Enhanced control of a flexure-jointed micromanipulation system using a vision-based servoing approach

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Abstract. This paper describes a high-precision motion control implementation for a flexure-jointed micromanipulator. A desktop experimental motion platform has been created based on a 3RUU parallel kinematic mechanism, driven by rotary voice coil actuators. The three arms supporting the platform have rigid links with compact flexure joints as integrated parts and are made by single-process 3D printing. The mechanism overall size is approximately 250x250x100 mm. The workspace is relatively large for a flexure-jointed mechanism, being approximately 20x20x6 mm. A servo-control implementation based on pseudo-rigid-body models (PRBM) of kinematic behavior combined with nonlinear-PID control has been developed. This is shown to achieve fast response with good noise-rejection and platform stability. However, large errors in absolute positioning occur due to deficiencies in the PRBM kinematics, which cannot accurately capture flexure compliance behavior. To overcome this problem, visual servoing is employed, where a digital microscopy system is used to directly measure the platform position by image processing. By adopting nonlinear PID feedback of measured angles for the actuated joints as inner control loops, combined with auxiliary feedback of vision-based measurements, the absolute positioning error can be eliminated. With controller gain tuning, fast dynamic response and low residual vibration of the end platform can be achieved with absolute positioning accuracy within ±1 micron.

1. Introduction
High-precision micromanipulation systems have been increasingly applied for various automated tasks over the last two decades, such as biological micromanipulation [1, 2, 3], micro-assembly tasks for MEMS [4] and optical components [5], specimen handling [6, 7], micro positioning stages [8], scanning microscopy and atomic force microscopy (AFM) [9]. Most of these applications involve the use of compliant mechanisms (composed of flexure joints instead of bearing joints) due to their advantages in achieving high-fidelity, friction-free motion. Issues of backlash, wear and lubrication are avoided and they can also be easier to fabricate.

Due to assembly error, kinematic model error, thermal drift and elastic effects, a micromanipulation system may still not be sufficiently accurate when using local/decentralized control of actuators. To improve accuracy requires additional sensors to measure the position of the end-effector/platform, ideally in real-time. However, standard sensor systems having micrometric resolution and centimeter ranges have restricted application. For instance, interferometers have large range and very high resolution but can be bulky and are able to measure rectilinear motion only. Multi-direction
measurement requires a combination of several sensors, which may not be possible due to restrictions on space or geometry [10]. An alternative for noncontact sensing with several measurement directions is to use a digital microscope vision system. However, this then requires developing a suitable approach for closed-loop visual servoing, which is the focus of the present work.

There have been several works on visual servoing with digital microscopy based on image feature tracking where the working area is limited to the field of view of the microscope [2, 11, 12]. A method to achieve increased measurement range and working area for an X-Y stage was shown in [10] and [13], where a pseudo-periodic pattern (PPP) imprinted on the end platform allowed absolute position information to be obtained by image processing. However, this approach required a specially designed and fabricated patterned plate. Also, the processing algorithm is computationally intensive, which means update rates may not be sufficient for real-time feedback in motion servoing. An alternative considered in this paper is to use a uniform grid pattern on the end platform and implement an incremental tracking algorithm via image processing. This approach enables vision-based measurements over an extended workspace and allows update rates suitable for real-time servoing.

This paper describes a vision-based control approach for a flexure-jointed micromanipulation system with a Delta-like parallel kinematic architecture and rotary voice coil actuation. An initial comparison of linear and nonlinear PID feedback control in joint space is made. Nonlinear PID control is then augmented with task-space visual servoing to achieve enhanced speed, accuracy and stability of motion. The remainder of the paper is organized as follows: section 2 gives a system description. Basic dynamic characteristics and results from step response testing under PID control are presented in section 3. Section 4 describes the vision-based control method. Section 5 introduces an enhanced control combining nonlinear PID control with vision-based servoing. The final section draws conclusions.

2. System Description

2.1. A Flexure-jointed Micromanipulator

A desktop experimental motion platform has been created based on a Delta-type (3RUU) parallel kinematic architecture (figure 1). The system has been designed to achieve high fidelity translational motion of the end platform. The supporting arms for the platform have rigid links with compact flexure joints as integrated parts made by single-process 3D printing (stereolithographic process with photoreactive resin). This allows simple and low-cost manufacture of the system without sacrificing attainable motion precision. The three arms are driven by rotary voice coil actuators having angular range of ±17º. The mechanism overall size is approximately 250x250x100 mm. A selection of flexure-hinge designs are shown in figure 2. A simple notch design with a round cutout from both sides (figure 2a) is commonly used in micro-positioning manipulators, e.g. [8, 14]. Longer beam-like flexures, as shown in figures 2b-2d can achieve higher range of bending motion. To achieve high angular range with a more compact joint, a series connection of flexures may be adopted [5]. The design used for the current system is a compact S-beam flexure, as shown in figure 2e. The joint is sufficiently compliant to give an angular range of motion of approximately ±16º.

2.2. Workspace Simulation

The kinematic equations for the mechanism can be derived using a pseudo-rigid-body modeling (PRBM) approach where a revolute joint is considered to be located at the center of each flexure [15]. Hence, we consider 3 parallel RUU chains (as in [16]) but with some additional joint offset parameters that account for non-collocation of the revolute joints. This leads to an inverse kinematic solution in the form:

\[ \theta_i = 2 \tan^{-1} \left( \frac{-F_i \pm (E_i^2 + F_i^2 + G_i^2)^{1/2}}{G_i - E_i} \right), \quad i = 1,2,3 \tag{1} \]

where \( \theta_i \) are the angles for each actuator and \( E_i, F_i \) and \( G_i \) are length parameters that are functions of the link parameters and the Cartesian position of the end-platform.
**Figure 1.** Flexure-jointed micromanipulator with moving end-platform based on PKM architecture

**Figure 2.** Different types of flexure joints: (a)-(d) are from [5], (e) is current design

**Figure 3.** Simulated mechanism workspace: red dots define the reachable workspace and the blue box shows the operating workspace.

By using equation (1), an approximate workspace analysis for the flexure-jointed micromanipulator can be undertaken. Figure 3 shows the reachable workspace with boundary defined by red dots and the target operating workspace with boundary shown by the blue box having dimensions of 20x20x6 mm.
2.3. Experimental Setup

The experimental setup shown in figure 4 comprises the Delta mechanism, with three rotary voice coil actuators, placed on a vibration isolation table. A digital microscope (Point Grey FL3-U3-13Y3M-C camera with 10X DIN plan objective lens) is used for end platform observation. Rotation of the actuators is measured by 14-bit rotary magnetic absolute encoders (AS5048A). Joint control servo-loops are implemented on a microcontroller (STM32F4 Discovery) with a sampling frequency of 1000 Hz. The control actuation signal is output through DACs (MCP4922) via SPI communication, and these signals are input to H-bridge driver circuits which power the actuator coils.

![Figure 4. Experimental set-up for visual servoing.](image)

Image processing is performed on a desktop PC using OpenCV libraries. The camera image is 1280x1048 pixels on a 1/2-inch CMOS detector. Consequently, with 10X objective lens, the image scale factor is 0.48 μm per pixel. The image data can be used

1. to verify the accuracy of kinematic models
2. to assess performance of the joint control loops
3. for feedback control of measured platform position

The platform position measurement is achieved by observing the motion of a uniform grid pattern fixed on the top surface of the platform, as shown in figure 5. This grid pattern is a standard microscope reticle with grid spacing of 100 μm. The image processing technique is to be described in detail in section 4.

3. Behavior under PID Joint Angle Feedback

3.1. Frequency Response Characteristics

The dynamic properties of the mechanism can be assessed by frequency response testing. This requires measurement of how the system reacts to a sinusoidal input signal. The frequency of the input signal driving a single actuator was varied between 0.5 Hz and 200 Hz. Response information (amplitude/phase) was extracted from the output signal, which is the rotation angle for the actuated joint. The frequency response is acquired as shown in figure 6. Note that these results are for the open-loop (uncontrolled) mechanism.

![Figure 5. Grid pattern on platform top surface.](image)

Four resonant peaks are seen in the data at 5, 14.5, 16.5 and 75.5 Hz. The three low frequency modes relate to 3-DOF translational motion of the end platform. These natural frequencies are non-zero due to the intrinsic stiffness of the flexure joints: the joints produce elastic forces under rotation that tend to resist motion. The high frequency mode is associated with a resonance of the compliant structure and involves a more complex vibration pattern for the mechanism links.
These results show that the flexure-based mechanism exhibits a complex multi-mode response behavior due to the vibratory dynamics associated with the joint compliance. Although we can anticipate that established approaches to the control of parallel kinematic mechanisms (such as PID control or active disturbance rejection) might be applicable, the selection and tuning of controllers for good performance is more challenging.

Figure 6. Measured frequency response data for open loop system (excited by single actuator).

3.2. Task Space Transient Response

To control motion of the mechanism, the rigid body inverse kinematic model (RBIK) from equation (1) may be applied in combination with localized feedback control loops for each actuated joint, as shown in figure 7. In this way, the task-space (x-y-z) position demand variables may be specified to achieve the desired motion of the end platform. There are three main considerations for the control performance, which are

1. speed of response (settling time and rise time)
2. steady-state positioning accuracy
3. effect of disturbances, including noise

These aspects should be assessed with respect to the actual motion of the end platform. Without visual servoing, however, the steady-state positioning accuracy is highly dependent on the accuracy of the kinematic model.

An initial investigation of step response behavior under PID control of the actuators was performed focusing on planar (x-y) motion of the end platform. For each step response test, the x-position demand was changed repeatedly from 0 to 100 µm and then back to 0. Each step occurs immediately after the position of the platform has been maintained within δ pixels for 0.5 seconds. This allowed a comparison of basic performance measures for different controller gain settings. These were assessed using vision-based measurements. Rise time is assessed as the time taken to move between 10% and 90% of the final position change. Note that the steady-state response is subject to noise disturbance. Therefore, the settling time is defined as the time to reach and stay within δ pixels of the quasi-steady position (determined by a moving window average). Note that the value of δ for the settling criterion must be chosen to exceed the noise-induced oscillation of the end-platform. Therefore, a suitable value for δ must match the noise attenuation performance of the controller.

Experimental results are presented in figure 8 where the upper graph shows joint angle response at actuator 1 and the lower graph shows the end-platform motion in x direction. The measured angular position (red line) from the magnetic sensor has significant noise and is subject to a fairly coarse quantization. These sensors have 14-bit resolution and so the angle is quantized in steps of 0.022°. The
green line shows the same signal but with low-pass filtering. This is shown for visualization only. A red line on the lower graph shows the measured x-position of the end-platform obtained from the digital microscope via image processing (as detailed in the next section). The blue line on both graphs represents the reference (demand) signal in joint-space and task-space respectively.

![Figure 8](image)

(a) linear, low gain: PID1  (b) linear, high gain: PID2  (c) nonlinear: NPID

**Figure 8.** Step response measurements for different PID joint controllers.

Figures 8a and 8b show the responses obtained with different linear gain settings: low gain (PID1) and high gain (PID2). In figure 8a, gains are tuned to minimize noise-induced oscillation of the end-platform in steady state. This requires a low-gain setting which then gives a slow rise time but can achieve a small bound on the variation (oscillations) in steady-state positioning (to within 2 pixels or ±0.48 μm). On the other hand, in figure 8b gains were tuned as high as possible before the system became unstable. This gain setting gives fast rise time but there are large noise-induced oscillations under steady-state positioning (within 10 pixels or ±2.4 μm).

In order to exploit the advantage of both gain settings, nonlinear feedback gains are introduced. The nonlinear feedback gains are defined as

\[ K(\bar{e}, \alpha, \beta, \gamma, C) = \begin{cases} 
C \cdot \beta^{\alpha-1} & ; \ |\bar{e}| < \beta \\
C \cdot |\bar{e}|^{\beta} \text{sign}(\bar{e}) & ; \ \beta \leq |\bar{e}| < \gamma \\
C \cdot \gamma^{\alpha-1} & ; \ |\bar{e}| \geq \gamma
\end{cases} \]  

with

\[ \alpha = \ln \left( \frac{k_{h} \beta}{k_{l} \gamma} \right) / \ln \left( \frac{\beta}{\gamma} \right), \quad C = k_{h} \gamma^{1-\alpha} \]  

where \( k_{h} \) is maximum gain value, \( k_{l} \) is minimum gain value. Defining the joint angle error as \( e \) and low-pass filtered error \( \bar{e} \) and derivative \( \dot{\bar{e}} \), the control law is given by
\[ u = K_p(\varepsilon) + \int_0^\tau K_i(\varepsilon) d\tau + K_d(\dot{\varepsilon}) \dot{\varepsilon} \]  

(4)

\[ K_p(\varepsilon) = K(\tilde{e}, \alpha_p, \beta_p, \gamma_p, C_p) \]

\[ K_i(\varepsilon) = K(\tilde{e}, \alpha_i, \beta_i, \gamma_i, C_i) \]

\[ K_d(\varepsilon) = K(\tilde{e}, \alpha_d, \beta_d, \gamma_d, C_d) \]

This nonlinear PID law is adapted from [17, 18]. The basic form of the nonlinear gain function is shown in figure 9. It can be seen that when the error is large, the gain is large, which helps to achieve fast response when there is a large initial positioning error. When the error is small, the gain also becomes small, which helps to reduce the noise-induced oscillations for steady-state positioning. An upper bound on the gain value \( k_h \) is imposed to avoid issues with control input saturation. In the experiments, we set the maximum gain values to those used in figure 8b while the minimum gain values are those used in figure 8a. The limits of the transition interval \( [\beta, \gamma] \) were set by trial and error under observation of the response under step changes in position demand.

![Figure 9. The nonlinear gain as function of error.](image)

The step response under nonlinear PID control is shown in figure 8c. Fast rise time and small platform oscillation in steady-state are achieved. The details of the controller gain settings and step response performances are summarized in table 1.

It is clear from the results in figure 8 that the kinematic model error is significant. This is due to the limitations of the pseudo-rigid-body modeling approach, which does not capture the flexure deformation very accurately. It is seen that although the position demand in x direction is 100 \( \mu m \), the end platform moves by only 80 \( \mu m \), approximately. Compensation of errors in the inverse kinematic model can be achieved by the introduction of visual servoing, which will be discussed in the next section.

**Table 1. Controller gains and performance.**

| Parameter      | PID1 | PID2 | NPID       |
|----------------|------|------|------------|
| \( K_p \)      | 25   | 200  | 25-200     |
| \( K_i \)      | 500  | 5000 | 500-5000   |
| \( K_d \)      | 0.7  | 5    | 0.7-5      |
| Settling band  | 2 (0.96) | 10 (4.8) | 3 (1.44)   |
| Response times | \( T_{rise} \) | 1.2 | 0.3 | 0.3 |
|                | \( T_{settle} \) | 3.5 | 1 | 1 |
4. Visual Servoing Implementation

4.1. Image Processing
Real-time image processing is used to extract the end-platform position information from the digital microscope image. Previous work on the image processing problem and recognition algorithms for automated cell detection and injection has been reported in [1] and [12]. However, the processing problem here is quite different as motion tracking is achieved using a periodic pattern rather than a unique feature of the image.

The image processing procedure is shown in figure 10. First, a grey-level image is received from the microscope camera (figure 10a). This is converted to a binary image by adjusting the threshold intensity and then using a blurring function to isolate the grid crossing points. The blurring transforms the binary image back to grey-scale but with high intensity at the grid crossing points and low intensity elsewhere. Converting back to a binary image gives an array of white squares where each square matches a crossing point on the original grid pattern (figure 10b). By using standard functions from the OpenCV library (i.e. findcontour() and moments()), the center position of each square can be determined. The position measurement algorithm operates by tracking the grid intersection point that falls within a central region of the image, as shown by the red square in figure 10a. When the currently tracked intersection point moves outside the central region, a new intersection point moves inside, and this point is then tracked instead. In this way the position tracking operates similarly to an incremental encoder where the known spacing of the grid can be used to determine the absolute position of the end platform.

The image processing takes about 35 milliseconds. Following communication with the microcontroller to send the position data, the total elapsed time is approximately 45 milliseconds. Therefore, the update/sampling frequency for the vision-based control can be set to 20 Hz.

4.2. Coordinate Relations
To execute the vision-based position measurement, it is necessary to know the relation between the discretized image space and the task space. Here, we consider motion of the end-link platform in the horizontal plane only, i.e. for fixed z position.

The coordinate frames for the image space and task space are shown on figure 11 where the following elements are indicated:

\{O\}  Image coordinate frame (fixed in image)
\{S\}  Fixed frame for task space (fixed in image)
B     Current tracked point on end-link
A     End-link datum (fixed on end-link)
D     Reference point (target for end-link)

The image coordinate frame \{O\} is at the corner of the image space and is fixed with respect to the global reference frame (as the camera is fixed to the base frame). The global datum for the task space is
the frame \{S\} and the end-link datum (point \(A\)) is initially coincident with its origin. The position of the currently tracked point \(B\) in the image space is \(\mathbf{o}B = [u \ v]^T\). This may be offset from the end-link datum (point \(A\)) as the tracked point changes during motion. The position of the currently tracked point in the task space \(\mathbf{t}B = [x_m \ y_m]^T\) is obtained by a transformation \(^sA_o\) involving a shift and rotation operation, followed by a scaling by the image resolution \(\lambda\):

\[
^sB = \ ^sA_o(\mathbf{t}B - \mathbf{o}A)\]

where \(\ ^sA_o\) denotes the location of the origin of frame \{S\} with respect to frame \{O\} and

\[
^sA_o = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}.
\]

For the experiments, the image resolution is 0.48 \(\mu\)m/pixel.

![Figure 11. Frame of image and task space on the end-platform.](image)

The current tracked point will be translated from the end-link datum by an integer number of grid spacings. This offset is known if the changes in tracking point are counted during motion (similar to an incremental encoder but in 2D). This offset is given by

\[
\Delta p = \begin{bmatrix} m\Delta x \\ n\Delta y \end{bmatrix}^T
\]

where
- \(m\) is the grid increments in \(x\) direction
- \(n\) is the grid increments in \(y\) direction
- \(\Delta x\) is the grid spacing of in \(x\) direction
- \(\Delta y\) is the grid spacing of in \(y\) direction

Combining the current tracked point position with the offset correction gives the absolute position of the platform as

\[
p_m = \ ^sA = \ ^sB + \Delta p = [x_m + m\Delta x \ y_m + n\Delta y \ -]^T
\]

Note that position information for the \(z\) direction cannot be obtained from the image data and, hence, no image-based correction is applied to the \(z\) axis control.

The positioning error, based on the current demand position (point \(D\)), is

\[
e = p_d - p_m = \ ^sD - \ ^sA
\]

This information is used to modify the input to the inverse kinematics, as described in the next subsection.
4.3. Visual Servoing Strategy

Visual servoing will correct for the residual errors after using the inverse kinematic model for the initial joint commands. The image-based position error is operated on by a PI controller, as shown in figure 12. Definitions of the variables in figure 12 are given in table 2. In this way, the input to the kinematic model is compensated so that zero error can be achieved in steady-state. This type of control structure may be termed direct visual servoing as set-point adjustments for the joint control loops occur continuously (at the image update rate) [19]. There is still a challenge to achieve satisfactory dynamic performance as there is a dynamic coupling between the inner joint control loops and the outer vision-based feedback loop. It can be expected, based on quasi-static conditions, that using low gain settings for the vision feedback will achieve stable operation, but elimination of positioning error will then be slow. An empirically tuned visual servoing control, implemented with the optimized nonlinear PID joint control, is considered as a means to achieve enhanced performance, as detailed in the following section.

![Figure 12. Control block diagram for visual servoing.](image)

| Table 2. Definition of variables in figure 12. |
|-----------------------------------------------|
| Variable | Definition |
| $\theta_d = [\theta_{d1}, \theta_{d2}, \theta_{d3}]^T$ | demand angles for actuators |
| $\theta_e = [\theta_{e1}, \theta_{e2}, \theta_{e3}]^T$ | angle errors for actuators |
| $\theta_m = [\theta_{m1}, \theta_{m2}, \theta_{m3}]^T$ | actuator angles (measured) |

5. Enhanced Control

In this section, experimental results are reported for both step response and trajectory tracking tasks where the combination of joint feedback control and visual servoing is employed.

The step response tests involved the same operations as in figure 8, where step changes in demand of 100 microns were introduced. As before, three different cases are considered involving different PID joint controllers. Figures 13a and 13b show results with the linear PID gain settings (PID1 and PID2).
Figure 13c shows results with the nonlinear PID feedback (NPID). The vision-based PI feedback controller was applied for all three cases but was tuned empirically with joint controller PID1.

Note that the vision-based feedback is paused immediately following the step change in demand. This is because the initial motion (driven by the joint feedback loops) is so fast that reliable position information cannot be ensured. The vision feedback is enabled again when the speed of motion has dropped below a threshold level so that accurate vision-based tracking can be resumed. The remaining position error is then compensated through the vision feedback, which is evident as an additional change in the joint angle reference demand (that compensates for the kinematic model error).

Comparing figure 13 with figure 8, it is clear that the error related to kinematic modelling is compensated in steady-state but different rise times and settling times are achieved due to the different gain settings. The nonlinear PID controller again shows the best performance with rise time of approximately 1 second and settling time of approximately 1.5 seconds. Also, the end-platform position can be maintained within a range of 3 pixels in steady state. Note that, due to the vision-based compensation, this figure now relates to the absolute positioning accuracy, which is within ±0.72 microns.

In further experiments, tracking of a circular trajectory with a diameter of 1 mm was considered, as shown in figure 14 where the upper graph shows the task space trajectory and the lower graph shows the measured errors in x and y coordinates during motion. Test results are shown for vision-based servoing combined with linear (PID1) and with nonlinear (NPID) joint control. Figures 14a and 14b are for path velocities of 52 and 104 microns per second respectively.

It can be seen that tracking errors are similar for both controllers for the slower speed task, and stay within approximately 6 microns (neglecting transients at start/end of motion). However, for the faster velocity task, tracking error is significantly increased for the linear PID controller (within approximately 20 microns), whereas the nonlinear PID controller maintains accuracy within approximately 8 microns.

6. Conclusions
A 3D-printed Delta-like micromanipulator with flexure-joints has been created as an experimental motion platform with nominal workspace of 20x20x6 mm. Using linear PID control of the actuated joints was found to have significant limitations as low gain settings gave good platform stability (noise rejection) but speed of response and tracking accuracy were poor. High gain settings gave improved speed of response but resulted in unacceptable platform vibration. By using a nonlinear PID controller, advantages from both low gain (less oscillation) and high gain settings (fast response time) could be realized in a methodical and effective manner.
With joint feedback control only, significant errors in absolute positioning occurred due to deficiencies in the inverse kinematic model, which was based on pseudo-rigid-body modelling methods. To eliminate steady-state positioning error, a vision-based feedback control was implemented via a digital microscope system. This allowed high accuracy to be achieved in both step response and trajectory tracking tasks. The best performance was obtained in combination with nonlinear PID joint control, for which absolute positioning accuracy within 3 pixels, (1.44 μm) could be achieved and tracking errors were maintained within approximately 8 microns for contouring tests with circular trajectories.

There is scope for improvement for this system, as response times were still affected by error in the kinematic model. Although errors are compensated by the vision-based feedback, the speed of compensation was limited due to the relatively slow sample rates. Further work will aim to improve control performance by refining the kinematic model, either through on-line calibration/adaptation or by improving the theoretical model to better account for compliance behavior of the flexures.

![Image](a) path velocity of 52 microns per second (b) path velocity of 104 microns per second

**Figure 14.** Tracking performance for circular trajectory.

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