The Depth Information Estimation of Microscope Defocus Image Based-on Markov Random Field

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***Abstract*—For depth information estimation of microscope defocus image, a blur parameter model of defocus image based on Markov random field has been present. It converts problem of depth estimation into optimization problem. An improved Iterated Conditional Modes Algorithm has been applied to complete optimization problem, which the select of initial point employed Least squares estimate algorithm prevents that the result gets into local optimization. The experiments and simulations prove that the model and algorithm is efficiency.**

***Keywords*—microscope vision, Markov random field, depth estimation, the blur model, Iterated Conditional Modes**

I. INTRODUCTION

The microscope vision is a stress approach which micromanipulation robotic obtains external information. As we know, the microscope vision with single CCD camera can only obtain 2D information in task space. In order to operate the object in 3D space, It is a exigent problem we encountered that obtains the depth of the object (namely, Z direction position of robotic.). To obtain the depth of micromanipulation from 2D plane image is a research hot topic in microscope vision. Many peoples[3][4][5][6] have done something to deal with it. Usually, There are several methods to obtain the depth of object. One is that employs stereo vision to restore the 3D image from the 2D image, which the algorithm of stereo match is very difficult. The second method we focused on is that computes blur characterization of image in the frequency domain to obtain depth. Third, As a representative, Pentland[7][15] has presented the method of Depth from Defocus based the blur image, which computes image object's depth from two blur images in same scene, with changing the inner and external parameter of CCD camera. Pentland's method depends on CCD camera system model and precise system parameter.

Since the change in the depth of a scene is usually gradual, the blur parameter tends to have local dependencies. Hence, we are motivated to model the blur parameter as a MRF[1][9]. A defocus image blur parameter model base MRF has been presented in this paper. It converts the depth problem into energy function optimization problem. Then, applies an improved Iterated Conditional Modes algorithm to optimization energy function, which the select of initial point employed Least squares estimate (LSE) algorithm prevents that the result gets into local optimization. Experiments and simulations confirm the efficiency of model and algorithm. This paper is organized as follows. Section two gives CCD camera imaging model of microscope vision defocus image, Section three constructs a blur parameter model of microscope defocus image based on MRF, The improved ICM[2][14] algorithm and it's implementation is presented in section four. Section five carries out experiments and simulations and conclusion is given in section six.

II. CCD CAMERA IMAGING MODEL OF DEFOCUS IMAGE

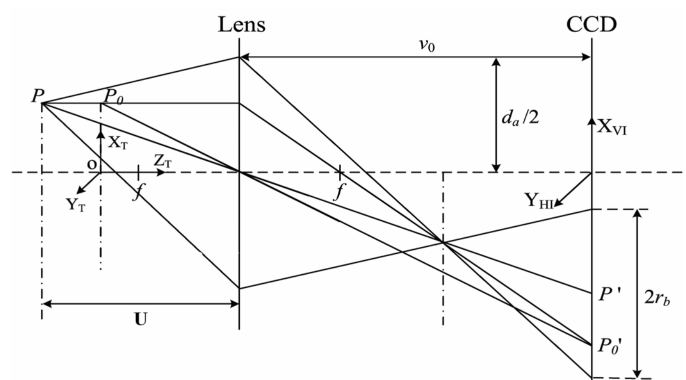

Figure 1. CCD imaging principle of microscope defocus image

CCD imaging principle is shown in Fig.1. According to CCD imaging principle, we can give formula as shown in (1)

$$\frac{1}{f}=\frac{1}{u0}+\frac{1}{v0} \tag{1}$$

Where f is the focus length, $u0$ is the distances from object to camera, and $v0$ is the distances from image focus point to camera lens. When the distances from object to camera lens is $u0$ and the distances from camera plane to camera lens is $v0$, we can obtain a clear image. If changes the distances from camera plane to camera lens, a blur image can be seen in CCD camera plane. When keeps a constant for camera parameter, It can be given the relationship between image defocus radius and the depth of image as shown in (2)

$$u = \frac{fv0}{v0 - f - Fr_b} \quad (2)$$

For formula (2), F is the F number of CCD lens. r_b is the defocus radius of image and u is the depth of the image. Therefore, There is a corresponding function relationship between the distances from CCD lens to object and the defocus radius of blur image, which can be used to obtain the depth of the image. According to formula (2), the positive or negative of distances u depends on if the focus image locates fore or back in image plane. We restrict that the distances of object is higher than the distances of image. The formula (2) can be converted into (3)

$$r_b = \frac{fv0}{F}\left(\frac{1}{f} - \frac{1}{v0} - \frac{1}{u}\right) \quad (3)$$

For two captured image with different focus length setting, we have formula (4)

$$r_b^{\,i} = \frac{f_i v_i}{F}\left(\frac{1}{f_i} - \frac{1}{v_i} - \frac{1}{u}\right) \quad \text{i=1,2} \quad (4)$$

For defocus image, the blur parameter is ρ and is given by $\rho = \beta r_b$, With giving value i=1 2 and eliminating u, the relationship of two defocus image's blur parameter is shown as (5)

$$\rho^1 = m\rho^2 + n \quad (5)$$

Since the blur parameter ρ^i at location (x, y) is related to the depth of the scene, we can construct a model of the blue parameter based on MRF, meaning that the depth of the scene can be obtained indirectly.

III. CONSTRUCTING THE BLUR PARAMETER MODEL BASED MRF

A. MRF and Gibbs distribution

For image function X in 2D image plane, it is thought as a 2D random field. Random variable set $X = \{X_s : s \in S\}$, it presumes that x_s is the realization of X_s. Pixel S's the neighborhood is N_s and meets the conditions of probability distribution as follows:

(1) $P(X_s = x_s) > 0$

(2) $P(X_s = x_s \mid X_r = x_r, r \in S, r \neq s) = P(X_s = x_s \mid X_r = x_r, r \in N_s)$

We calls that X is Markov random field[1][16] with neighborhood N_s. Gibbs distribution keeps a close relationship with MRF. Gibbs distribution with neighborhood N_s is expressed in formula (6)

$$P(X = x) = \frac{1}{Z} e^{-U(x)} \quad (6)$$

Where $U(x)$ is the energy function and represents as shown in (7)

$$U(x) = -\sum_{c \in C} V_c(x) \quad (7)$$

For formula (7), C is the set of cliques included by neighborhood N_s and $V_c(x)$ represents the potential function of clique. And $Z = \sum_x e^{-U(x)}$ is the partition function. For the model base on MRF, the second order neighborhood specifies some parameters. Then, we can define the corresponding potential function as follows:

$$V_c(x) = \begin{cases} +\lambda, & \text{if pixel value is same} \\ 0, & \text{otherwise} \end{cases} \quad (8)$$

Where λ represents clique parameter.

B. A blur parmeter model based MRF

Let X denotes the random fields corresponding to the blur parameter ρ^i, X can be modeled by MRF. Namely, it shows as in (8)

$$P(X = x) = \frac{1}{Z} e^{-U(x)} \quad (8)$$

If Y_1, Y_2 denote the random fields corresponding to the two observed images, the posterior probability can be expressed as (9)

$$P(X \mid Y_1, Y_2) = \frac{P(Y_1, Y_2 \mid X) P(X)}{P(Y_1, Y_2)} \quad (9)$$

Where $P(Y_1, Y_2)$ is a constant and $P(X)$ is the previous probability of the blur parameter. $P(X \mid Y_1, Y_2)$ is the posterior probability of the initial image, with knowing Y value .So, according to Bayes rules, the depth restoration of the defocus image can be converted into the problem that seeks the estimation of the original image when the posterior probability is maximization. Surely, There are two main problems we have deal with. (1) computes the previous probability; (2) computes the maximization posteriori probability (MAP). Now, we give the implementation above two problems, respectively.

IV. Implementation

A. The previous probability computation

Given X as the blur parameter of the defocus image, Let thinks X as a MRF, the previous probability $P(X)$ can be used Gibbs distribution to descript.

$$P(X)=\frac{1}{z}\left[e^{-\sum_{c\in C}V_c(x)}\right] \tag{10}$$

For given the observed images y1, y2, $P(Y_1=y1,Y_2=y2)$ is a constant. Considering the observation model given by (11)

$$y_k(i,j)=h_k(i,j)*f(i,j)+w_k \quad \kappa=1,2 \tag{11}$$

Where $f(i,j)$ is the clear focus image, $y_k(i,j)$ is the blur defocus image, $h(i,j)$ is the point spread function (PSF), w_k is the observed noise. $h(i,j)$ has a relation corresponding to the blur radius. Following, we assume the observations of the MRF image y_s obeys the model in (12)

$$y_s=f(x_s)+w_s \tag{12}$$

Where $f(x_s)$ is a function that maps x_s to μ_{x_s} and w_s are independently distributed Guassian random vectors with zero mean and unknown covariance matrix Θ_{x_s}. The PSF $h(i,j)$ is Gaussian with blur parameter. Hence, the probability $P(Y_1=y1,Y_2=y2\mid X)$ can be descript as Gaussian distribution and be shown as (13)

$$P(Y_1=y1,Y_2=y2|X)=e^{-\sum_s\frac{1}{2\sigma^2}(y_1-\mu_1)^2-\sum_s\frac{1}{2\sigma^2}(y_2-\mu_2)^2} \tag{13}$$

Then, formula (9) can be converted into (14)

$$P(X|Y_1=y1,Y_2=y2)=\frac{1}{z}e^{\left[\sum_{c\in C}V_c(x)-\sum_s\frac{1}{2\sigma^2}(y_1-\mu_1)^2-\sum_s\frac{1}{2\sigma^2}(y_2-\mu_2)^2\right]} \tag{14}$$

Based on the observed image y1, y2, the problem of depth estimation is to find the estimation $\hat{x}$ of X, which can computes the depth indirectly.

B. Improved ICM algorithm implementation

Base on discussion above, the posterior probability $P(X\mid Y_1,Y_2)$ about the original image can be converted into the optimization problem as shown in formula (15)

$$\min\left[-\sum_{c\in C}V_c(x)+\sum_s\frac{1}{2\sigma^2}(y_1-\mu_1)^2+\sum_s\frac{1}{2\sigma^2}(y_2-\mu_2)^2\right] \tag{15}$$

Now we employ Besag's Iterated Conditional Modes algorithm to complete the optimization problem. ICM algorithm has a highest efficiency and reliable performance[10][14]. Compared with simulation annealing[17] algorithm applying condition distribution to extract X, ICM algorithm searches condition distribution X when it is maximization. Note that, when each pixel has a few neighbours, this class is highly restricted by unobvious consistency conditions, it is necessary to preserve symmetry in naming neighbours: that is, if j is a neighbour of i then i must be a neighbour of j. As a result, we meet the conditions which ignores the large scale deficiencies of p(x) and selects a reasonable initial point to achieve a satisfactory result.

Besag's suggestion for initial parameter estimation adopts Maximum Likelihood Estimation (MLE). The MLE method has many large sample properties that make it attractive for use. It is asymptotically consistent, which means that as the sample size gets larger, the estimates converge to the right values. It is asymptotically efficient, which means that for large samples, it produces the most precise estimates. It is asymptotically unbiased, which means that for large samples one expects to get the right value on average. Unfortunately, the size of the sample necessary to achieve these properties can be quite large: thirty to fifty to more than a hundred exact failure times, depending on the application. With fewer points, the methods can be badly biased.

The least squares estimation method is quite good for functions that can be linearized. The calculations are relatively easy and straightforward, having closed-form solutions which can readily yield an answer without having to resort to numerical techniques or tables. Further, this technique provides a good measure of the goodness-of-fit of the chosen distribution in the correlation coefficient. Least squares is generally best used with data sets containing complete data, that is, data consisting only of single times-to-failure with no censored or interval data. Therefore, The choice of initial point is employed Least squares estimate (LSE) to complete.

1) Least squares estimate of initial parameters

The conditional distribution is given in (14) and the observations of the MRF obeys the model in (12). Choose parameter estimates to minimize sum of squared errors

$$N(\overset{\wedge}{\mu}_s)=\sum_{s=1}^{n}(y_s-\overset{\wedge}{\mu}_s)^2 \tag{16}$$

Differential with respect to parameter and set to 0 to get least squares estimates

$$\frac{\partial N}{\partial \hat{\mu}_s} = -2\sum_{s=1}^{n}(y_s - \hat{\mu}_s) = 0 \tag{17}$$

Then, the LSE are

$$\hat{u}_{x_s} = \frac{1}{n}\sum_{s} y_{x_s} \tag{18}$$

$$\hat{\Theta}_{x_s} = \frac{1}{M^2}\sum_{\Omega}(y - \hat{\mu}_{x_s})^2 \tag{19}$$

Where Ω is the complete set of M^2 pixels. We use (18) and (19) as the initial point of the ICM algorithm.

2) Steps of improved ICM algorithm

The steps of improved ICM algorithm as follows:

Step one: Obtain an initial estimate $\hat{x}$ of the true x, with guesses for δ.

Step two: Estimate δ by the value $\hat{\delta}$ which maximizes $P(y_1, y_2 \mid \hat{x}; \delta)$.

Step three: Carry out a single cycle of ICM (Step five to Step seven) based on the current $\hat{x}$,and $\hat{\delta}$, to obtain a new $\hat{x}$.

Step four: return to 2 for a fixed number of cycles or until computes repeat up to convergence.

Step five:(a single cycle of ICM) Given $\hat{x}$ denotes a estimate of the true scene x^*.

Step six: obtain a new $\hat{x}_i$ and use it to maximizes $P(y_{1i}, y_{2i} \mid x_i)$ at each i.

Step seven: judge if the number of cycles is arrived or not.

V. EXPERIMENTS AND SIMULATIONS

Microscopic visual servoing is the sensor-based control strategy in micro-assembly. The microscopic vision feedback has been identified as one of the more promising approaches to improve the precision and efficiency of micromanipulation tasks. Micromanipulation robotic system includes 3D micro-move platform(three micro manipulation hands.),micro-gripper driven by piezoelectricity, micro-adsorption hand driven by vacuum, microscope vision and so on, which microscope vision includes stereo microscope with variable times panasonic CCD camera, Tianmin SDK2000 image capture board. The captured image in visual system is 640X480 pixels.

Firstly, we construct the restoration model of the microscope vision defocus image based on MRF the same as (14). Presumes that the observed images are y1, y2 and defines Y as the restoration image. Y is thought as a MRF. Then, we can restore the defocus image similarly as (14). During micromanipulation experiments, presumes the microscope work distances (the distances from object lens to clear imaging plane.) u0 = 80mm, and gives that micro-move platform zero point corresponding micro-effector tip position as original point in coordinate. Then, we revise microscope vision system in order to locate original point in clear imaging plane.

Fig.2 and Fig.3 show the initial defocus image of micro-gripper driven by piezoelectricity with different camera setting. Fig.4 gives the restoration image of micro-gripper driven by piezoelectricity.

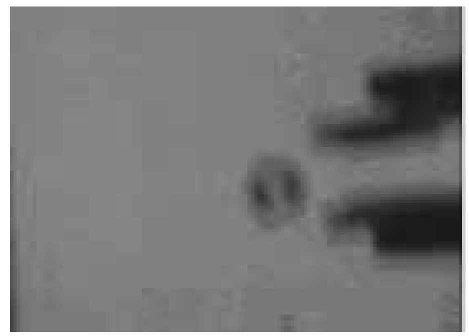

Figure 2. The initial image of defocus image micro-gripper driven by piezoelectricity

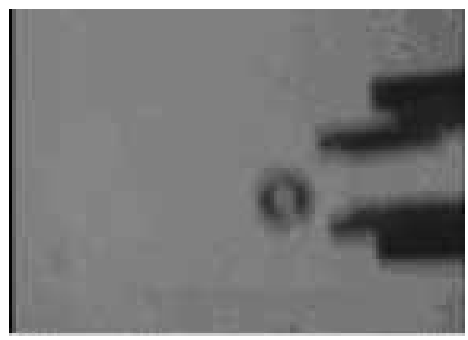

Figure 3. The initial image of defocus image micro-gripper driven by piezoelectricity with different camera parameters settings

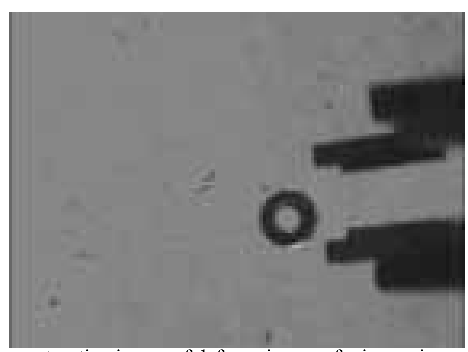

Figure 4. the restoration image of defocus image of micro-gripper driven by piezoelectricity

Secondly, We give the performance of estimation of depth method. The image is magnified using the Taike XSZ monocular optics microscope (0.7-4.5x) and is captured by

Panasonic WV-CP450 CCD camera with focus length of 2.5cm. The lens aperture was kept constant at an f-number of 6. Two defocused images of the scene are taken for two different focusing ranges of 80cm and 105cm, which the nearest and the farthest points were at a distance of 90cm and 105cm from the camera to the object.

We demonstrate the performance of the method in estimating blur parameter and recovering the depth. The method of Subbarao[8] is employed to obtain initial estimates of ρ . We choose $\rho_{i,j}^{\ 2} = 0.6\rho_{i,j}^{\ 1}$ and the number of level for the blur parameter is 30. Figs. 5,6,7,8 show the experiment results. The original defocus image with blur ρ^1 and blur ρ^2 is shown in Fig5 and Fig6, respectively. Fig7 shows the estimated value of depth obtained using DFD, which the initial point is given randomly(according to equation of the blur parameter.). Correspondingly, the estimated value of the depth employed the proposed method that the initial point is chose using LSE is shown in Fig8. Fig.9 shows the estimated value of the blur parameter using the proposed method. From this figures, Compared with DFD that the initial point is given randomly, we note that the planar nature of the variation in the depth of the scene is better brought by the proposed method.

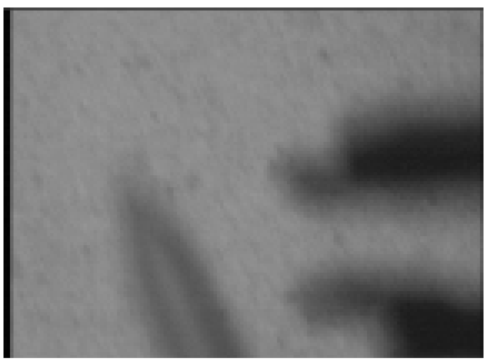

Figure 5. the original defocus image of micro-gripper and vacuum micro-adsorption with the blur ρ^1

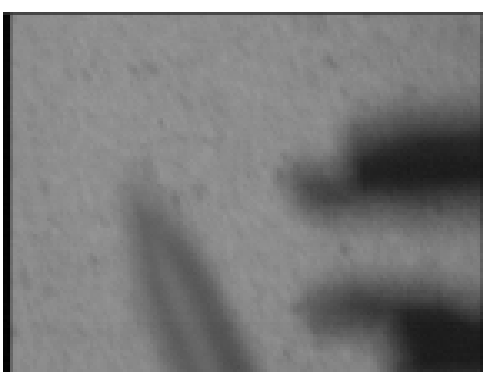

Figure 6. the original defocus image of micro-gripper and vacuum micro-adsorption with the blur ρ^2

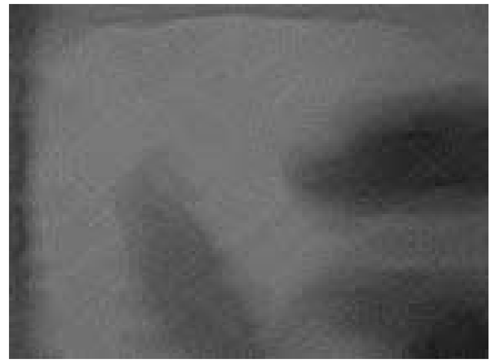

Figure 7. estimated value of the depth obtained using DFD with random the initial point

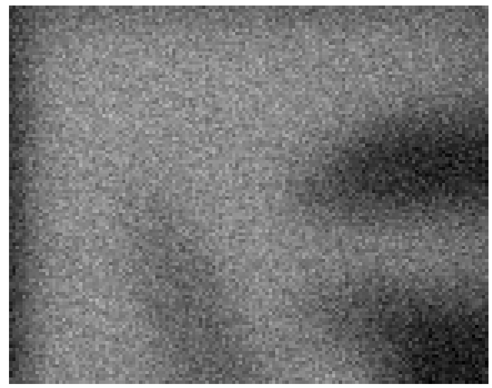

Figure 8. estimated value of the depth obtained using proposed method

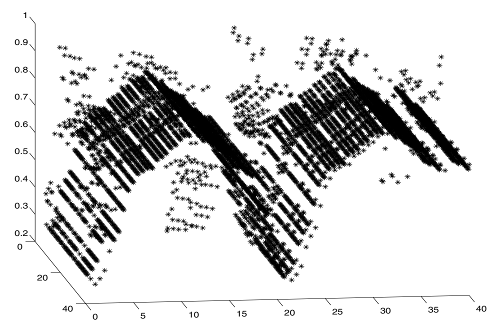

Figure 9. estimated values of the blur parameter using proposed method

VI. CONCLUSION

The depth estimation in micromanipulation tasks is a key technology in microscope vision system. For the depth estimation of microscope vision image, This paper presents a blur parameter model of the defocus image based on MRF. It converts problem of depth estimation into optimization problem. An improved Iterated Conditional Modes Algorithm has been applied to complete optimization problem, which prevents that performance result gets into local optimization. The experiments and simulations prove that the model and algorithm is efficiency. It provides the probability that finishes visual servoing control in 3D space.

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