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Instantaneous Velocity Estimation of Magnetic Microrobots with Visual Tracking *

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***Abstract* - Motion controlling the magnetic microrobot automatically is a huge challenge. A closed-control of magnetic microrobots actuated by electromagnetic manipulation systems can realize the precise and automatic motion control. In order to control the microrobot automatically, tracking and calculating the instantaneous velocity of microrobots are necessary in closed-loop state. A fast tracking via spatio-temporal context（STC） learning algorithm is applied for real-time microrobot tracking. In precision, success rate and computing times that is better than other tracking methods. The instantaneous velocity of magnetic microrobots for different rotational propulsion frequencies was estimated by STC method in real time. The experimental results show that proposed tracking algorithm can be used for visual servo of magnetic microrobots.**

Index Terms – Instantaneous velocity. Magnetic microrobots. Spatio-temporal context.

I. Introduction

Magnetic microrobots have potential applications[1] in biomedicine such as targeted therapy[2], biopsy[3]and in-vivo sensing[4]. Magnetic helical microrobots (Figure 1) have been fabricated and can rotate by following a rotating magnetic field in a liquid environment. They use a bio-inspired corkscrew strategy for propulsion in which rotational motion converts to translational motion. The velocity of the magnetic microrobot can be controlled by changing the frequency of the rotating magnetic field, and by changing the direction of the axis of rotation of the magnetic field the motion direction of the magnetic microrobot can be controlled. Their motion behavior must be understood so that they can be effectively controlled and application.

The motion performance of the magnetic microrobot determines the difficulty of the microrobot control. For a single magnetic microrobot the average velocity can be used to characterize the motion performance. If the positions of the microrobot in the first time and the last are known, as well as the flight time, the average velocity can be easily calculated by known displacement and time. But this is an offline approach to study the magnetic microrobots. It can't be used to control the microrobot. The purpose of the fabricated microrobot is to realize the automation application. Motion controlling the magnetic microrobot automatically needs a closed-control. Due to the size of microrobots, On-board sensors can't be applied to measure the position of the microrobot. External sensing method is required to position the magnetic microrobot, such as computer vision. The instantaneous velocity has to be estimated in real time with computer vision for controlling the magnetic microrobot primely.

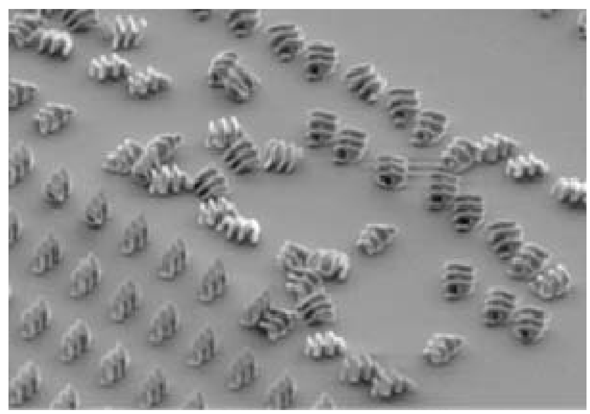

Fig.1 Helical microrobots fabricated with Direct Laser Writing.

Visual tracking techniques can be used to estimate the instantaneous velocity of microrobots. Many tracking methods have been proposed for object tracking, but selecting the best tracker remains a challenging and somewhat complicated task. In controlling the microrobot, we need the tracker to be fast, and the delay is as small as possible. In this paper, a STC learning algorithm was applied for real time microrobot tracking. This tracking method has higher tracking performance than other tracking methods in precision, success rate and computing times. After we know the position of the magnetic microrobot in each frame image, it is easy to precisely evaluate the instantaneous velocity of microrobots viewed under a microscope in real time.

This paper is organized as follows: In Section II the instantaneous velocity estimation of microrobots is briefly introduced. In Section III the STC method for positioning the microrobots in each frame image is presented in detail. In section IV all kinds of experiments verify that the used method

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can estimate the instantaneous velocity of microrobots. Finally, conclusions are drawn.

II. INSTANTANEOUS VELOCITY ESTIMATION OF MICROROBOTS

If we know the position of the microrobot in the each frame image and the frame rate of the used camera, the instantaneous velocity can be calculated easily. The instantaneous velocity can be calculated as

$$\mathbf{v} = \frac{\Delta s}{\Delta t} \tag{1}$$

Where v is the instantaneous velocity vector of the magnetic microrobot and $\mathbf{v} \in \mathbb{R}^2$ (one camera is used in 2D space), Δs is displacement of the magnetic microrobot and $\Delta s \in \mathbb{R}^2$. The displacement expresses the position changing of the magnetic microrobot during the time interval Δt . The Δt is the time between two successive frames. If we get the position of magnetic microrobot between two successive frames, we can get the displacement vector Δs. It is computed using the Euclidean distance formula.

$$\Delta s = \sqrt{(x_A - x_B)^2 + (y_A - y_B)^2} \tag{2}$$

Where $(x_A, y_A)$is the previous position in image and $(x_B, y_B)$is present position in image.

III. POSITION OF MICROROBOTS IN EACH FRAME IMAGE

In order to get the accurate instantaneous velocity, it is necessary to accurately obtain the position of the microrobot in each frame image. This is a target tracking problem in computer science. Generally, all tracking methods face many challenges including sensor noise, scene changes, object pose changes, occlusions and illumination changes[5]. Here the positioning of the magnetic microrobots has a higher request to the target tracking method. The application of the tracking method must be highly precision, high success rate and less time consumption.

There is a strong spatio-temporal relationship with the local scenes containing the microrobot in consecutive frames. When the microrobot is moving, the local context containing the microrobot changes weakly as the overall appearance is similar and only a small part of the context region is changed. In this method a confidence map was computed[6].

$$\begin{aligned} c(x) &= P(x \mid o) \\ &= \sum_{c(z)\in X^c} P(x, c(z) \mid o) \\ &= \sum_{c(z)\in X^c} P(x \mid c(z), o) P(c(z) \mid o) \end{aligned} \tag{3}$$

Where x is a microrobot location and o is the microrobot present in the scene. The context prior probability $P(c(z) \mid o)$ represents appearance of the local context. The conditional probability $P(x \mid c(z), o)$ represents the spatial relationship between the microrobot location and its context information.

The conditional probability function is defined as

$$P(x \mid c(z), o) = h^{sc}(x - z) \tag{4}$$

The context prior probability is defined as

$$P(c(z) \mid o) = I(Z)\omega_\sigma(z - x^*) \tag{5}$$

I(z) is the image intensity. ω_σ is the weighted function.

$$\omega_\sigma(z) = ae^{-\frac{|z|^2}{\sigma^2}} \tag{6}$$

Where a is normalization constant that makes $P(c(z)|o)$ to range from 0 to 1 and σ is a scale parameter.

The confidence map of a microrobot location is modeled as

$$\begin{aligned} c(x) &= P(x \mid o) = be^{-|\frac{x-x^*}{\alpha}|^\beta} \\ &= \sum_{z\in\Omega_c(x^*)} h^{sc}(x - z) I(z)\omega_\sigma(z - x^*) \\ &= h^{sc}(x) \otimes (I(z)\omega_\sigma(z - x^*)) \end{aligned} \tag{7}$$

Where ⊗ denotes the convolution operator.

First, the tracking location in the first frame was initialized. We can track the microrobot as follows,

At the t frame,

(1)Learning spatial context model,

$$h^{sc}(x) = F^{-1}\left(\frac{F(be^{-|\frac{x-x^*}{\alpha}|^\beta})}{F(I(z)\omega_\sigma(x - x^*))}\right) \tag{8}$$

(2)Update of spatio-temporal context

$$H^{stc}_{t+1} = (1-\rho)H^{stc}_t + \rho h^{sc}_t \tag{9}$$

At the t+1 frame,

(1) Calculate the confidence map,

$$h^{sc}(x) = F^{-1}\left(\frac{F(be^{-|\frac{x-x^*}{\alpha}|^\beta})}{F(I(z)\omega_\sigma(x - x^*))}\right) \tag{10}$$

(2)Find the maxim value in the confidence map,

$$x^*_{t+1} = \arg\max c_{t+1}(x) \tag{11}$$

From (10) we can see that calculating confidence map can be transformed to the frequency domain. It is a Fast Fourier Transform(FFT) algorithm using fast convolution. With this spatio-temporal relationship we can track the position of the magnetic microrobot in the each frame image.

IV. EXPERIMENTS

In order to verify the capability of the STC method for positioning the magnetic microrobot in the each frame image and the accuracy of the calculated instantaneous velocity, a series of experiments are done.

The magnetic microrobots in the experiments are helical microstructures and were fabricated using 3D direct laser writing. Magnetic material was deposited on the surface of the structures by electron beam evaporation. The detailed fabrication process and the fabrication protocol can be found in [7]. Figure 2 shows the fabricated helical microrobots. The fabricated helical microrobots have the same magnetization direction and are controlled with an electromagnetic manipulation system(Helmholtz coils). It can control the motion of the magnetic microrobots in 6-DOF(x, y, z, roll, pitch, yaw). The system can produce rotating magnetic fields up to 10 mT and at frequencies up to 200 Hz. Detailed information about this system can be found in these literature [7]. The motion of the microrobots is recorded by a top camera. In Figure 2 black points are the magnetic helical microrobots. In order to see multiple microrobots and its long distance movement in one scene, low magnification is necessary to see all microrobots. The magnetic microrobots are actuated at a frequency range from 10 Hz to 90 Hz.

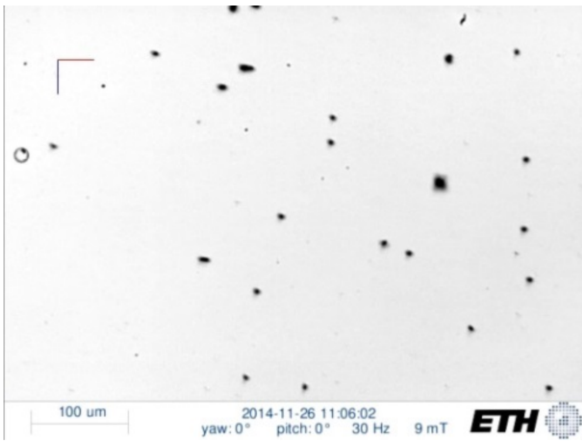


Fig.2 Snapshot of image sequence. The black points are the microrobots.

Before we select the STC tracker, we evaluate the twelve trackers in tracking precision and time consumed. According to the overall scores, the STC tracker is the best tracker and selected from the twelve trackers. Table I shows the twelve tracking methods.

To measure the tracking precision the center location error in pixels is defined as the Euclidean distance between the manually labelled ground truth centers and the estimated microrobot centers. However, when the target is not tracked, the tracking location is random and the center location error may be calculated incorrectly[19]. The tracking precision is as the percentage of frames whose estimated location is within the given threshold distance of the ground truth. The threshold=20 pixels is the representative precision score for each tracking method. We use STC method to compare with other tracking methods.

TABLE I. TRACKING METHODS

Method	Implementation	Image Features	Approach
STC[6]	Matlab	correlation between low level features	Bayesian framework
CT[8]	Matlab	Low dimensional Compressive feature	Tracking by detection
FCT[9]	Matlab	dimensional compressive feature	Tracking by detection
TLD[10]	Matlab	Gray Level image patches	Hybrid tracking
STRUCK[11]	C++	Gray Level image patches	Tracking by detection
IVT[12]	Matlab	Grayscale image vectors	Particle filters
VTS[13]	Matlab	Hue, saturation intensity, edge	Particle filters
SRPCA[14]	Matlab	Gray level image patches	Particle filters
KFC[15]	Matlab	Gray level image patches	Correlation filters
LSR[16]	Matlab	Grayscale image patches	Tracking by detection
PLS[17]	Matlab	Low-dimensional discriminative feature subspace	Particle filters
SCM[18]	Matlab	Haar like features	Tracking by detection

Figure 3 and figure 4 show the error plots for a video sequence. In the figure the color lines show the precision of each tracking method at the different pixel threshold. From the test results it can be seen that the success rate of nine methods is100% when the pixel threshold is more than 5. The methods TLD and VTS have low success rate. The success rate of the method IVT is 100% when the pixel threshold is more than 10. The methods STC and LSR were the most accurate methods in the video. The methods were tested with the same initial tracking window. In fact, some of the trackers are sensitive to the initial tracking window. Moreover, different parameters of the trackers may affect the precision.

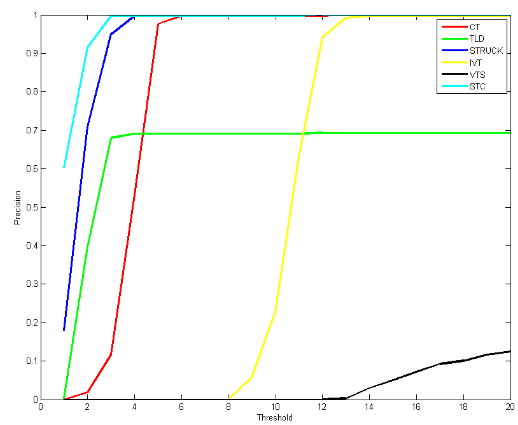


Fig.3 Center location error in pixel threshold for one video sequence.

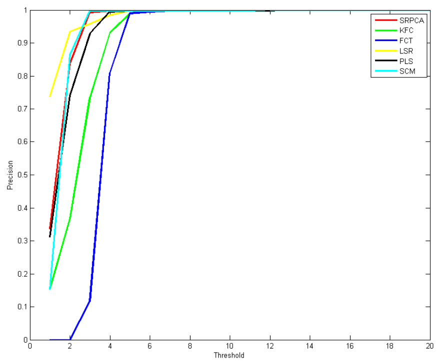


Fig.4 Center location error in pixel threshold for one video sequence.

When the tracker is to be used in a closed-loop control system to obtain the location and instantaneous velocity of a microrobot, the processing speed of the tracker is very important. We also compared the computing time of each method in table 1. The experiments are conducted on a Windows PC equipped with 2.4GHz dual core processor and 8GB RAM. All algorithms were programmed in MATLAB except STRUCK. Figure 5 shows the computation times of the algorithms. The computing times of the algorithms is less for three tracking methods STC, KFC and FCT. It is clear that STC can track about 90 frames per second and reach real time performance. Meanwhile, it has high tracking precision. The trackers VTS and LSR are processing less than one frame per second. LSR has the highest tracking precision. CT, TLD and STRUCK were processing about 30 frames per second. These trackers can track objects with low speed.

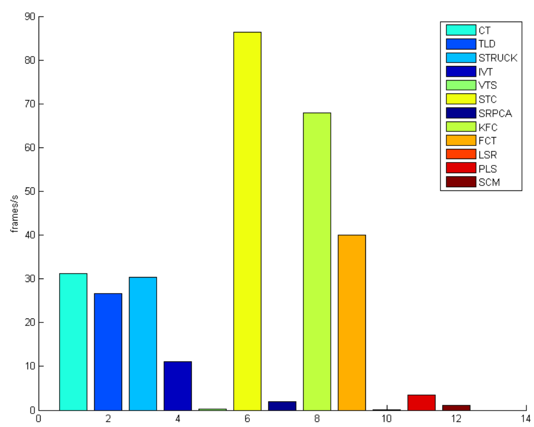


Fig.5 Comparison of computation time for different trackers

The performance testing results show that STC is the best method to position the magnetic microrobot in precision, success rate and computation time. It can be applied to evaluate the instantaneous velocity of the magnetic microrobot in real time. Figure 6 shows the tracking trajectories of different microrobots with the electromagnetic manipulation system at 25Hz, 35Hz, 45Hz and 55Hz using STC. It shows that each microrobot has its own motion trajectory and a different motion direction.

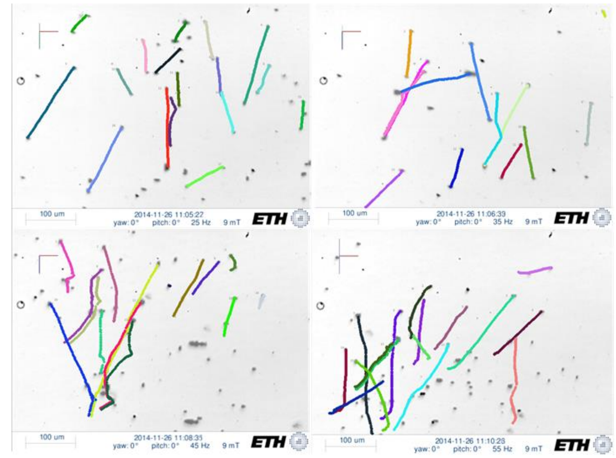
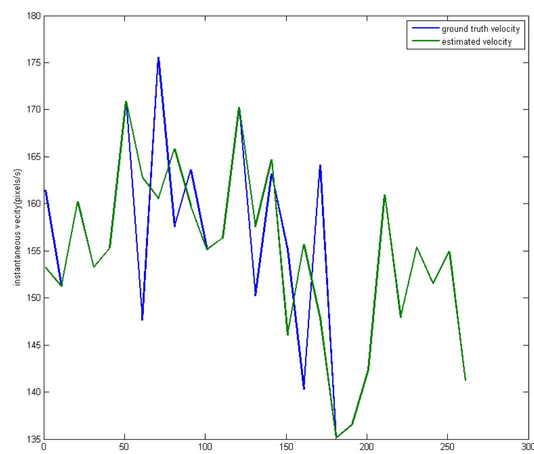
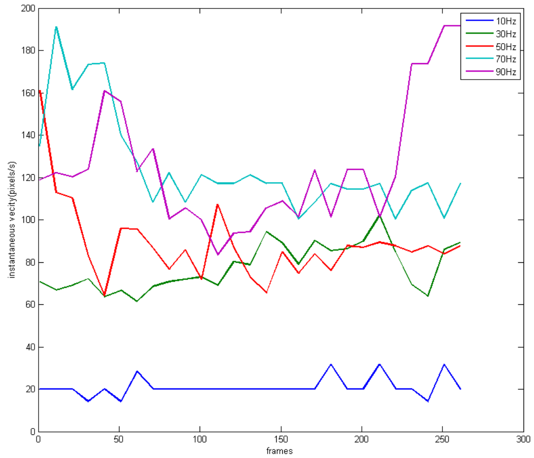


Fig.6 Tracking trajectories of different microrobots with STC.

The instantaneous velocity was calculated by formula (1). STC was applied to get the position of the magnetic micrrorobot in each frame image in real time. The time interval was recorded between two successive frames. We use many videos to evaluate the instantaneous velocity with proposed method. Figure 7(a) shows the instantaneous velocity of one of many magnetic microrobots. The blue line is the ground truth instantaneous velocity and the green line is the estimated instantaneous velocity. From the figure we find that the ground truth instantaneous velocity and the estimated instantaneous velocity is basically the same.



(a)



(b)

Fig.7 (a) Instantaneous velocity of one microrobot with STC, (b) Instantaneous velocity of a microrobot with STC at different control frequencies.

Figure 7(b) shows the instantaneous velocity of one microrobot at different control frequencies. From the figure we can see that at a low frequency the microrobot has a constant velocity, and, with the frequency increased, the instantaneous velocity is higher and its fluctuations are intense. This result only represents the motion of one magnetic microrobot. In one scene the differences of the instantaneous velocities of multiple microrobots actuated at the same control frequency are more obvious.

V. CONCLUSION

The position and instantaneous velocity of magnetic microrobots are important for closed-loop control. The visual tracking technique can position and estimate the instantaneous velocity. In order to track the microrobots precisely, robustly and fast, in this paper we use STC method to position the magnetic microrobots in the each frame image and estimate the instantaneous velocity of the microrobot. The experimental results show that the STC has the best performance of the tracking method in precision, success rate and computing time comparing with other tracking method. It can be applied to the automatic control of the magnetic microrobot. In the future we will apply the instantaneous velocity for evaluating the performance of the magnetic microrobot and controlling the microrobots automatically.

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