POSE ESTIMATION OF MOBILE MICROROBOTS IN A SCANNING ELECTRON MICROSCOPE A cross-correlation based approach using ROI's

Torsten Sievers, Sergej Fatikow Division of Microrobotics and Control Engineering, University of Oldenburg Uhlhornsweg 84, 26111 Oldenburg, Germany

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Abstract: In this paper, current research towards an automated micro/nano handling station using mobile microrobots is presented. Mobile microrobots with piezo slip-stick actuation and more than one degree of freedom mostly don't have internal pose sensors; therefore a global sensor is needed. This paper focuses on the pose estimation of the mobile microrobots. One possibility for fast pose estimation is the application of video cameras as global sensors. For pose estimation with accuracy even in the nanometer range high resolution sensors are necessary. In consideration of resolution, image acquisition time and depth of focus a Scanning Electron Microscope (SEM) is a powerful sensor for high resolution pose estimation. But the use of a SEM makes high demands on the image processing. High update rates of the pose data for the robot control enforce a short image acquisition time of the SEM images. Hence the image noise increases, because frame averaging or averaging of the detector signal is time consuming. This paper presents a method to calculate the x,y position and the orientation of a micro object in a strongly noised SEM image stream with cross-correlation in real-time. To make real-time pose estimation possible, only a region-of-interest (ROI) is correlated with the target pattern. The SEM is almost predestined to work with ROI's, because the scan area of the electron beam can be chosen arbitrarily.

1 INTRODUCTION

Micro- and nanohandling covers the field of handling objects with sizes in the range of µm, subum and even a few nm. The most important applications today are microassembly, semiconductor technology, nanotechnology, material research, medicine and biology. Within the last years a trend towards the automation of nanohandling processes emerged (Nakajima et al, 2004, Yang et al, 2003). The nanohandling station that is currently being developed aims at performing diverse nanohandling operations in the vacuum chamber of SEM by several mobile microrobots. In the next sections an experimental set-up as well as the visual sensor system architecture for an SEM-based nanohandling station is presented. The focus will be the image processing algorithms that determine the poses of the mobile microrobots. The pose information is directly used as visual feedback for

telemanipulation or by the control system of the workstation (Garnica et al, 2003).

2 EXPERIMENTAL SETUP

The setup of the mobile microrobot-based nanohandling station, which has been used, is depicted in Fig. 1. For an easy handling, the setup is mounted on a removable SEM door for LEO 1450. In detail, the setup mainly consists of mobile microrobots, a linear z-stage and a visual sensor system consisting of cameras and the SEM. The concept of the presented setup is that a mobile platform works as sample holder to move a sample in the correct pose in the field of view of the SEM. A second mobile platform carries micro/nano tools like micro grippers or AFM tips for the manipulation of the sample. In (Kortschack et al, 2004) the functionality and characteristics of the mobile

Sievers T. and Fatikow S. (2005). POSE ESTIMATION OF MOBILE MICROROBOTS IN A SCANNING ELECTRON MICROSCOPE - A cross-correlation based approach using ROI's. In Proceedings of the Second International Conference on Informatics in Control, Automation and Robotics - Robotics and Automation, pages 193-198 DOI: 10.5220/0001178201930198 Copyright © SciTePress platforms has been described. The high-level control architecture and low-level control algorithms are presented in (Hülsen, 2004).

The sample holder consists of a mobile platform moving on a glass plate. This glass plate can be moved in z-direction via a piezo actuator (PiezoMotorTM) with a traveling range of 2 cm. For the pose estimation of the z-position the optical sensor Mercury 3000V from MicroETM has been used. Both mobile platforms (stage platform with sample holder and manipulator platform) are built up on the stick slip principle and have three degrees of freedom – two translational and one rotational.

Additionally, on top of the stage platform another platform has been mounted upside-down. However, instead of using it as a translational stage, a metal sphere is put on the ruby spheres. This sphere serves as the sample holder. By applying a saw-tooth voltage to the piezo discs, the upper platform is able to rotate the sphere around three axes, whereby only two rotational movements are allowed by the control software.



Figure 1: Setup of the mobile microrobot based nanohandling station (outside the SEM)

In summary, the whole stage has seven degrees of freedom, whereby one rotational degree is blocked by the control software.

To begin a manipulation process, the sample to be manipulated and the manipulator have to be positioned in field of view of the SEM. First, the sample is positioned by the sample platform, and then the manipulator is positioned in the center of the SEM image. The positioning tasks for both platforms are divided into the two sub task coarse and fine positioning. Coarse positioning is carried out with visual feedback from CCD cameras (sec. 3) and fine positioning by processing SEM images (sec. 4).

3 VISUAL SENSORS

Because of the fact that the mobile platforms have no internal position sensors analogue CCD cameras with PAL resolution (768x576 pixels) have been used to determine a global pose (x, y, φ). Each camera is equipped with an IR-LED ring light. Because the secondary electron detector of the SEM is sensitive to light in the visual spectrum infrared LEDs are necessary. One approach for the automated coarse positioning of a mobile microrobot has been described in (Fatikow et al, 2004).

Pose estimation of the micro robot has been achieved by a small marker placed onto the underside of the robot, which will be tracked (Fig. 2). The estimated poses of the micro robot are represented as a string and sent to the control PC by TCP/IP communication protocol. The approach described in (Fatikow et al, 2004) used the Geometric Model Finder (GMF) of the Matrox Imaging Library 7.5 (MIL) to determine the orientation of the mobile platform (www.matrox.com). With this algorithm a resolution better than 0.5 mm is possible, which will be sufficient to position the microrobot's end-effector into the scan-field of the SEM, if the magnification of the SEM is low. The algorithm allows a sensor update rate of 15 poses per second, by using a standard PC (2.6 GHz) (Fatikow et al, 2004).



Figure 2: View from the CCD cameras (top left: sphere, top right: manipulator platform, bottom: sample platform)

The requirement for live processing of SEM images is a fast access to the digitized images. We are using two SEM's in our lab, a Zeiss DSM 950 and a LEO 1450. The Zeiss DSM 950 has no built-in digital image acquisition. Thus we are using additional hardware from point electronic[™] with an external beam control and digital image acquisition via a PC interface (www.pointelectronic.de) (Fig. 3). Although the LEO 1450 is equipped with a digital image acquisition the point electronic hardware is used, too, because no software interface for directly accessing the images and controlling the electron beam is delivered by the SEM vendor. A second advantage of using the point electronic hardware for both devices is that the developed software doesn't have to be SEM specific.



Figure 3: Setup of the image processing system

4 POSE ESTIMATION WITH SEM IMAGES

4.1 Region of interest

Due to the fact that the control system needs the position and orientation e.g. of an end-effector, the scan speed of the SEM has to be well above 1 frame per second. Approximately 10 poses per second is a good data rate for the control system. However, this leads to low image quality and noisy images. Therefore a trade-off between image quality and scanning speed is looked for. A good solution to find such a trade-off is the definition of a Region of Interest (ROI), which can be done with the digital SEM hardware with software interface from point electronic. Using ROI's is common in image processing especially in visual tracking to decrease computational costs, but with a SEM as sensor

The advantage of the ROI is that the electron beam of the SEM scans only a small part of the whole scan field. This leads to a higher scan speed, whereby the image acquisition time can be decreased. In addition, the ROI can be defined in a way that only the interesting object is in the ROI. This leads to a matching of the target without any miss matches. If the target is moving, then a new ROI will be defined around the centre of gravity of the next pattern match. Only in the worst case that the target can't be determined, the whole scan field will be used again. With this technique the processing speed and the robustness of the algorithm can be improved.

4.2 Cross-correlation

Powerful methods for object detection and position estimation in extremely noisy images are correlation techniques. Detailed work regarding correlation based techniques for processing noisy images and many applications are presented in (Goudail, Réfrégier, 2003). In this paper the application of correlation to SEM images is described.

Correlation is a very useful method to find objects in extremely noisy SEM images. The disadvantage is a high computational cost, which will increase with the image resolution. If orientation and scale of the target object are needed the computational cost will increase further. Hence, there are limits when applying correlation to realtime object tracking. With the use of ROI's, as described in the previous chapter, the performance drawback can be overcome. A solution for the estimation of the orientation is presented in the next chapter.



Figure 4: SEM image (640x480 pixels) of the gripper with an acquisition time of 0.1s (lower left). The pattern is an average of 10 images with a size of 128x128 pixels. The gripper is described in (Mølhave et al., 2004)

The result of a cross correlation between two images is a matrix which shows possible displacements of similar input images. Cross correlation is defined as (Weisstein):

$$\mathbf{C} = F^{-1} \left[\mathbf{I} \cdot \mathbf{P}^* \right]$$

Where I is the Fourier transformed of the input image i and P^* is the complex conjugated of the Fourier transformed of the target pattern p. F^{-1} denotes the inverse Fourier transformation and C the correlation coefficient matrix. To get the correlation coefficients in the range [-1...1] normalization is needed:

$$N = \frac{1}{\sqrt{\sum_{k,l} i_{k,l}^2 \cdot \sum_{k,l} p_{k,l}^2}}$$

This leads to the normalized cross correlation matrix:

$$C_N = C \cdot N$$

If the maximum value of C_N is equal to 1, both images are completely correlated. The combination of using cross correlation with ROI's is depicted in figure 3.

If the maximum exceed a predefined threshold, the position of the maximum peak of the correlation matrix defines the position of the gripper.

4.2.1 Orientation estimation

The estimation of the orientation of the gripper with cross correlation is more complex. One possibility is correlating the input ROI with rotated patterns. Thus the time consumption for the pose estimation will increase strongly. To limit this disadvantage the maximum number of correlations per slope cycle has been restricted. Therefore a pattern vector has been generated with 360 components, each rotated by one degree. For every slope cycle only three adjacent patterns (p_{j-1}, p_j, p_{j+1}) will be selected from the pattern vector and are correlated, where j denotes the angle. If the starting orientation is known, the pattern p with the same orientation and the patterns with $+1^{\circ}$ and -1° are chosen. For every slope cycle the pattern with the maximum correlation will be estimated and set as p_j . Subsequently the new p_{j-1} and p_{j+1} are selected. The flow diagram of the algorithm is depicted in figure 4. To detect rotations with more than 1 degree between two frames the orientation estimation is repeated a few times for the current frame. If the cross-correlation coefficient for p_{i+1} (respectively p_{i-1}) is smaller than p_i , the correct orientation is estimated.



Figure 5: Cycle of the pose estimation algorithm using cross correlation

The limit of this approach is that only continuous orientation changes can be measured. Orientation changes between two frames with more than a few degrees cannot be tracked fast enough. For the pose estimation of an end-effector mounted on a mobile platform, this drawback is negligible because only slow rotations are possible.

4.2.2 Start ROI

To start the tracking, the target pattern has to be found in the full size SEM image. The starting problem can be solved by using the algorithm described above. Therefore, the SEM image is separated into sub images, each with the same size as the pattern. Experiments carried out so far have shown that an overlap of the sub images isn't necessary. Generally, an overlap of some pixels is meaningful to make sure that the correct target will be found. For every sub image and every component of the orientation pattern vector the crosscorrelation has to be calculated. The position of the maximum of the sub image with the highest correlation is set as the centre of the start ROI.

The disadvantage of this approach is the high computing time, which depends on the size of the image and the pattern. One possibility to speed up the estimation of the start ROI is image resizing. Decreasing image and pattern by a factor 8, for example ($640x480 \rightarrow 80x60$ pixels and $128x128 \rightarrow 16x16$ pixels), results in an approximately 8 times

faster ROI estimation. To reduce the number of calculations the number of components of the pattern vector has been reduced to 18. The accuracy loss has been compensated by one succeeding cross-correlation calculation with full resolution (ROI and pattern with 128x128 pixels) and complete pattern vector. Another possibility is a hierarchical search in the frequency domain. But if only one resize step is needed the performance difference is negligible

5 RESULTS

The algorithm has been tested with two micro objects, a gripper and TEM-lamellae. The gripper is mounted on the manipulator platform and the wafer with the lamellae is fixed on the sample platform. In the presented case the frame rate of the SEM is set to 11 fps (frames per second) with an image resolution of 640x480. Frame averaging is switched off, thus all frames have been captured with the worst quality. The 128x128 pixel patterns have been generated by averaging 10 frames. In figure 3 an image of the gripper can be seen. The TEM-lamellae is depicted in figure 5. The captured sequence is a typical visual servoing task for mobile microrobots of the nanohandling cell, presented in Sec.1. First, a micro or nano object has to be positioned to a predefined pose in the SEM image automatically. Accordingly, the manipulator tool has to be positioned close to the object. Because the accuracy of the coarse positioning is too low, three SEM magnification steps with different patterns will be used. Changing the magnification of the SEM doesn't lead to a break in the automation process, because the LEO 1450 is equipped with a remote control via RS232.



Figure 6: TEM-lamellae with box dimension of $18\mu m \ x \ 10\mu m$

The accuracy of the pose estimation is 1 pixel for the x,y position, which means approximately 40 nm in real world coordinates. The accuracy of the orientation estimation is 1°. The computation speed depends strongly on the pattern size and the number of cross-correlations per frame. In the presented case the average number of cross-correlations per frame is between 3 and 4. With a standard PC (P4, 2.6 GHz), the computation time is 0.02 s for one pose estimation without orientation calculation and approximately 0.07 s with orientation. With a SEM frame rate of 10 fps real-time capability has been demonstrated. Only for the first frame 0.8 s are needed to determine the start ROI.

The acquisition time for one pixel is 250 ns. Therefore the minimum image acquisition time for a 128x128 ROI is about 4.1 ms. The user can chose between a high frame rate with low image quality and a slower frame rate with better image quality. In general, one should adopt the frame rate to the processing time of the pose estimation algorithm. Therefore an adaptive scan speed has been implemented.

The disadvantage of the cross correlation approach is that changes of the targets shape are hard to recognize. For every magnification of the SEM, the pattern has to be adapted, because the scale of the target changes with the magnification. If only few magnification steps are used this problem can overcome by using additional patterns. A more serious problem is shape variation by deformation, e.g. while a gripping process.

6 CONCLUSION

The real-time pose estimation of micro- and nanoobjects inside a SEM image stream requires image processing algorithms with high robustness against noise. Cross correlation is a powerful method to overcome this problem. The disadvantage that computation time is very high can be compensated by using ROI's. Here an advantage of the image acquisition process of SEM's can be used. Because only a small region will be scanned, one can choose between high image acquisition speed and high image quality in comparison with a full size scan. Overall this leads to real-time capability for the sensor system. The presented approach enables automatic positioning of mobile microrobots with nanometer resolution, which is a further step towards automatic nanohandling.

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