



Robust micro/nano-positioning by visual servoing

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IRISA

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Micro/nano-technology



Project context

- ANR (French National Research Agency) Nanorobust project
- Fundamental aspects in micro/nano-materials characterization and positioning in Scanning electron microscopes (SEM)
- Collaboration of 4 French laboratories



• IRISA



• ISIR-UPMC





DES SYSTÈME





Robotics in micro/nano-scale

- Automated micro/nano-manipulation and assembly
 - to characterize the properties of nanostructures
 - for nanomaterial manufacturing
- Visual information is one of the most important way to observe the micro/nano-object
- Motivation: achieve robust micro/nano-positioning tasks using visual servoing techniques



One-by-one positioning of seven nanodiamonds using a nanomanipulation stage in a SEM (MIT,US)



A microfabricated electrostatic gripper inside a SEM to pick up silicon nanowires (DTU, Denmark)





Vision-based control in micro/nano-scale

• Visual servoing: control the robot motion based on visual information [Hutchinson,96] [Chaumette,06]



- Vision-based control in micro/nano-scale
 - Handling guidance [Koyano,96] [Vikramaditya,97]
 - Fusion of force sensing and visual feedback [Zhou,98]
 - Multiview system [Sun,04][Probst,09]
 - 2 DoFs [Marturi,14], 3 DoFs [Sievers,05] [Ru,11] [Tamadazte,12] [Gong,14],
 6 DoFs (by CAD model-based tracking) [Kratochvil,09] [Tamadazte,10]





Challenges

- Vision instrument: *microscope*
 - Scanning electron microscope (SEM)
 - Image formation process & geometric projection models : different from the optical camera
- Robotic platform
 - Installed inside the SEM vacuum chamber
 - Small step resolution (increment) and high accuracy









Scanning Electron Microscope

- Generating images by scanning the surface of the sample using electron beam
- Magnification: 10x to 500,000x



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SEM image issues

• Image quality vs. scan speed: find a good compromise



Medium scan speed

Fast scan speed

images acquired by Zeiss EVO LS 25 SEM (ISIR)





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SEM image issues

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- Image quality vs. scan speed: find a good compromise
- Image drift: almost insignificant in a short time



Image at Time1Image at Time2Observe the same area on the fixed sample

Image difference

images acquired by Zeiss EVO LS 25 SEM (ISIR)





Content



Outline

SEM calibration

- Controlling the motion along the depth direction
- Micro and nano-positioning by visual servoing
- SEM autofocusing
- Visual tracking and pose estimation







SEM calibration

• To determine the relation between the 3D coordinates of a point on the observed sample and its projection on the image plane



- Challenges with a SEM
 - Geometric projection models selection [Sinram,02] [Cornille,03]
 - Spatial distortions [Schreier,04] [Malti,12]









- Perspective projection
 - at low magnifications







- Perspective projection
 - at low magnifications
- Parallel projection
 - at high magnifications







- Perspective projection
 - at low magnifications
- Parallel projection
 - at high magnifications







Geometric projection models [Sinram,02] [Cornille,03]

Perspective projection

- at low magnifications
- Parallel projection
- at high magnifications Image spatial distortions
 - a) Radial distortion
 - b) Skewness
 - c) Spiral distortion







SEM calibration parameters

Parameters to be estimated in calibration:

- Intrinsic parameters: SEM property provided by manufacturers p_x, p_y : pixel/meter ratio $\xi = (p_x, p_y, u_0, v_0)$ u_0, v_0 : coordinates of the principle point
- Extrinsic parameters: microscope pose in the world coordinates

$$\mathbf{r} = (X, Y, Z, \theta_X, \theta_Y, \theta_Z)$$

Perspective projection

• Parallel projection
$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} p_x & 0 & u_0 \\ 0 & p_y & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} c_X \\ c_Y \\ c_Z \\ 1 \end{bmatrix}$$
Point coordinates in image plane in pixel
$$V = \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} p_x & 0 & 0 \\ 0 & p_y & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} c_X \\ c_Y \\ c_Z \\ 1 \end{bmatrix}$$

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$$\mathbf{r} = (X, Y, Z, \theta_X, \theta_Y, \theta_Z)$$

• Perspective projection

• Parallel projection
$$\begin{bmatrix}
u \\
v \\
1
\end{bmatrix} =
\begin{bmatrix}
p_x & 0 & u_0 \\
0 & p_y & v_0 \\
0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0
\end{bmatrix}
\begin{bmatrix}
c_X \\
c_Y \\
c_Z \\
1
\end{bmatrix}$$
Point coordinates in image plane in pixel
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1 & 0 & 0 \\
0 & 1 & 0 \\
0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
c_X \\
c_Y \\
c_Z \\
1
\end{bmatrix}$$



Non-linear calibration process

- Minimize the residual error by modifying the intrinsic parameters and the extrinsic parameters simultaneously
- Cost function $(\widehat{\mathbf{r}}, \widehat{\xi}) = \underset{\mathbf{r}, \xi}{\operatorname{argmin}} \sum_{i=1}^{N} ({}^{i}\mathbf{x}_{p}(\mathbf{r}, \xi) {}^{i}\mathbf{x}_{p}^{*})^{2}$
- Initial estimation computed by a linear algorithm [Zhang,00]
- Update the pose **r** and the intrinsic parameters ξ iteratively $\mathbf{v} = \begin{bmatrix} \dot{r} \\ \dot{\xi} \end{bmatrix}$

$$\mathbf{V} = -\lambda \mathbf{J}_p^+(\mathbf{x}_p(\mathbf{r},\xi) - \mathbf{x}_p^*)$$

• Temporal variation of pixel positions

$$\dot{\mathbf{x}}_p = \frac{\partial \mathbf{x}_p}{\partial \mathbf{r}} \frac{d \mathbf{r}}{d t} + \frac{\partial \mathbf{x}_p}{\partial \xi} \frac{d \xi}{d t} \quad \Longrightarrow \quad \dot{\mathbf{x}}_p = \mathbf{J}_p \mathbf{V} \quad \mathbf{J}_p = \begin{bmatrix} \frac{\partial \mathbf{x}_p}{\partial \mathbf{r}} & \frac{\partial \mathbf{x}_p}{\partial \xi} \end{bmatrix}$$



Multi-image calibration

Use images from different poses of the calibration pattern:

 \mathbf{x}_{p}^{i} : a set of images features extracted from the *i*th image:



Jacobian:





Pose 1

Pose 2



Pose 3

Pose 4

Experimental validations

- Zeiss Auriga 60 SEM (Femto-ST) and Zeiss EVO LS 25 (ISIR)
- Magnification : 300x to 10,000x
- Medium and fast scan speeds
- Multi-scale calibration pattern: square size from 1 µm to 25 µm
 - Rotation around Z axis from 0° to 40°
 - Tilt from 0° to 8°



(Femto-ST)







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Experimental images from Auriga 60 SEM (Femto-ST)



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Experimental images from Auriga 60 SEM (Femto-ST)



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images acquired at



Experimental validations





green: yellow: estimated (4) points positions points reprojection computed from intrinsic & extrinsic parameters



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Experimental results

Spatial distortions insignificant

Magnification M (x)	estimated distortion parameters				
	k	γ	<i>s</i> ₁	<i>s</i> ₂	
500	-5.65x10 ⁻⁹	0.0024	8.64x10 ⁻⁷	7.19x10 ⁻⁷	
2000	-3.67x10 ⁻¹⁰	0.0033	-1.28x10 ⁻⁷	2.79x10 ⁻⁷	
5000	-1.15x10 ⁻¹⁰	0.0061	-2.87x10 ⁻⁷	9.68x10 ⁻⁷	

Estimated distortion parameters (Auriga 60 SEM)

L. Cui, E. Marchand. Calibration of Scanning Electron Microscope using a multi-images non-linear minimization process. In *IEEE Int. Conf. on Robotics and Automation*, ICRA'14, Pages 5191-5196, Hong Kong, China, June 2014.

L. Cui, E. Marchand. Scanning electron microscope calibration using a multi-image non-linear minimization process. *Int. Journal of Optomechatronics*, 9(2):151-169, May 2015.





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Experimental results

- Spatial distortions insignificant
- Difficult to observe the motion along the depth direction
 - Perspective projection is not validated

Magnification (x)	$Z_I(\mu m)$	P _x	P _y	residual error (pixel)
500	15752.7	70168.0	70058.3	0.15
1000	22302.1	201505.3	199729.8	0.08
2000	6803.4	122073.3	122312.0	0.12
5000	2316.2	103917.4	105067.7	0.23

Calibration results with perspective projection (Auriga 60 SEM)

Badly estimated Z position and intrinsic parameters

L. Cui, E. Marchand. Calibration of Scanning Electron Microscope using a multi-images non-linear minimization process. In *IEEE Int. Conf. on Robotics and Automation*, ICRA'14, Pages 5191-5196, Hong Kong, China, June 2014.

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Experimental results

- Spatial distortions insignificant
- Difficult to observe the motion along the depth direction

o_x , p_y (pixel/µm)

- Perspective projection is **not** validated
- Parallel projection is validated

Mag. <i>M</i> (x)	P_x/M	P_y/M
500	0.00895	0.00888
1000	0.00898	0.00895
2000	0.00898	0.00904
5000	0.00897	0.00910

ratio for parallel projections are constant



Estimated intrinsic parameters w.r.t. magnifications with parallel projection (by Auriga 60 SEM)

L. Cui, E. Marchand. Calibration of Scanning Electron Microscope using a multi-images non-linear minimization process. In *IEEE Int. Conf. on Robotics and Automation*, ICRA'14, Pages 5191-5196, Hong Kong, China, June 2014.

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Observation along the depth direction

To obtain the depth information from microscopic images:

• Stereo vision [Tunell,11] [Fan,14]

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- Using image sharpness information
 - Depth from focus [Nayar,94] [Subbarao,95]
 - Depth from defocus [Subbarao,94] [Ziou,01]



Varying depth position

images acquired by Zeiss EVO LS 25 SEM (ISIR)



Observation along the depth direction

To obtain the depth information from microscopic images:

- Stereo vision [Tunell,11] [Fan,14]
- Using image sharpness information
 - Depth from focus [Nayar,94] [Subbarao,95]
 - Depth from defocus [Subbarao,94] [Ziou,01]



Varying depth position

To achieve visual servoing tasks along the depth direction:

 observing the image sharpness as a visual feature to perform the control law



images acquired by Zeiss EVO LS 25 SEM (ISIR)



Visual feature to control Z motion

- Sharpness function selection for microscopic images [Sun,05] [Rudnaya,10]
 - derivative-based functions: gradient, Laplacian...
 - statistical functions: variance, autocorrelation, histogram, entropy...
 - transform-based functions: DFT, DWT...



Image defocus model

Using a general imaging model for SEM images [Nicolls, 97]

$$\mathbf{I}(x, y, Z) = \mathbf{I}^*(x, y, Z^*) * \underbrace{f(x, y)}_{\text{depends on } |Z - Z^*| \text{ and SEM}}$$
$$\mathbf{I}(x, y, Z) = \sum_{u} \sum_{v} \mathbf{I}^*(x - u, y - v, Z^*) f(u, v)$$

• Point spread function: using a Gaussian kernel

$$f(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}}$$

 σ : Standard deviation of Gaussian kernel





Control law

• Visual feature: image gradient

$$G = \sum_{x=0}^{M} \sum_{y=0}^{N} (\nabla I_x^2(x,y) + \nabla I_y^2(x,y))$$

Cost function

$$\hat{Z} = \operatorname{argmin}_{Z} \left(G(Z) - G^* \right)^2$$

Control law

$$v_z = -\lambda L_G^{-1}(G(Z) - G^*)$$

• Compute Jacobian

$$\dot{G} = L_G v_z \implies L_G = \frac{\partial G}{\partial \sigma} \frac{\partial \sigma}{\partial Z}$$
 approximated as a constant [Lai,92]

• Derivative of the image gradient

$$\frac{\partial G}{\partial \sigma} = \sum_{x=0}^{M} \sum_{y=0}^{N} 2\left(\nabla I_x(x,y) \frac{\partial \nabla I_x(x,y)}{\partial \sigma} + \nabla I_y(x,y) \frac{\partial \nabla I_y(x,y)}{\partial \sigma}\right)$$



Experimental validation along depth direction

Magnification: 1000x

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Hybrid visual servoing for 6-DoF positioning tasks

- Image sharpness information as a visual feature for the motion along the depth direction
- Image photometric information as a visual feature for other 5 DoFs




Image intensity as a visual feature

• Minimize the image intensity error [Collewet, TRO, 11] between the desired image and current image:

$$\mathbf{e}_I(\mathbf{r}) = \mathbf{I}(\mathbf{r}) - \mathbf{I}^*(\mathbf{r}^*)$$

Control law

$$\dot{\mathbf{q}} = -\lambda \mathbf{J}_I^+ \mathbf{e}_I$$

• Time deviation of a pixel intensity *I* is $\dot{I} = -\nabla I \mathbf{L}_{\mathbf{x}} \mathbf{v}$ where $\nabla I = \begin{bmatrix} \frac{\partial I}{\partial x} & 0\\ 0 & \frac{\partial I}{\partial y} \end{bmatrix}$

For a whole image

$$\dot{\mathbf{I}} = \begin{pmatrix} -\nabla I_{00} \mathbf{L}_{\mathbf{x}} \\ \vdots \\ -\nabla I_{MN} \mathbf{L}_{\mathbf{x}} \end{pmatrix} \mathbf{v} = \mathbf{L}_{\mathbf{I}} \mathbf{v}$$





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L. Cui, E. Marchand, S. Haliyo, S. Régnier. 6-DoF automatic micropositioning using photometric information. In *IEEE/ASME Int Conf. on Advanced Intelligent Mechatronics*, AIM'14, Pages 918-923, Besançon, July 2014.



Hybrid visual servoing

- use image intensity
 - velocities along 5 DoFs:

$$\dot{\mathbf{q}} = -\lambda \mathbf{J}_I^+ \mathbf{e}_I$$

• for eye-to-hand visual servoing

$$\mathbf{J}_{I} = -\mathbf{L}_{\mathbf{I}}{}^{c}\tilde{\mathbf{V}}_{F}{}^{F}\tilde{\mathbf{J}}_{n}(\mathbf{q})$$

 ${}^{c}\tilde{\mathbf{V}}_{F}$ the spatial motion transform matrix (5 DoFs) ${}^{F}\tilde{\mathbf{J}}_{n}(\mathbf{q})$ the robot Jacobian (5 DoFs)

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- use image gradient
 - velocity along depth direction:

$$\dot{Z} = -\lambda_z J_G^{-1} e_G(Z)$$

• Jacobian

$$J_G = -L_G{}^c \tilde{V}_F{}^F \tilde{J}_n(Z)$$



Experimental setup

- Positioning stage
 - SmarPod: 6-DoF parallel kinematics robot
 - Travel range (by manufacturer):
 - Translation: +/- 6 mm for x,y; +/-3 mm for z
 - Rotation: $+/- 8^{\circ}$ mm for x,y; $+/- 15^{\circ}$ mm for z
- Vision sensor
 - Optical microscope: Basler acA1600-60gm
 - SEM: Zeiss EVO LS 25









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Experiments conducted at



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Experimental validation using an optical microscope

Magnification: 60x

[ICRA,2015]



L. Cui, E. Marchand, S. Haliyo, S. Régnier. Hybrid Automatic Visual Servoing Scheme using Defocus Information for 6-DoF Micropositioning. In *IEEE Int. Conf. on Robotics and Automation*, ICRA'15, Pages 6025-6030, Seattle, WA, May 2015.

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Experimental setup in a SEM

- Specimen:
 - Membrane (indium phosphide and silicon)
 - Calibration rig (gold and silicon)
 - MEMS (silicon and oxide)



Experiments conducted at



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Experimental validation with a SEM

Magnification: 1000x





Outline

- SEM and calibration
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SEM autofocusing

- Autofocus
 - Correct device focus by automatically regulating the focus sets
- Challenges
 - Robust and fast SEM autofocusing scheme is required
 - SEM imaging is different from the optical camera imaging









SEM focusing geometry

- SEM components
 - Condenser lens
 - Objective aperture
 - Objective lens
- (Electronic) Working distance W





SEM focusing geometry

- SEM components
 - Condenser lens
 - Objective aperture
 - Objective lens
- (Electronic) Working distance W







SEM focusing geometry

- SEM components
 - **Condenser lens**
 - **Objective aperture**
 - **Objective lens**
- (Electronic) Working distance W





SEM Autofocus approach

- Objective
 - Maximize the image sharpness by changing the working distance
- Possible ways to reach the optimum of image sharpness
 - Searching-based [Batten,00] [Rudnaya,09]: Fixed stepsize search, Fibonacci search...
 - Polynomial regression [Rudnaya,12]
 - On-line estimation [Marturi, 13]
- Designing a closed-loop control system
 - Visual feature: image gradient
 - Control law



Control law

• Visual feature: image gradient

$$G(W) = \sum_{x=0}^{M} \sum_{y=0}^{N} (\nabla I_x^2(x, y) + \nabla I_y^2(x, y))$$

• Minimize the function

$$\varepsilon(W) = \alpha e^{-\beta G(W)} - \gamma$$

• Working distance update:

$$\dot{W} = -\lambda J_{\varepsilon}^{-1}\varepsilon$$

Jacobian

$$J_{\varepsilon} = \frac{\partial \varepsilon}{\partial W} \\ = -(\varepsilon + \gamma)\beta J_G$$





Experimental validation

- Jeol JSM 820 SEM (Femto-ST)
 - magnification: 300x to 2000x
 - different scan speeds
- Specimen:
 - calibration rig
 - silicon micropart





L. Cui, N. Marturi, E. Marchand, S. Dembélé, N. Piat. Closed-Loop Autofocus Scheme for Scanning Electron Microscope. In *Int. Symp. of Optomechatronics Technology*, ISOT 2015, Neuchatel, Switzeland, October 2015.



Experimental validation



Experiments conducted at



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Outline

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Visual tracking and pose estimation in SEM

- Current tracking algorithm in SEM
 - Template-based matching [Jasper,10]
 - Active contours model [Sievers,06] [Fatikow,08]
 - CAD model-based matching [Kratochvil,09] [Tamadazte,10]
- Challenges
 - Images could be blurred due to the motion along z axis
 - Difficult to estimate the depth information
- Proposed solution
 - Involve the defocus in the template-based matching approach

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• Estimate depth position from defocus information



Template-based tracking in presence of defocus blur

4-DoF motion tracking

- Template registration
 - Transformation: $w(\mathbf{x}, \mathbf{p}), \mathbf{p} = (\theta, t_x, t_y)$
 - Defocus: Gaussian kernel $f(\mathbf{x}, \sigma)$
- σ : standard deviation of Gaussian kernel

 $w(\mathbf{x}, \mathbf{p}), f(\mathbf{x}, \sigma)$ \mathbf{x} \mathbf{x} \mathbf{x} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{x} \mathbf{y} \mathbf{x} \mathbf{x}





Template-based tracking in presence of defocus blur

4-DoF motion tracking

- Template registration
 - Transformation: $w(\mathbf{x}, \mathbf{p}), \mathbf{p} = (\theta, t_x, t_y)$
 - Defocus: Gaussian kernel $f(\mathbf{x}, \sigma)$
 - σ : standard deviation of Gaussian kernel
- Minimize the dissimilarity between the appearance of the template and the current image at a certain position.

Consider sum of squared differences (SSD):

$$\begin{cases} \hat{\mathbf{p}} = \underset{\mathbf{p}}{\operatorname{arg\,min}} \sum_{\mathbf{x} \in W} (\mathbf{I}(w(\mathbf{x}, \mathbf{p}), \sigma) - \mathbf{I}^{*}(\mathbf{x}))^{2} \\ \hat{\sigma} = \underset{\sigma}{\operatorname{arg\,min}} \sum_{\mathbf{x} \in W} (G(\mathbf{I}(w(\mathbf{x}, \mathbf{p}), \sigma)) - G(\mathbf{I}^{*}(\mathbf{x})))^{2} \end{cases}$$

G: norm of image gradient

$$G = \sum_{x=0}^{M} \sum_{y=0}^{N} (\nabla I_x^2(x, y) + \nabla I_y^2(x, y))$$





x-y translation t_x, t_y *z* rotation θ

Defocus blur level



Experiments on 4 DoFs



Medium scan speed 383 ms/frame



Fast scan speed 95 ms/frame





Partial pose estimation by image registration

• The projection $\mathbf{x} = (u, v, 1)^{\top}$ of a point ${}^{w}\mathbf{X} = ({}^{w}X, {}^{w}Y, {}^{w}Z, 1)^{\top}$:

 $\mathbf{x} = \mathbf{K} \boldsymbol{\Pi}^c \mathbf{T}_w{}^w \mathbf{X}$

- ${\bf K}\,$: sensor intrinsic parameters estimated in calibration process
- Π : parallel projection matrix

 ${}^{c}\mathbf{T}_{w}$: sensor/object frame transformation to be estimated

• Estimate point position from warping

$$\hat{\mathbf{x}}_2 = \mathbf{R}\bar{\mathbf{x}}_1 + \mathbf{t}$$
 $\mathbf{t} = (t_x, t_y)^{\top}$
 $\mathbf{R} = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix}$

 Minimize the error between the re-projected position and the estimated position using non-linear optimization

$$\hat{\mathbf{r}} = \operatorname*{arg\,min}_{\mathbf{r}} \sum_{i=1}^{N} ({}^{i}\mathbf{x}(\mathbf{r}) - {}^{i}\hat{\mathbf{x}})^{2} \quad \mathbf{r} = (X, Y, \theta_{Z})$$



Depth position estimation

- General idea: estimating depth position from image gradient
- Hidden Markov model



- Particle filter: Bayesian-based method
 - State: position on depth direction

$$\mathbf{S}_k = \mathbf{F}(\mathbf{S}_{k-1}, \boldsymbol{\nu}_{k-1})$$

• Observation: image gradient

$$\mathbf{O}_k = \mathbf{H}(\mathbf{S}_k, \boldsymbol{\varepsilon}_k)$$





Depth position estimation

• State evolution model

$$\mathbf{S}_{k} = \begin{pmatrix} Z_{k} \\ \dot{Z}_{k} \end{pmatrix} = \begin{pmatrix} 1 & \Delta t \\ 0 & \alpha \end{pmatrix} \begin{pmatrix} Z_{k-1} \\ \dot{Z}_{k-1} \end{pmatrix} + \begin{pmatrix} 0 \\ \beta \end{pmatrix} \nu_{k-1}$$

- Observation: image gradient
 - approximate the relation between image gradient and depth position





Depth position estimation

• State evolution model

$$\mathbf{S}_{k} = \begin{pmatrix} Z_{k} \\ \dot{Z}_{k} \end{pmatrix} = \begin{pmatrix} 1 & \Delta t \\ 0 & \alpha \end{pmatrix} \begin{pmatrix} Z_{k-1} \\ \dot{Z}_{k-1} \end{pmatrix} + \begin{pmatrix} 0 \\ \beta \end{pmatrix} \nu_{k-1}$$

- Observation: image gradient
 - approximate the relation between image gradient and depth position

$$\mathbf{O}_k = G(Z) = \frac{p_0 + p_1 Z + p_2 Z^2}{q_0 + q_1 Z + Z^2} + \varepsilon$$

• Prediction [Arulampalam,02]

$$p(\mathbf{S}_k | \mathbf{O}_{1:k}) \approx \sum_{i=1}^{N_p} \omega_k^i \delta(\mathbf{S}_k - \mathbf{S}_k^i)$$

 ω_k^i weight of particle i in $k^{ ext{th}}$ iteration

Updating weights

 $\omega_k^i \propto \omega_{k-1}^i e^{-\tau \epsilon_k}$

 ϵ_k registration error



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Experimental results





images acquired at



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SEM Calibration

- parallel projection validated
- distortions: insignificant



[ICRA,14] [Int. J. Optomechatronics]





SEM Calibration

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[ICRA,14] [Int. J. Optomechatronics]

difficult to observe the motion along Z axis





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[ICRA,14] [Int. J. Optomechatronics]

difficult to observe the motion along Z axis

Robot motion control along depth direction

• using defocus information





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[ICRA,14] [Int. J. Optomechatronics]

difficult to observe the motion along Z axis

Robot motion control along depth direction

• using defocus information

6-DoF micro/nanopositioning



hybrid visual servoing

[AIM,14] [ICRA,15]





SEM Calibration

- parallel projection validated
- distortions: insignificant



[ICRA,14] [Int. J. Optomechatronics]

difficult to observe the motion along Z axis

Robot motion control along depth direction

• using defocus information







- parallel projection validated
- distortions: insignificant







Perspective

- Visual servoing for micro/nano-positioning tasks
 - More experimental validations
 - at high magnifications (e.g. 10,000x)
 - with different samples (3D objects, complex textures)
 - by new SEM and new robotic platform (Femto-ST)
 - Depth direction motion control
 - frequency domain based method
 - on-line estimation of Jacobian





Perspective

- Visual servoing for micro/nano-positioning tasks
 - More experimental validations
 - at high magnifications (e.g. 10,000x)
 - with different samples (3D objects, complex textures)
 - by new SEM and new robotic platform (Femto-ST)
 - Depth direction motion control
 - frequency domain based method
 - on-line estimation of Jacobian
- SEM autofocus
 - by controlling image rotation





Perspective

- Visual servoing for micro/nano-positioning tasks
 - More experimental validations
 - at high magnifications (e.g. 10,000x)
 - with different samples (3D objects, complex textures)

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- by new SEM and new robotic platform (Femto-ST)
- Depth direction motion control
 - frequency domain based method
 - on-line estimation of Jacobian
- SEM autofocus
 - by controlling image rotation
- Visual tracking and pose estimation in a SEM
 - Observation of magnification changes
 - Tracking the motion on 6 DoFs


Perspective

- Visual servoing for micro/nano-positioning tasks
 - More experimental validations
 - at high magnifications (e.g. 10,000x)
 - with different samples (3D objects, complex textures)
 - by new SEM and new robotic platform (Femto-ST)
 - Depth direction motion control
 - frequency domain based method
 - on-line estimation of Jacobian
- SEM autofocus
 - by controlling image rotation
- Visual tracking and pose estimation in a SEM
 - Observation of magnification changes
 - Tracking the motion on 6 DoFs
- Micro/nano-manipulation tasks by visual servoing









Thanks for your attention

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