation instruments, which utilize optical traps to manipulate the microscopic objects without physical contact. A typical optical tweezers system is usually constituted of modules for sensing and execution. The sensing module consists of a microscope and a CCD camera, while the execution module consists of the holographic optical trapping and the motorized stage. The manual operations with optical tweezers are involved with laborious work such as cell structure recognition, image coordinates selection and positioning of laser source, which requires lengthy training and easily induces the operator fatigue and thus the reduction of success rate. To improve the efficiency

and the reproducibility, several automatic control methods for optical tweezers have been reported in the literature.⁵⁻⁹

In current control techniques using optical tweezers, open-loop strategies are used to move the laser source as the position of the laser beam is not used as a feedback information but treated as an input in the design of the controller. While dynamic control has been extensively studied in the literature of robot control, the optical manipulation problems of cells or microscopic particles with the consideration of the effects of the manipulator dynamics are less understood. The dynamic interaction between the robotic manipulator and the cell was investigated such that the position of the laser source is controlled by closed-loop techniques with the consideration of the dynamics of robotic manipulator.^{10,11} However, the control methods^{10,11} assume that the mapping from the Cartesian space to the image space is exactly known.

In this paper, a vision-based control strategy is developed for optical manipulation of microscopic particles. A general model of robotic manipulator is introduced to manipulate the laser source in the optical tweezers system, so that the position of the laser position is controlled by vision-based closed-loop techniques. The relation from the joint space of the robot to the image space of the camera is described by a Jacobian matrix, which directly transforms the image-space task error into the torque input of the manipulator. Since it is difficult to obtain the exact Jacobian matrix in presence of camera calibration errors, a new adaptive Jacobian controller is proposed for the regulation problem. The proposed controller is able to ensure the convergence of image error even with uncalibrated camera. The stability of the closed-loop system is analyzed by using Lyapunov-like analysis. Simulations results are presented to illustrate the performance of the proposed adaptive control method.

2. Optical Tweezers System

The basic principle of optical trap is based on the transfer of momentum from photons to microscopic objects, when a focused light travels through the object that is immersed in a medium. The refraction of the photons at the boundary between the object and the medium, results in a stable trap of the object.⁴

Optical tweezers are the scientific instruments based on the optical trap, which can manipulate the microscopic objects without physical contact. A typical optical manipulation system is shown in Fig. 1. The laser beam is expanded using a beam expander, reflected on a Dichroic mirror, and introduced into the microscope.

2.1. Dynamic Model of Microscopic Particles

In this paper, the optical tweezers are employed to manipulate the microscopic particle, and the dynamic model is described by the following equation:

$$M\ddot{x} + B\dot{x} + k(x, p)(x - p) = 0, \quad (1)$$

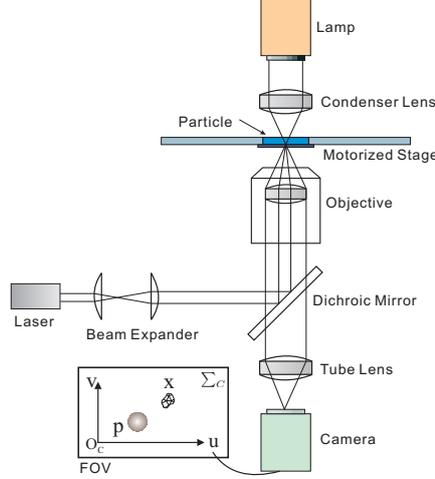


Fig. 1. A typical optical tweezers system.

where $\mathbf{M} \in \mathbb{R}^{2 \times 2}$ denotes the inertia matrix, and $\mathbf{B} \in \mathbb{R}^{2 \times 2}$ represents the damping matrix, and $k(\mathbf{x}, \mathbf{p})$ denotes the stiffness, and $\mathbf{x} = [x_1, x_2]^T \in \mathbb{R}^2$ is the position of the particle in image space, and $\mathbf{p} = [p_1, p_2]^T \in \mathbb{R}^2$ is the position of the laser in image space. Both \mathbf{x} and \mathbf{p} are specified in the coordinate of camera frame Σ_C , both \mathbf{M} and \mathbf{B} are diagonal and positive definite, and the terms $\mathbf{M}\ddot{\mathbf{x}} + \mathbf{B}\dot{\mathbf{x}}$ in equation (1) is linear in a set of parameters $\boldsymbol{\theta}_d = [\theta_{d1}, \dots, \theta_{dn_d}]^T \in \mathbb{R}^{n_d}$ as:

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{B}\dot{\mathbf{x}} = \mathbf{Y}_d(\dot{\mathbf{x}}, \ddot{\mathbf{x}})\boldsymbol{\theta}_d, \quad (2)$$

where $\mathbf{Y}_d(\dot{\mathbf{x}}, \ddot{\mathbf{x}}) \in \mathbb{R}^{2 \times n_d}$ is a dynamic regressor matrix, and n_d represents the dimension of the unknown physical parameters.

The stiffness $k(\mathbf{x}, \mathbf{p})$ in equation (1) is specified as a function of offset between the position of the particle and the center of laser beam, which is described as:¹¹

$$k(\mathbf{x}, \mathbf{p}) = \begin{cases} k_c, & \|\mathbf{x} - \mathbf{p}\| \leq R, \\ k_c e^{-(\|\mathbf{x} - \mathbf{p}\| - R)^2}, & \|\mathbf{x} - \mathbf{p}\| > R, \end{cases} \quad (3)$$

where k_c is a positive constant, and R denotes the trapping radius. From equation (3), note that if the particle is far away from the laser beam, then $k(\mathbf{x}, \mathbf{p}) \rightarrow 0$, thus there is no interaction between the particle and the laser beam. When the particle is very near the laser beam, $\mathbf{x} - \mathbf{p} \rightarrow \mathbf{0}$, $k(\mathbf{x}, \mathbf{p}) \rightarrow k_c$, thus the particle can be trapped by the laser beam.

2.2. Movement Control of Laser Source

The interaction between the particle and the laser beam is dependent on the offset between the particle and the center of laser beam, and the laser beam is manipulated by a robotic manipulator with the dynamic model as follows:¹²

$$\mathbf{M}_q(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}_q(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \mathbf{u}, \quad (4)$$

where $\mathbf{q} \in \mathfrak{R}^n$ represents a vector of joint angles, $\mathbf{M}_q(\mathbf{q})$ is the inertial matrix, $\mathbf{C}_q(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}}$ includes centripetal and Coriolis forces, $\mathbf{g}(\mathbf{q})$ represents the gravitational force, and \mathbf{u} denotes the control input which is the torque exerted on the manipulator. The matrix $\mathbf{M}_q(\mathbf{q})$ is positive definite, $\frac{1}{2}\dot{\mathbf{M}}_q(\mathbf{q}) - \mathbf{C}_q(\mathbf{q}, \dot{\mathbf{q}})$ is skew symmetric, and the dynamic model described by equation (4) can be parameterized as:

$$\mathbf{M}_q(\mathbf{q})\ddot{\mathbf{q}} + \mathbf{C}_q(\mathbf{q}, \dot{\mathbf{q}})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}) = \mathbf{Y}_q(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}})\boldsymbol{\theta}_q, \quad (5)$$

where $\mathbf{Y}_q(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}) \in \mathfrak{R}^{n \times n_q}$ is a known regressor matrix, and $\boldsymbol{\theta}_q = [\theta_{q1}, \dots, \theta_{qn_q}]^T \in \mathfrak{R}^{n_q}$ represents a set of dynamic parameters. The velocity of laser beam in Cartesian space is hence related with the joint velocity as:¹³

$$\dot{\mathbf{r}} = \mathbf{J}_r(\mathbf{q})\dot{\mathbf{q}}, \quad (6)$$

where $\dot{\mathbf{r}} \in \mathfrak{R}^m$ represents the velocity of laser beam in Cartesian space, and $\mathbf{J}_r(\mathbf{q}) \in \mathfrak{R}^{m \times n}$ denotes the Jacobian matrix from joint space to Cartesian space.

2.3. Camera Model

In optical tweezers system, the relationship between the robot frame and the camera is to be derived. In general, the relationship is defined by a projection between the robot workspace and the camera image plane via the imaging geometry of the camera. The pinhole camera model¹⁴ is widely used to represent the mapping from Cartesian space to image space, and hence the projection of a point onto the image plane is modeled as a central projection through the center of the lens,¹⁵ which is illustrated in Fig. 2.

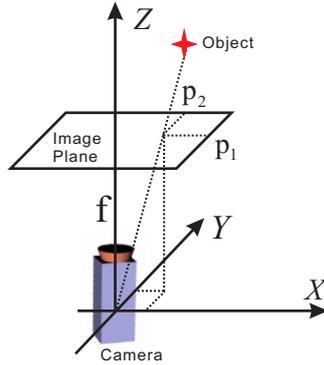


Fig. 2. The projection for a pinhole camera model.

Based on the pinhole camera model, the velocity of the image feature is related to the velocity of the feature point in Cartesian space by using the image Jacobian matrix.^{16,17} The image-space velocity of laser beam is related with the velocity of laser beam in Cartesian space as:

$$\dot{\mathbf{p}} = \mathbf{J}_p(\mathbf{r})\dot{\mathbf{r}}, \quad (7)$$

where $\mathbf{J}_p(\mathbf{r}) \in \mathbb{R}^{2 \times m}$ is the image Jacobian matrix.

The position of laser beam in image space \mathbf{p} is obtained by image-processing techniques, while the position of laser beam in Cartesian space \mathbf{r} is obtained by computing the forward kinematics of the manipulator. From equations (6) and (7), the velocity of the image feature $\dot{\mathbf{p}}$ is related to the joint velocity $\dot{\mathbf{q}}$ as:

$$\dot{\mathbf{p}} = \mathbf{J}(\mathbf{q})\dot{\mathbf{q}}, \quad (8)$$

where $\mathbf{J}(\mathbf{q}) \in \mathbb{R}^{2 \times n}$ is the Jacobian matrix from joint space to image space. In addition, the right side of equation (8) is also linear in a set of constant kinematic and camera parameters $\boldsymbol{\theta}_k = [\theta_{k1}, \dots, \theta_{kn_k}]^T \in \mathbb{R}^{n_k}$, which can be expressed as:

$$\dot{\mathbf{p}} = \mathbf{J}(\mathbf{q})\dot{\mathbf{q}} = \mathbf{Y}_k(\mathbf{q}, \dot{\mathbf{q}})\boldsymbol{\theta}_k, \quad (9)$$

where $\mathbf{Y}_k(\mathbf{q}, \dot{\mathbf{q}}) \in \mathbb{R}^{2 \times n_k}$ is a regressor matrix. In the case that the camera is uncalibrated, it is difficult to obtain the exact Jacobian matrix, and the estimated image-space velocity of laser beam is expressed as:

$$\dot{\hat{\mathbf{p}}} = \hat{\mathbf{J}}(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)\dot{\mathbf{q}} = \mathbf{Y}_k(\mathbf{q}, \dot{\mathbf{q}})\hat{\boldsymbol{\theta}}_k, \quad (10)$$

where $\hat{\mathbf{J}}(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)$ is the approximate Jacobian matrix, and $\hat{\boldsymbol{\theta}}_k$ is a set of estimated kinematic parameters.

3. Uncalibrated Vision-Based Setpoint Control

In this section, an adaptive controller is proposed for the regulation problem of optical manipulation. Firstly, based on the dynamic model of the particle in equation (1), a desired position input of laser beam \mathbf{p}_d is developed to ensure the convergence of the image error. Then based on the manipulator dynamics in equation (4), a backstepping procedure is used to derive a control input \mathbf{u} for the robotic manipulator of the laser source to guarantee that the actual position input \mathbf{p} tracks the desired position input \mathbf{p}_d .

3.1. Desired Position Input of Laser Beam

Supposing the desired position input of the laser beam in image space is denoted as \mathbf{p}_d , then equation (1) can be written as:

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{B}\dot{\mathbf{x}} + k(\mathbf{x}, \mathbf{p})\mathbf{x} = k(\mathbf{x}, \mathbf{p})\Delta\mathbf{p} + k(\mathbf{x}, \mathbf{p})\mathbf{p}_d, \quad (11)$$

where $\Delta\mathbf{p} = \mathbf{p} - \mathbf{p}_d$ represents an input perturbation to the particle dynamics. The system in equation (11) can be viewed as being controlled by the input $k(\mathbf{x}, \mathbf{p})\mathbf{p}_d$ with the perturbation $k(\mathbf{x}, \mathbf{p})\Delta\mathbf{p}$.

The desired position input specified in image space is proposed as:

$$\mathbf{p}_d = \mathbf{x} - k^{-1}(\mathbf{x}, \mathbf{p})\mathbf{K}_p\Delta\mathbf{x} - k^{-1}(\mathbf{x}, \mathbf{p})\mathbf{K}_d\dot{\mathbf{x}}. \quad (12)$$

where \mathbf{K}_p and \mathbf{K}_d are diagonal and positive definite, $\Delta \mathbf{x} = \mathbf{x} - \mathbf{x}_d$ and \mathbf{x}_d is the desired position of the particle. Substituting the desired position input of the laser beam (12) into equation (11), it is obtained that:

$$\mathbf{M}\ddot{\mathbf{x}} + \mathbf{B}\dot{\mathbf{x}} + \mathbf{K}_p\Delta \mathbf{x} + \mathbf{K}_d\dot{\mathbf{x}} = k(\mathbf{x}, \mathbf{p})\Delta \mathbf{p}. \quad (13)$$

3.2. Control Input of Manipulator of Laser Beam

In the previous section, the desired position input for the trapped particle \mathbf{p}_d is proposed, we now proceed to formulate a control input for the manipulator of the laser beam \mathbf{u} which ensures the convergence of $\Delta \mathbf{p} \rightarrow \mathbf{0}$.

In the case that the camera is uncalibrated, it is difficult to obtain the exact Jacobian matrix. Using the approximate Jacobian matrix, another sliding vector is proposed as:

$$\hat{\mathbf{s}}_q = \dot{\mathbf{q}} - \dot{\hat{\mathbf{q}}}_r, \quad (14)$$

where $\dot{\hat{\mathbf{q}}}_r$ is a reference vector defined as:

$$\dot{\hat{\mathbf{q}}}_r = \hat{\mathbf{J}}^+(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)\dot{\mathbf{p}}_d - \alpha_q\hat{\mathbf{J}}^+(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)\Delta \mathbf{p}, \quad (15)$$

and α_q is a positive constant, and $\hat{\mathbf{J}}^+(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)$ is the pseudo-inverse matrix of $\hat{\mathbf{J}}(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)$.

Next, the control input for the robotic manipulator of laser beam is proposed as:

$$\mathbf{u} = -\mathbf{K}_s\hat{\mathbf{s}}_q - \hat{\mathbf{J}}^T(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)\mathbf{K}_q\Delta \mathbf{p} + \mathbf{Y}_q(\mathbf{q}, \dot{\mathbf{q}}, \dot{\hat{\mathbf{q}}}_r, \ddot{\hat{\mathbf{q}}}_r)\hat{\boldsymbol{\theta}}_q, \quad (16)$$

where \mathbf{K}_s and \mathbf{K}_q are diagonal and positive definite matrices, and the estimated parameters $\hat{\boldsymbol{\theta}}_q$ and $\hat{\boldsymbol{\theta}}_k$ are updated by the following update laws:

$$\begin{aligned} \dot{\hat{\boldsymbol{\theta}}}_q &= -\mathbf{L}_q\mathbf{Y}_q^T(\mathbf{q}, \dot{\mathbf{q}}, \dot{\hat{\mathbf{q}}}_r, \ddot{\hat{\mathbf{q}}}_r)\hat{\mathbf{s}}_q, \\ \dot{\hat{\boldsymbol{\theta}}}_k &= \mathbf{L}_k\mathbf{Y}_k^T(\mathbf{q}, \dot{\mathbf{q}})\mathbf{K}_q\Delta \mathbf{p}, \end{aligned} \quad (17)$$

where $\mathbf{L}_q \in \Re^{n_q \times n_q}$ and $\mathbf{L}_k \in \Re^{n_k \times n_k}$ are positive definite matrices.

By using the sliding vector $\hat{\mathbf{s}}_q$, the manipulator dynamics in equation (4) can be rewritten as:

$$\mathbf{M}_q(\mathbf{q})\dot{\hat{\mathbf{s}}}_q + \mathbf{C}_q(\mathbf{q}, \dot{\mathbf{q}})\hat{\mathbf{s}}_q + \mathbf{Y}_q(\mathbf{q}, \dot{\mathbf{q}}, \dot{\hat{\mathbf{q}}}_r, \ddot{\hat{\mathbf{q}}}_r)\hat{\boldsymbol{\theta}}_q = \mathbf{u}. \quad (18)$$

Substituting the control input (16) into (18), the closed-loop equation is given as:

$$\mathbf{M}_q(\mathbf{q})\dot{\hat{\mathbf{s}}}_q + (\mathbf{C}_q(\mathbf{q}, \dot{\mathbf{q}}) + \mathbf{K}_s)\hat{\mathbf{s}}_q + \hat{\mathbf{J}}^T(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)\mathbf{K}_q\Delta \mathbf{p} + \mathbf{Y}_q(\mathbf{q}, \dot{\mathbf{q}}, \dot{\hat{\mathbf{q}}}_r, \ddot{\hat{\mathbf{q}}}_r)\Delta \boldsymbol{\theta}_q = \mathbf{0}. \quad (19)$$

To prove the stability, a Lyapunov-like candidate is proposed as:

$$\begin{aligned} V_s &= \frac{1}{2}\dot{\mathbf{x}}^T\mathbf{M}\dot{\mathbf{x}} + \frac{1}{2}\Delta \mathbf{x}^T\mathbf{K}_p\Delta \mathbf{x} + \frac{1}{2}\hat{\mathbf{s}}_q^T\mathbf{M}_q(\mathbf{q})\hat{\mathbf{s}}_q + \frac{1}{2}\Delta \mathbf{p}^T\mathbf{K}_q\Delta \mathbf{p} \\ &\quad + \frac{1}{2}\Delta \boldsymbol{\theta}_q^T\mathbf{L}_q^{-1}\Delta \boldsymbol{\theta}_q + \frac{1}{2}\Delta \boldsymbol{\theta}_k^T\mathbf{L}_k^{-1}\Delta \boldsymbol{\theta}_k. \end{aligned} \quad (20)$$

Differentiating V_s in equation (20) with respect to time, and substituting equations (13), (14), (17), and (19) into it, we have:

$$\begin{aligned}
\dot{V}_s &= \dot{\mathbf{x}}^T \mathbf{M} \ddot{\mathbf{x}} + \dot{\mathbf{x}}^T \mathbf{K}_p \Delta \mathbf{x} + \hat{\mathbf{s}}_q^T \mathbf{M}_q(\mathbf{q}) \dot{\hat{\mathbf{s}}}_q + \frac{1}{2} \hat{\mathbf{s}}_q^T \dot{\mathbf{M}}_q(\mathbf{q}) \hat{\mathbf{s}}_q \\
&\quad + \Delta \mathbf{p}^T \mathbf{K}_q \Delta \dot{\mathbf{p}} - \hat{\boldsymbol{\theta}}_q^T \mathbf{L}_q^{-1} \Delta \boldsymbol{\theta}_q - \hat{\boldsymbol{\theta}}_k^T \mathbf{L}_k^{-1} \Delta \boldsymbol{\theta}_k \\
&= -\dot{\mathbf{x}}^T (\mathbf{B} + \mathbf{K}_d) \dot{\mathbf{x}} + k(\mathbf{x}, \mathbf{p}) \dot{\mathbf{x}}^T \Delta \mathbf{p} - \alpha_q \Delta \mathbf{p}^T \mathbf{K}_q \Delta \mathbf{p} \\
&\quad - \hat{\mathbf{s}}_q^T \mathbf{K}_s \hat{\mathbf{s}}_q + \Delta \mathbf{p}^T \mathbf{K}_q (\mathbf{J}(\mathbf{q}) \dot{\mathbf{q}} - \hat{\mathbf{J}}(\mathbf{q}, \hat{\boldsymbol{\theta}}_k) \dot{\mathbf{q}}) - \hat{\boldsymbol{\theta}}_k^T \mathbf{L}_k^{-1} \Delta \boldsymbol{\theta}_k \\
&= -\hat{\mathbf{s}}_q^T \mathbf{K}_s \hat{\mathbf{s}}_q - [\dot{\mathbf{x}}^T \Delta \mathbf{p}^T] \mathbf{Q} [\dot{\mathbf{x}}^T \Delta \mathbf{p}^T]^T.
\end{aligned} \tag{21}$$

where $\mathbf{Q} = \begin{bmatrix} \mathbf{B} + \mathbf{K}_d & -\frac{k(\mathbf{x}, \mathbf{p})}{2} \mathbf{I}_2 \\ -\frac{k(\mathbf{x}, \mathbf{p})}{2} \mathbf{I}_2 & \alpha_q \mathbf{K}_q \end{bmatrix}$, and $\mathbf{I}_2 \in \mathbb{R}^{2 \times 2}$ is an identity matrix. Note that $k(\mathbf{x}, \mathbf{p}) \leq k_c$. Let $\lambda_{\min}[\cdot]$ denote the minimum eigenvalue of the matrix, if we choose the controller parameters α_q and \mathbf{K}_q sufficiently large so that

$$\alpha_q \lambda_{\min}[\mathbf{K}_q \mathbf{B}] > \frac{k_c^2}{4}, \tag{22}$$

then the matrix \mathbf{Q} is positive definite and hence $\dot{V} \leq 0$. We can now state the following theorem:

Theorem: *If the manipulator control input \mathbf{u} given by equations (16), (17), and (12) is applied to the robot-assisted optical tweezers system described by (1), (4), then the closed-loop system gives rise to the convergence of $\mathbf{x} \rightarrow \mathbf{x}_d$ as $t \rightarrow \infty$ when the control parameters α_q and \mathbf{K}_q are chosen to satisfy condition (22).*

Proof: If equation (22) is satisfied, we have $V_s > 0$ and $\dot{V}_s \leq 0$. Therefore, V_s is bounded, and $\dot{\mathbf{x}}$, $\Delta \mathbf{x}$, $\hat{\mathbf{s}}_q$, $\Delta \mathbf{p}$, $\Delta \boldsymbol{\theta}_q$ and $\Delta \boldsymbol{\theta}_k$ are bounded. The boundedness of $\dot{\mathbf{x}}$, $\Delta \mathbf{x}$ and $\Delta \mathbf{p}$ ensures the boundedness of $\ddot{\mathbf{x}}$ from equation (13), and the boundedness of $\ddot{\mathbf{x}}$ and $\dot{\mathbf{x}}$ ensures the boundedness of $\dot{\mathbf{p}}_d$ from equation (12). Since $\dot{\mathbf{p}}_d$, $\Delta \mathbf{p}$, and $\hat{\mathbf{s}}_q$ are all bounded, $\dot{\mathbf{q}}$ is bounded from equation (14). The boundedness of $\dot{\mathbf{q}}$ ensures the boundedness of $\dot{\mathbf{p}}$ since the Jacobian matrix $\mathbf{J}(\mathbf{q})$ is bounded. In addition, the boundedness of $\dot{\mathbf{p}}$ and $\dot{\mathbf{p}}_d$ ensures the boundedness of $\Delta \dot{\mathbf{p}}$. Therefore, $\Delta \mathbf{p}$ is uniformly continuous. In addition, since $\ddot{\mathbf{x}}$ is bounded, $\dot{\mathbf{x}}$ is also uniformly continuous. From equation (21), it is easy to verify that $\dot{\mathbf{x}}, \Delta \mathbf{p} \in L_2(0, +\infty)$. Then it follows^{12, 18, 19} that $\dot{\mathbf{x}}, \Delta \mathbf{p} \rightarrow \mathbf{0}$. From equation (13), it is concluded that $\mathbf{x} \rightarrow \mathbf{x}_d$.

△△△

Remark: In this paper, the problem of optical manipulation using uncalibrated camera is formulated and solved. The interaction between the manipulator and particle results in a fourth-order system. For the purpose of illustrating the concept of uncalibrated visual servoing in optical manipulation, the backstepping technique is used directly and hence the acceleration information and its derivatives are required in the proposed controller. To eliminate this problem, adaptive observer techniques^{11, 20} can be similarly developed for the proposed controller.

4. Simulation

Simulations were carried out to verify the performance of the proposed control method. The optical tweezers system is illustrated in Fig. 3. In Fig. 3, the particle is placed on a stage and the laser beam is fixed downwards, and the offset between the laser beam and the microscopic particle is varied by moving the motorized stage which thus acts as a robotic manipulator. In the simulations, the variable \mathbf{p} is set as the position of the laser beam with respect to the motorized stage.

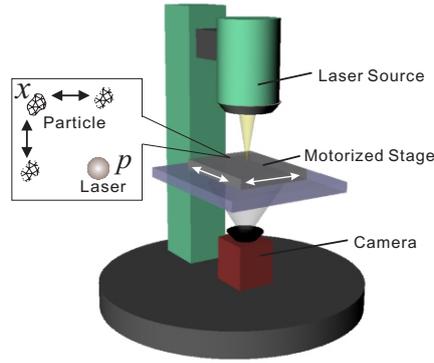


Fig. 3. The optical tweezers system. The laser beam is fixed downwards, and the relative distance between the particle and the laser is varied by moving the stage.

The parameters of the dynamic model of the particle in equation (1) were set as: $\mathbf{M} = \text{diag}\{10^{-10}, 10^{-10}\}$ kg, $\mathbf{B} = \text{diag}\{1.8 \times 10^{-9}, 1.8 \times 10^{-9}\}$ kg/s, $k_c = 2 \times 10^{-5}$, and $R = 18\mu\text{m}$.⁸ The dynamic parameters of the motorized stage were set as: $\mathbf{M}_q = \text{diag}\{0.02218, 0.011386\}$ kg, $\mathbf{C}_q = \text{diag}\{0.04749, 0.04023\}$ kg/s. Since the laser beam evolves in a 2-D plane while the camera is perpendicular to the evolving plane of the laser beam, the image Jacobian matrix is specified as:

$$\mathbf{J}_p = \frac{1}{z} \begin{bmatrix} \beta_1 f & 0 \\ 0 & \beta_2 f \end{bmatrix} \in \mathfrak{R}^{2 \times 2}, \quad (23)$$

where z is the depth information, f is the focal length of the camera, and β_1 and β_2 are the scaling factors in two coordinates respectively. In the simulations, $\frac{\beta_1 f}{z} = \frac{\beta_2 f}{z} = \gamma = 10^{-3}$.

In the simulation, both the laser beam and the particle start from an initial position at $(90, 335) \mu\text{m}$, and the trapped particle was manipulated to the desired point at $(200, 0) \mu\text{m}$. In presence of the uncalibrated camera, the initial estimate is set as $\hat{\gamma}(0) = 0.95 \times 10^{-3}$. Therefore, the Jacobian matrix is uncertain. Using the approximate Jacobian matrix $\hat{\mathbf{J}}(\mathbf{q}, \hat{\boldsymbol{\theta}}_k)$, the uncalibrated vision-based setpoint controller in equations (12) and (16) were implemented in the optical tweezers system.

The parameters of the desired position input for the trapped particle in equation (12) were proposed as: $\mathbf{K}_p = 2.6 \times 10^{-5} \mathbf{I}_2$, and $\mathbf{K}_d = 10^{-9} \mathbf{I}_2$, and the parameters

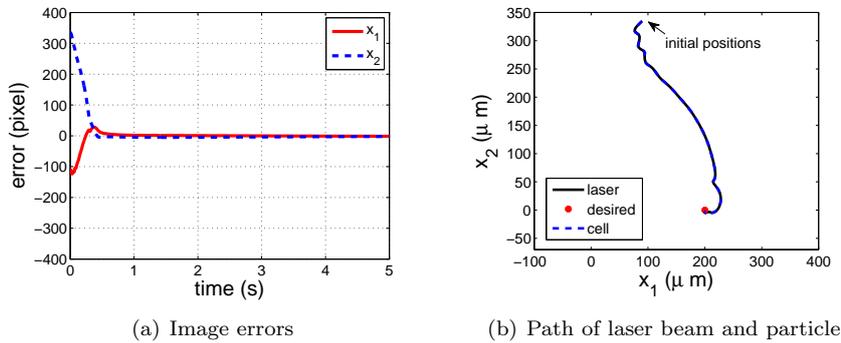


Fig. 4. Setpoint control.

of the control input for the manipulator of the laser beam in equations (16) and (17) were set as: $\alpha_q = 3$, $\mathbf{K}_q = 50\mathbf{I}_2$, $\mathbf{K}_s = 50\mathbf{I}_2$, $\mathbf{L}_q = 13\mathbf{I}_5$ where $\mathbf{I}_5 \in \mathbb{R}^{5 \times 5}$ is an identity matrix, and $\mathbf{L}_k = 0.01\mathbf{I}_4$ where $\mathbf{I}_4 \in \mathbb{R}^{4 \times 4}$ is also an identity matrix.

The image errors are shown in Fig. 4(a), and the image errors converge to zero in less than 0.3 s. The path of the laser beam and the particle is shown in Fig. 4(b), which indicates that the trapped particle is successfully manipulated to the desired point.

5. Conclusions

In this paper, an uncalibrated vision-based adaptive control method has been proposed for the regulation control problems in optical manipulation. A general model of robotic manipulator is introduced in the optical tweezers system so that the position of the laser beam is controlled by vision-based closed-loop techniques. The Jacobian matrix is explicitly introduced in the control input of the robotic manipulator to directly relate the joint space of robot to the image space of microscope. The proposed adaptive Jacobian control method is able to guarantee the convergence of image error even in presence of uncalibrated camera. The stability of the closed-loop system is analyzed by using Lyapunov-like analysis. Simulation results are presented to illustrate the performance of the proposed method.

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