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The Uncalibrated Microscope Visual Servoing for Micromanipulation Robotic System

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1. Introduction

MEMS technology exploits the existing microelectronics infrastructure to create complex machines with micron feature sizes. These machines can perform complex functions including communication, actuation and sensing. However, micron sized devices with incompatible processes, different materials, or complex geometries, have to be 'assembled'. Manual assembly tasks need highly skilled operator to pick and place micro-parts manually by means of microscopes and micro-tweezers. This is a difficult, tedious and time consuming work. Visual feedback is an important approach to improve the control performance of micro manipulators since it mimics the human sense of vision and allows for operating on the noncontact measurement environment.

The image jacobian matrix model has been proved to be an effective tool to approach the robotic visual servoing problem theoretically and practically. It directly bridges the visual sensing and the robot motion with linear relations, without knowing the calibration model of the visual sensor such as cameras. However, image jacobian matrix is a dynamic time-varying matrix, which cannot be calibrated by fix robotic or CCD camera parameters, especially for micro-manipulation based on micro vision. So, it is an exigent request for us to estimate parameters of image jacobian matrix on-line.

Many papers about image jacobian matrix online estimation have been reported. Clearly, Performance of the online estimation of the image jacobian matrix is the key issue for the quality of the uncalibrated micro-vision manipulation robotic. Unfortunately, the current estimation methods have problems such as estimation-lag, singularity, convergence and its speed. Especially in dynamic circumstances, these problems become more serious. There are other efforts to deal with the online estimation of the image jacobian matrix and the uncalibrated coordination control. Piepmeier et al. present a moving target tracking task based on the quasi-Newton optimization method. In order to compute the control signal, the jacobian of the objective function is estimated on-line with a broyden's update formula (equivalent to a RLS algorithm). This approach is adaptive, but cannot guarantee the stability of the visual servoing. Furthermore, the cost function using RLS is restricted by prior knowledge for obtaining some performance.

To deal with those problems discussed above, we apply an improved broyden's method to estimate the image jacobian matrix. Without prior knowledge, the method employs chebyshev polynomial as a cost function to approximate the best value. Our results show that, when calibration information is unavailable or highly uncertain, chebyshev polynomial

algorithm can achieve a satisfactory result, which can bring additional performance and flexibility for the control of complex robotic systems. To verify the effectiveness of the method, both the simulations and experiments are carried out, and its jacobian estimation results show that our proposed method can attain a good performance.

2. Overview of micromanipulation robotic system

IRIS have developed the autonomous embryo pronuclei DNA injection system, visual servoing and precision motion control are combined in a hybrid control scheme. Experimental results demonstrate that the success rate of automatic injection is 100%. The time required of performing the injections is comparable with manual operation by a proficient technician. Nagoya University Fukuda Professor's research team have developed nano manipulation hybrid system based on the scanning electron microscope (FE-SEM) and the emission electron microscopy, which has been used for operating the single-cell and the individual biological cells. Columbia University Dr. Tie Hu and Dr. Allen have developed the medical micro-endoscopic imaging system. Georgiev has employed the micro-robotic system to manipulate the protein crystal and his team have established the planting robot – automatic stripe planting robotics. Ferreira has presented a self-assembly method based on the microscopy visual servoing and virtual reality technology. Kemal has proposed a visual feedback method based on the closed-loop control.

The complete micromanipulation system in our lab consists of micromanipulation stage, microscopes vision and micro-gripper. The system construction is showed in Fig.1.
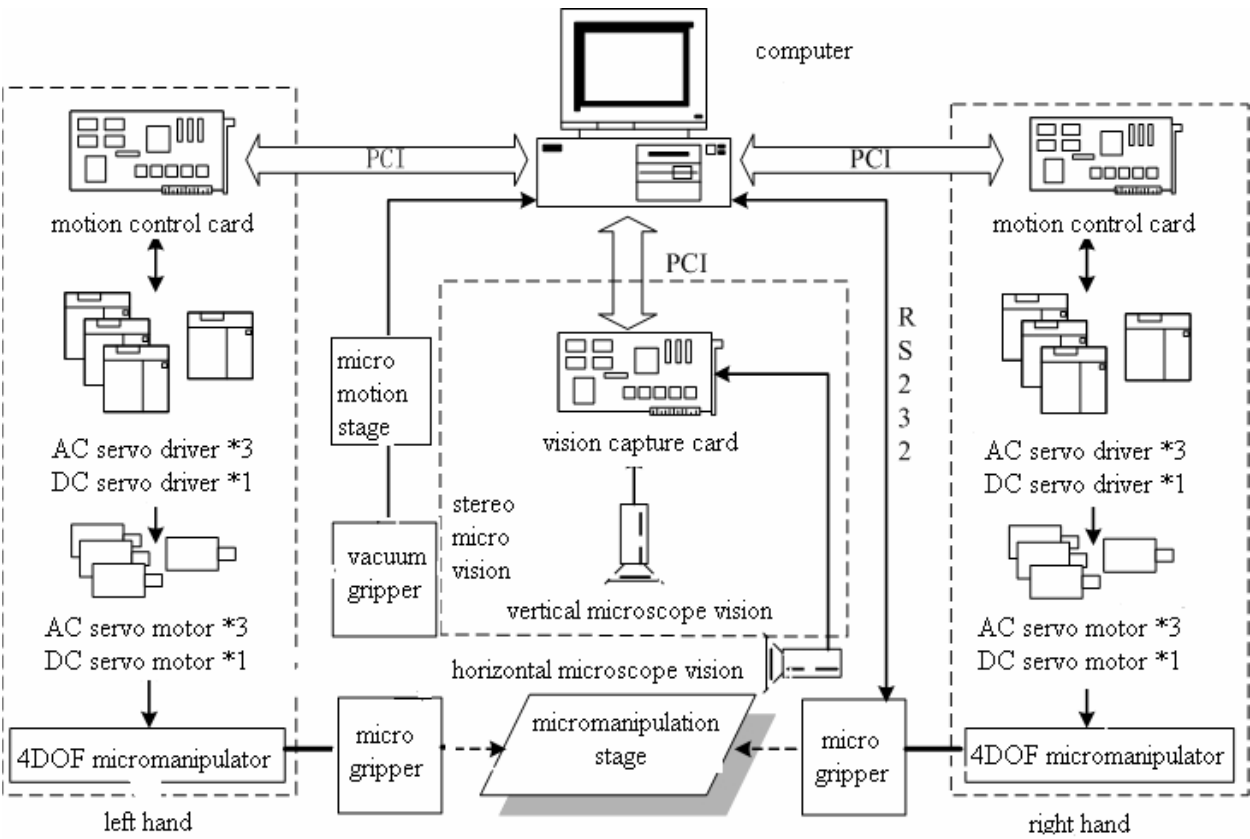

Fig. 1. The system construction of three hands cooperation micromanipulation stage

Micromanipulation hands

The left and right hands consist of 3D high precise micro-motion stage driven by the AC servoing motor and one DOF pose adjust joint driven by the DC servoing motor. The motion range of the 3D micro-motion stage is 50 x 50 x 50mm and the position of precise is 2.5µm. The rotary range of the pose adjust joint motor is ±180° and the resolution is 0.01. The third hand consists of three DOF motors driven by the DC servoing motor and the operation range is 20 x 20 x 20mm.

Microscope vision

Microscope vision is a main method that the micromanipulation robotic obtains environment information. A microscopic vision unit with two perpendicular views was developed to reduce the structural complexity of mechanism. The vision system consists of vertical crossed two rays, which can monitor micro-assembly space by stereo method and obtain the space and pose information of objects and end-effector, providing control and decision-making information for robotic.

End-effector

There are two driven types micro-gripper developed by us. One is driven by vacuum and the other one is driven by piezoelectricity ceramic, which can operate the micro parts with different size, shape and material.

3. Problems statement

Obtaining accurate camera parameters is crucial to the performance of an image-based visual controller because the image Jacobian or interaction matrix is widely used to map the image errors into the joint space of the manipulator. It is well known that camera calibration is tedious and time consuming. To avoid this, tremendous efforts have been made for on-line estimation of the image Jacobian.

The micro-assembly technology based on microscope visual servoing can be used to obtain good performance in micro size parts assembly. To obtain this level of performance and precision, one need is to identify and position the multi microsize objects. Therefore, we must consider the effective of the identifying algorithm and the position algorithm.

For an autonomous micro-assembly under microscope, it is difficult to maintain the identifying precisely since there are no reliable microsize objects sources for the reason of poor shine. So, the feature attributes reduce can become necessary for enhancing the identifying preciseness. After identifying the multi microsize parts, it is a very important issue we faced that converts the image space coordinate into robotic space coordinate, namely, how we compute the image jacobian matrix. Focusing on the microscope environment, calibrating the parameters may be not meet the requirement. So, using the uncalibrated microscope visual servoing method becomes the best path for us. Then, the uncalibrated microscope visual servoing systems can be built without considering the real-time performance and the stability of system. It means that we employ the time-consuming for exchanging the good performance. Nevertheless, the real-time performance and the stability of system are also important for micromanipulation. So the new algorithms have to be developed to cope with this information. The visual control law is essential to successfully produce high-resolution micro-assembly tasks. Its role is to improve control system performance. Are the classical control laws such as PID and intelligence control law

all adapted for the micromanipulation system? Therefore, we must consider this status. Now, we will discuss all the above problems.

4. Multi-objects identifying and recognizing

In order to assemble the multi micro objects under microscope, it is necessary that identifies firstly these objects. In pattern recognition field, the moment feature is one of the shape feature that be used in extensive application. Invariant moments are the statistical properties of the image, meeting that the translation, reduction and rotation are invariance. Hu (Hu, 1962)has presented firstly invariant moments to be used for regional shape recognition. For closed structure and not closed structure, because the moment feature can not be calculated directly, it needs to construct firstly regional structure. Besides, because the moment involves in the calculation of all the pixels of intra-regional and border, it means that it can be more time-consuming. Therefore, we apply the edge extraction algorithm to process image firstly, and then calculate the edge image's invariant moments to obtain the feature attribute, which solves the problem discussed above.

After feature attribute extraction, the classification algorithm should be provided during the final target identification. The main classifier used at present can be divided into three categories: one is the statistics-based method and its representatives are such as the bayes method, KNN method like centre vector and SVM (Emanuela B et al., 2003), (Jose L R et al., 2004), (Yi X C & James Z W, 2003), (Jing P et al., 2003), (Andrew H S & Srinivas M, 2003), (Kaibo D et al., 2002) ; One is the rule-based method and its representatives are decision tree and rough sets; the last one is the ANN-based method. Being SVM algorithm is a convex optimization problem, its local optimal solution must be global optimal solution, which is better than the other learning algorithms. Therefore, we employ SVM classification algorithm to classify the targets. However, the classic SVM algorithm is established on the basis of the quadratic planning. That is, it can not distinguish the attribute's importance from training sample set. In addition, it is high time to solve the large volume data classification and time series prediction, which must improve its real-time data processing and shorten the training time and reduce the occupied space of the training sample set.

For the problem discussed above, we present an improved support vector machine classification, which applies edge extraction's invariant moments to obtain object's feature attribute. In order to enhance operation effectiveness and improve classification performance, a feature attribute reduction algorithm based on rough set (Richard Jensen & Qiang Shen, 2007), (Yu chang rui et al., 2006) has been developed, with the good result to distinguish training data set's importance.

Invariant moments theory

Image (*p+q*) order moments: we presume that $f(i,j)$ represents the two-dimensional continuous function. Then, it's (*p+q*) order moments can be written as (1).

$$M_{pq} = \iint i^p j^q f(i,j)didj \quad (p,q=1,2,...) \tag{1}$$

In terms of image computation, we use generally the sum formula of (*p+q*) order moments shown as (2).

$$M_{pq} = \sum_{i=1}^{M} \sum_{j=1}^{N} f(i,j) i^p j^q \qquad (p,q=1,2,...) \tag{2}$$

Where p and q can choose all of the non-negative integer value, they create infinite sets of the moment. According to Papulisi's theorem, the infinite sets can determine completely a two-dimensional image $f(i,j)$.

In order to ensure location invariance of the shape feature, we must compute the image (p+q) order center moment. That is, calculates the invariant moments using the center of object as the origin of the image. The center of object (i', j') can be obtained from zero-order moment and first-order moment. The centre-moment formula can be shown as (3).

$$M_{pq} = \sum_{i=1}^{M} \sum_{j=1}^{N} f(i,j)(i-i')^p (j-j')^q \tag{3}$$

At present, most studies about the two-dimensional invariant moments focus on extracting the moment from the full image. This should increase the computation amount and can impact on the real-time of system. Therefore, we propose the invariant moments method based on edge extraction, which gets firstly the edge image and then achieves the invariant moments feature attribute. Obviously, it keeps the region feature of moment using the proposed method. In addition, being the role of edge detection, the data that participate calculation have made a sharp decline, reducing greatly the computation amount.The invariant moments are the functions of the seven moments, meeting the invariance of the translation, rotation and scale.

Improved support vector machine and target identify

1) Support Vector Machine: The basic idea of SVM is that applies a nonlinear mapping Φ to map the data of input space into a higher dimensional feature space, and then does the linear classification in this high-dimensional space.

Presumes that the sample set (x_i, y_i), $(i = 1,...,n)$, $x \in R_d$ can be separated linearly, where x is d dimensional feature vector and $y \in \{-1,1\}$ is the class label. The general form of judgement function in its linear space is $f(x) = w \bullet x + b$, Then, the classification hyperplane equation can be shown as (4).

$$w \bullet x + b = 0 \tag{4}$$

If class m and n can be separated linearly in the set, there exists (w, b) to meet formula as (5).

$$\begin{aligned} w \bullet x_i + b > 0, (x_i \in m) \\ w \bullet x_i + b < 0, (x_i \in n) \end{aligned} \tag{5}$$

Where w is weight vector and b is the classification threshold. According to (4), if w and b are zoomed in or out at the same time, the classification hyperplane in (4) will keep invariant . We presume that the all sample data meet $|f(x) \geq 1|$, and the samples that is closest classification hyperplane meet $|f(x) = 1|$, then, this classification gap is equivalent to $2 / \|w\|$. So the classification gap is biggest when $\|w\|$ is minimum.

Although the support vector machine with a better classification performance, but it can only classify two types of samples, and the practical applications often require multiple

categories of classification. As a result, SVM need to be extended to more categories of classification issues, For the identification of a number of small parts in micromanipulation, we applied the Taiwan scholar Liu presented method based on the "one-to-many" method of fuzzy support vector machine for multi-target classification.

2) Improved Support Vector Machine: For the completion of the sample training, it is a usual method that all the feature attribute values after normalization have been used for modeling, which will increase inevitably the computation amount and may lead to misjudge the classification system being some unnecessary feature attributes. Therefore, bringing a judgement method to distinguish the attribute importance may be necessary for us. So we employ rough set theory to complete the judgement for samples attribute's importance. Then, we carry out SVM forecast classification based on the reduction attributes.

Now, we introduce rough set theory. The decision-making system is $S = (U, A, V, f)$, where U is the domain with a non-null limited set and $A = C \bigcup D$. C, D represents conditions and decision-making attributes set respectively. V is the range set of attributes ($V = \bigcup_{a \in A} V_a$), V_a is the range of attribute a. f is information function ($f : UXA \rightarrow V$). If exists $f(x, a) \in V_a$ under $\forall x \in U$ $a \in A$ and $\forall B \subseteq A$ is a subset of the conditions attributes set, we call that $Ind(B)$ is S's un-distinguish relationship. Formula $Ind(B) = \{(x, y) \in UXU \mid \forall a \in B, f(x, a) = f(y, a)\}$ represents that x and y is indivisible under subset B. Given $X \subseteq U$, $B(x_i)$ is the equivalent category including x_i in term of the equivalent relationship $Ind(B)$. We can define the next approximate set $\underline{B(X)}$ and the last approximate set $\overline{B(X)}$ of subset X as follows:

$$\underline{B(X)} = \{x_i \in U \mid B(x_i) \subseteq X\}$$

$$\overline{B(X)} = \{x_i \in U \mid B(x_i) \bigcap X \neq \phi\}$$

If there is $\overline{B(X)} - \underline{B(X)} = \phi$, the set X is able to define set based on B. Otherwise, call X is the rough set based on B. The positive domain of X based on B are the objects set that can be determined to belong to X based knowledge B. Namely, $POS_B(X) = \underline{B(X)}$. The dependence of decision-making attributes D and conditions attributes C can be defined as follows.

$$\gamma(C, D) = card(POS_C(D)) / card(U)$$

Where $card(X)$ is the base number of the set X.

The attributes reduction of rough set is that the redundant attributes have been deleted but there is not loss information. The formula $R = \{R \quad R \subseteq C, \quad \gamma(R, D) = \gamma(C, D)\}$ is the reduction attributes set. Therefore, we can use equation attributes dependence as conditions for terminating iterative computing.

In order to complete the attribute reduction, we present a heuristic attribute reduction algorithm based-on rough set's discernibility matrix, which applies the frequency that attributes occurs in matrix as the heuristic rules and then obtains the minimum attributes's relative reduction.

The discernibility matrix was introduced by Skowron and has been defined as (6):

$$(c_{ij}) = \begin{cases} a \in A : r(x_i) \neq r(x_j) & D(x_i) \neq D(x_j) \\ \varnothing & D(x_i) = D(x_j) \\ -1 & \forall r, \exists r(x_i) = r(x_j) \quad D(x_i) \neq D(x_j) \end{cases} \tag{6}$$

According to formula (6), The value of elements is the different attributes combination when the attributes for the decision-making are different and the attributes for the conditions are different. The values of elements are null when the attributes for the decision-making are the same. The values of elements are -1 when the attributes for the decision-making are the same and the attributes for the conditions are different.

If p (a) is the attribute importance formula of attribute a, we can propose the formula as (7) according to the frequency that attribute occurs:

$$p(a) = \gamma \frac{1}{|U^2|} \sum_{a \in c_{ij}} \frac{1}{|c_{ij}|} \tag{7}$$

Where γ is the general parameter and c_{ij} are the elements of the discernibility matrix. Obviously, the greater the frequency that attribute occurs, the greater its importance is. Therefore, we can compute the importance of attributes and eliminate the attributes that its importance is the smallest using the heuristic rules in formula (7). And then, we can obtain the relative reduction attributes.

Now, we give the heuristics attribute reduction algorithm based-on rough set's discernibility matrix.

Input: the decision-making table (U, $A \cup D$, V, f)

Output: the relative attribute reduction

Algorithm steps:

Step I computes the identification discernibility matrix M.

Step II determines the core attributes and find the attributes combination that the core attributes is not included.

Step III obtains conjunctive normal form $P=\wedge(\vee c_{ij}:(i = 1, 2, 3…s; j = 1, 2, 3…m))$ of the attributes combination by step II, where c_{ij} are elements of each attribute combination. And then converts the conjunctive normal form to disjunctive normal form.

Step IV determines the importance of attribute according to formula (7).

Step V computes the smallest importance of attributes by steps IV and then eliminate the less importance attribute to obtain the attributes reduction.

After reducing the attribute, the samples feature attributes will be sent to SVM for establishing model. Support vector machines uses Gaussian kernel function, and Gaussian kernel function shows a good performance in practical applications of learning. Finally, we can finish the classification of the final prediction data.

Feature extraction and data pretreat

The main task of classification is to identify and classify the manipulator (microgripper, vacuum suction) and operation targets (cylindrical metal part, glass ball), which can provide convenience for follow-up visual servo task. Fig.2 shows the original image of operation targets and manipulator in microscopic environment.Fig.3 is the image after edge extraction of operation targets and manipulator in microscopic environment.
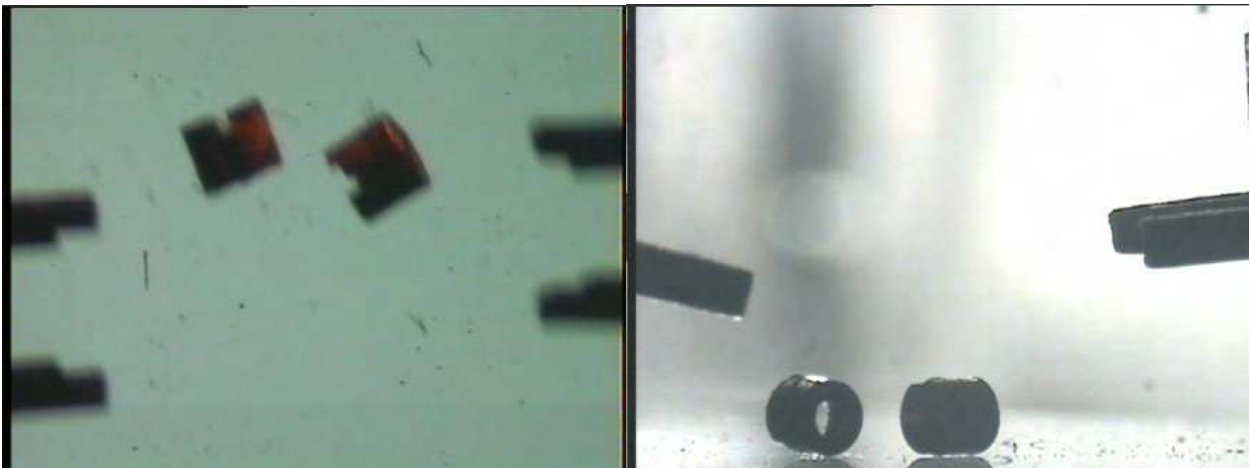
(a) Microscopic images in vertical view field (b) Microscopic images in horizontal view field

Fig. 2. The original microscopic image of object and the endeffector in vertical (a) and horizontal (b) view fields
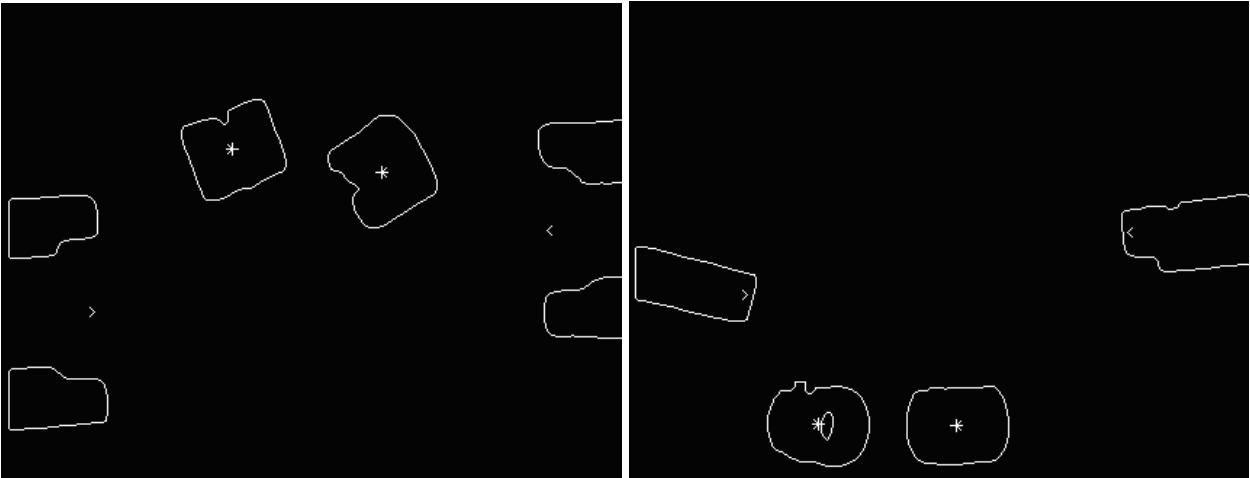
(a) Microscopic images in vertical view field (b) Microscopic images in horizontal view field

Fig. 3. The object centre image and the end centre of the endeffector after processing in vertical (a) and horizontal (b) view fields

Table 1 gives the feature attribute's normalization value of four different objectives using invariant moments algorithm. We compute the feature attribute of objects in all directions and only list one of the feature attribute.

Category	F1	F 2	F 3	F4	F5	F6	F7
Cyl. metal part	1.0000	-0.9910	0.9935	-0.1600	0.1076	1.0000	-0.5762
Glass Small Ball	1.0000	0.9900	-0.9946	0.1822	0.1178	0.9952	-0.5486
Micro Gripper	-0.9897	-0.7610	-1.0000	-1.0000	-0.9999	0.9554	-1.0000
Vacuum Suction	0.1673	0.9993	0.3131	0.9915	0.9857	-0.9577	0.9861

Table 1. The feature attribute's normalization value of different objects using invariant moments algorithm

Result of identification and analysis

We compare firstly the data classification effectiveness on a number of micro objects using the traditional support vector machines algorithm and rough set + SVM, and the results are shown in table 2.

	SVM		SVM +Rough set	
	Correction rate	Classification time (*ms*)	Correction rate	Classification time (*ms*)
Micro Object	93.45%	2108.24	95.89%	357.65

Table 2. The comparison results of using two classification methods

According to table 2, the correction rate of classification based on the proposed SVM classification algorithm has been over 95 pre cent, being higher than the single SVM algorithm's correction rate. So, we can draw the conclusion that the attribute reduction improves the classification ability. Besides, compared with the single SVM algorithm's calculation time,it can be seen clearly from Table 2 that the calculation time of the proposed algorithm is less than about five times, meaning that the system becomes more effective.

Then, Table 3 provides the comparison results of classification accuracy using SVM classification and SVM+rough set classification with joining the other 25 feature attributes (gray, area, perimeter, texture, etc.). In table 3, The first column is the times of data sets; second column is the number of conditions attributes after attribute reduction; third column is the classification accuracy using the SVM; fourth column is the classification accuracy using SVM and rough set algorithm. The number of conditions attributes of the final classification for entering to SVM is 14.25, less than 25 features attribute. Thus it simplifies the follow-up SVM forecast classification process.

Times	Property	classification accurateness	
		SVM	SVM + rough set
1	10	90.00 %	95.10 %
2	15	90.25 %	96.00 %
3	9	89.00 %	92.87 %
4	21	92.15 %	97.08 %
5	15	90.80 %	92.33 %
6	12	90.00 %	93.50 %
7	12	94.00 %	95.22 %
8	20	92.16 %	97.40 %

Table 3. The comparison results of classification accurateness using SVM and SVM + Rough set classification

5. The uncalibrated microscope visual servoing

As a result of the particularity of micro-manipulation and micro-assembly environment, we can not calibrate the parameter of micromanipulation robotic as the industrial robots calibration. So, we employ the uncalibrated visual servoing method. The uncalibrated visual servoing is a hot issue in the field of robot vision research over the past decade, which estimates the image jacobian matrix elements on-line, increasing the system's adaptability for environmental change.

Many scholars in this area have done a lot of researches. Piepmeier developed a dynamic quasi-Newton method. Using the least square method, Lu developed an algorithm for on-line calculating the exterior orientation. Chen proposed a homography based adaptive tracking controller by estimating the unknown depth and object parameters. Yoshimi and Allen proposed an estimator of the image Jacobian for a peg-in-hole alignment task. Hosoda and Asada employed the Broyden updating formula to estimate the image Jacobian. Ruf presented an on-line calibration algorithm for position-based visual servoing. Papanikolopoulos developed an algorithm for on-line estimating the relative distance of the target with respect to the camera.

Visual-servo architecture of the micro manipulator

The dynamic image-based look-and-move system is the most suitable visual servoing architecture for the micromanipulation operation, and some commercial software is available. In the micro-vision system based optic-microscope, a camera can only be mounted on the microscope. This control system has both the end-effector feedback and its joint level feedback. A classical proportional control scheme is given by:

$$V = -\lambda \hat{L}^+ e$$

Where L_e is defined by

$$\dot{e} = L_e V$$

In order to finish three-dimensional small object positioning task, in the actual operation, micro-manipulation tasks will be divided into horizontal direction (XY plane) movement and the vertical direction (YZ plane) movement. The manipulator in the XY plane moves first, positioning small parts in the above, then does so in the YZ plane movement, positioning small parts at the centre. Therefore, we apply two image jacobian matrixs, including horizontial view field of image jacobian matrix and vertical view field of image jacobian matrix, which can complete the positioning and tracking three-dimensional objects.

The change of robot movement $[dx, dy]^T$ and the change of image characteristics $[du, dv]^T$ can be wirte as (8):

$$\begin{bmatrix} dx \\ dy \end{bmatrix} = \dot{J} \begin{bmatrix} du \\ dv \end{bmatrix} \tag{8}$$

According to the online estimtion image Jacobian matrix J, set the position of the error $e = f^d - f^c$, which f^d is the expectations of position of objects (small cylindrical parts, 600 um diameter) and f^c is the centre of endeffector. Then, the control law of PD controller u (k) is:

$$u(k) = K_p(\dot{J}^T\dot{J})^{-1}\dot{J}^T e(k) + K_d(\dot{J}^T\dot{J})^{-1}\dot{J}^T \frac{\Delta e(k)}{T_s} \tag{9}$$

Where T_s is the time interval, and K_p is proportional gain and K_d is differential gain. Its control structure is shown in Fig.4.
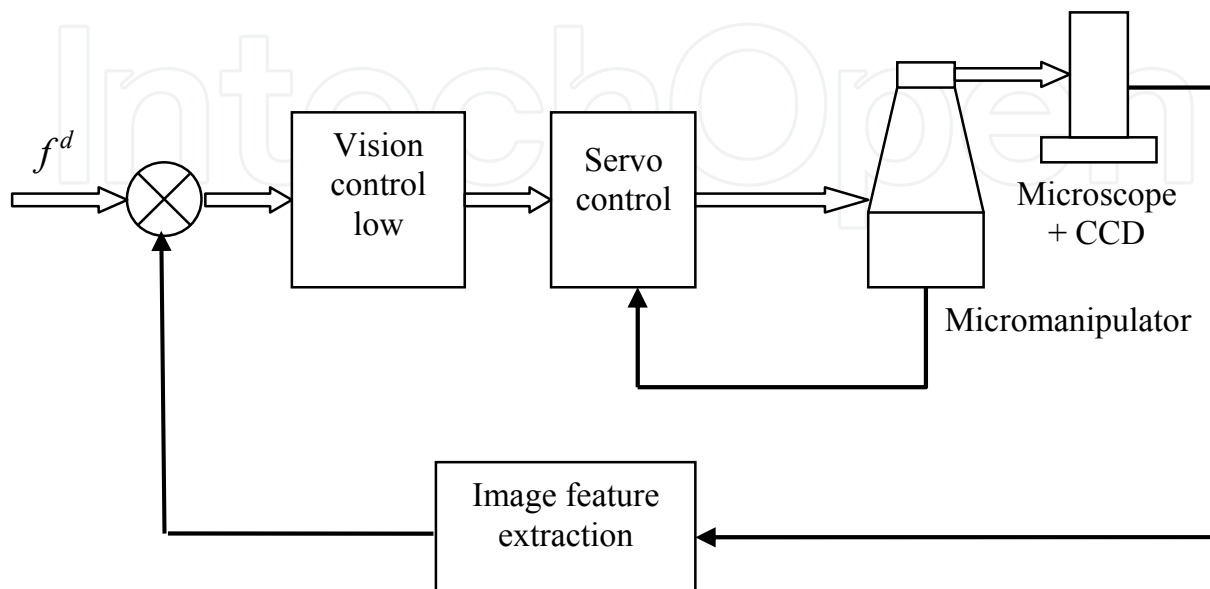

Fig. 4. Micromanipulator servo control structure

In the next section, the pseudo-inverse of image Jacobian will be addressed. In order to meet the request of the high precise micro-manipulation task, robotic must employ the visual servoing method. The methods of visual servoing need calibrate precisely intrinsic parameter of camera. However, the system calibration is the complicated and difficult problem, especially for micro-manipulation based on microscope vision. So, we present the uncalibrated method to estimate image jacobian matrix online.

Image jacobian

The image jacobian defines the relationship between the velocity of a robot end-effector and the change of an image feature. Considering q = [q1, q2…qm]^R represents the coordinates of robot end-effector in the task space. An n-dimensional vector: f = [f1, f2…fn]^T is corresponding position in image feature. Then, the image jacobian matrix J_q is defined as

$$\dot{f} = J_q(q)\dot{q} \tag{10}$$

where

$$J_q(q) = \left[\frac{\partial f}{\partial q}\right] = \begin{bmatrix} \dfrac{\partial f_1(q)}{\partial q_1} & \cdots & \dfrac{\partial f_1(q)}{\partial q_m} \\ \cdots & & \cdots \\ \dfrac{\partial f_n(q)}{\partial q_1} & \cdots & \dfrac{\partial f_n(q)}{\partial q_m} \end{bmatrix} \tag{11}$$

Broyden's method for image jacobian matrix estimation

The image jacobian matrix can be calculated by calibrating the inner and outer parameter of robotic system & sensor system. However, it is impossible to obtain precise system parameter under a dynamic or uncertainty environment. Considering those, we employ broyden's method to estimate the image jacobian matrix.

According to equation (10), Provided that two image feature error function $e_f(q) = f - f^*$, the Taylor series expansion of e_f is shown as

$$e_f(q) = e_f(q_m) + \frac{\partial e(q_m)}{\partial q}(q - q_m) + ... + R_n(x) \tag{12}$$

Where $R_n(x)$ is Lagrange remaining. We define $\overset{*}{J}_q(q_n)$ as the Nth image jacobian to be estimated, then

$$\overset{*}{J}_q(q) = \frac{\partial e(q_n)}{\partial q} \tag{13}$$

Ignoring the high order term and Lagrange remaining $R_n(x)$, Equation (14) can be obtained from (12) and (13), which is shown as

$$e_f(q) = e_f(q_m) + \overset{*}{J}_q(q_n)(q - q_m) \tag{14}$$

The broyden algorithm is described as

$$A_{k+1} = A_k + \frac{(y^{(k)} - A_k s^{(k)}) s^{(k)^T}}{\left\| s^{(k)} \right\|_2^2} \quad (k = 0,1,2,...) \tag{15}$$

Therefore, we can obtain image jacobian estimation $\overset{*}{J}_q(q_{k+1})$ as shown in (16)

$$\overset{*}{J}_q(q_{k+1}) = \overset{*}{J}_q(q_k) + \frac{(\Delta e - \overset{*}{J}_q(q_k)\Delta q)\Delta q^T}{\Delta q^T \Delta q} \tag{16}$$

In (16), We will apply the cost function to minimize $\overset{*}{J}_q(q_{k+1}) - \overset{*}{J}_q(q_k)$.

Chebyshev polynomial approximation algorithm

Provided that

$$N_K(q) = e_f(q_k) + \overset{*}{J}_q(q)(q - q_k) \tag{17}$$

If $N_k(q) \in c[-1,1]$, for Chebyshev polynomial serial $\{T_n, n = 0,1,...\}$ with weight $\rho(x) = (1 - x^2)^{-\frac{1}{2}}$, it's optimization square approximation polynomial can be shown as

$$s_n^*(x) = \frac{a_0}{2} + \sum_{i=1}^{n} a_i T_i(x) \tag{18}$$

where

$$a_i = \frac{2}{\pi} \int_{-1}^{1} \frac{N_k(x)T_i(x)}{\sqrt{1-x^2}} dx \quad (k = 0,1,2...n) \tag{19}$$

then

$$N(q) = \lim_{n \to \infty} (\frac{a_0}{2} + \sum_{i=1}^{n} a_i T_i(q)) \tag{20}$$

if we use part sum s_n^* as $N(q)$'s approximation, under some conditions, there is a fast speed for $a_n \to 0$.

Theoretically, Compared with RLS algorithm, Chebyshev polynomial approximation algorithm is independent of the prior knowledge of system, and it has fast approximate speed than that of other methods. Experiments will prove its correctness. Surely, The unsatisfied thing of chebyshev polynomial approximation algorithm, we encountered, lies in that it require N(q)'s good smoothness . It is a difficulty for us to meet this need for most conditions.

Chebyshev polynomial approximation algorithm implementation

Let's consider firstly the chebyshev polynomial approximation algorithm implementation. Usually, $N_K(q) = e_f(q_k) + J_q(q)(q - q_k)$ is a function whose variable interval lies in [a, b], it means that we need to convert variable interval of [a, b] into [-1, 1]. Thus, as shown in equation (21), it can finish this conversion

$$t = \frac{b-a}{2} x + \frac{b+a}{2} \tag{21}$$

Following task is that how to obtain parameter a_i (i = 0, 1, 2…) from formula (11). It presumes that we apply the zero point of $T_{n+1}(x)$ as discrete point set, namely, $x_i = \cos \frac{2i-1}{2(n+1)} \pi$ (i=1, 2…n+1), so a_i can be calculated as follows

$$a_i = \frac{2}{n+1} \sum_{i=1}^{n+1} N(x_i)T(x_i) \quad (i = 0,1,2...) \tag{22}$$

Comparison chebyshev polynomial approximation with RLS

Some papers [4][5] provide RLS algorithm to approximate best value for minimum cost function. The cost function using RLS is shown as equation (23).

$$Min(k) = \sum_{i=1}^{n} \lambda^{k-i} \|N_k(q_{i-1}) - N_{i-1}(q_{i-1})\|^2 \tag{23}$$

Where λ is a rate of dependency for prior data. As shown in equation (23), In order to obtain some performance, the cost function using RLS algorithm depends on the data of the several past steps, it mean that the prior knowledge must be obtained for finishing the task. Similarly, the cost function using chebyshev polynomial is shown as equation (24).

$$M(k) = \sum_{i=1}^{n} \left\| N_k(q_{i-1}) - N_{i-1}(q_{i-1}) \right\|^2 \tag{24}$$

Clearly, the cost function using chebyshev polynomial is independent of the prior data.

Jacobian estimator with improved broyden's method

As discussed in the above two sections, an improved broyden with chebyshev polynomial approximate algorithm estimator of image jacobian is developed. A graphical representation of the estimate process is shown in Fig.5. Firstly, the broyden estimator starts with initial endeffector position q^0 and precision ε. Then, Camera captures an image of endeffector for extracting corresponding image coordinate feature f^k, Which provides the possibility for calculating $\overset{*}{J}(q^k)$ by formula $\overset{*}{J}(q^k) = [f'(q^k)]^{-1}$. Secondly, Camera captures an image of target to obtain expectative image coordinate feature f^{k+1}. With the obtained $\overset{*}{J}(q^k)$, the servoing control law can be deduced in equation (25). Finally, Program judges whether precision ε satisfies system requirement or not. If precision ε arrives the requirement, system will be ended, otherwise system will be executed repeat processing.

$$u(k) = K\Delta q = K \overset{*}{J}^{+}(k)(f^{k+1} - f^k) \tag{25}$$

Where K is proportion gain.
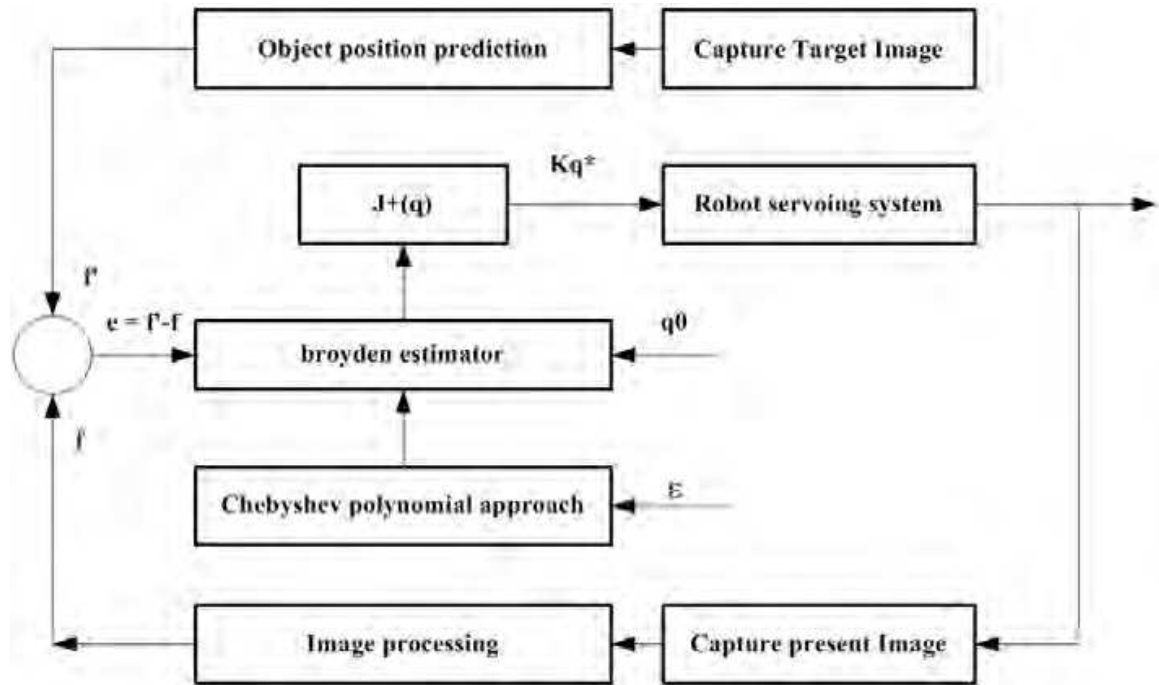
Fig. 5. A broyden with chebyshev polynomial approximation estimator of image jacobian

6. Experiments and simulations

Micro manipulation system

Microscopic visual servoing is the sensor-based control strategy in microassembly. The microscopic vision feedback has been identified as one of the more promising approaches to

improve the precision and efficiency of micromanipulation tasks. A robotic microassembly system has been developed in our lab. Fig.6 is three hands coordination micro-manipulation system.
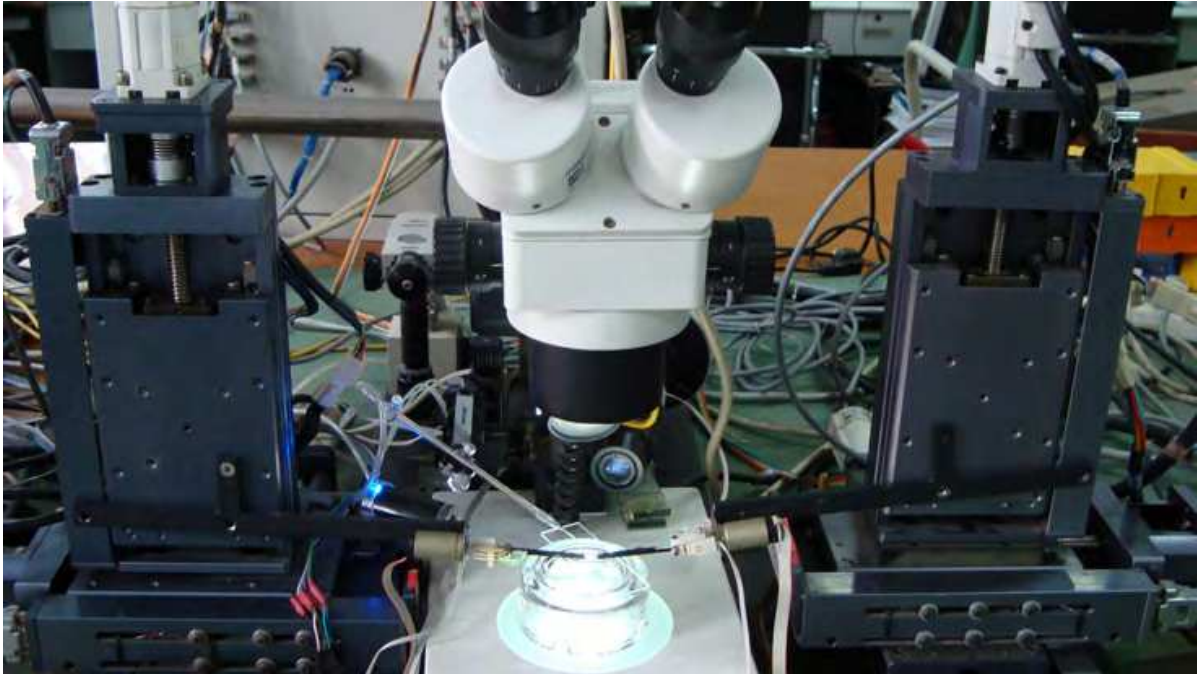

Fig. 6. Three hands coordination micro-manipulation system

Image jacobian estimation results

As the micromanipulator performs a continuous 4D movement with translation step of 10um and rotation step of 0.20, the broyden's method with chebyshev polynomial approximation algorithm executes an online estimation of the jacobian matrix elements. The manipulator kinematic parameters and microscopic vision parameters are not known in the estimation. The image size adopted in image processing is 400 X 300 pixels.

We test firstly the endeffector moving trajectory according to the online estimation method of the jacobian matrix. Fig.7 shows the endeffector moving trajectory in the vertical direction camera (left) and in horizontal direction camera (right).
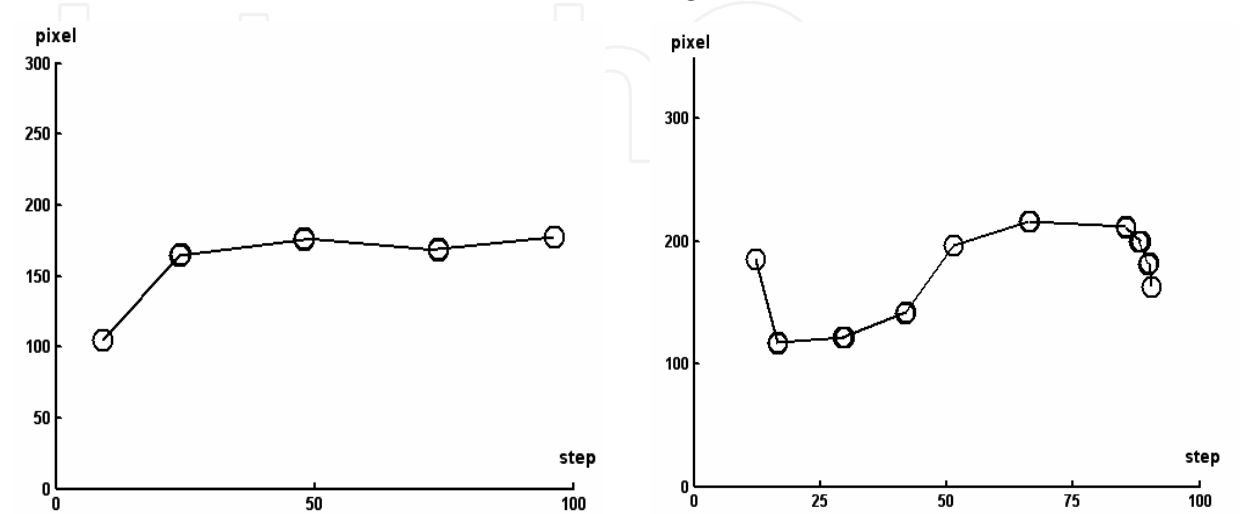
Fig. 7. The endeffector moving trajectory in vertical and horizontal direction camera

Next, we demonstrate the microscopic visual servoing experiment based on the improved broyden's method of image jacobian for a moving target. The initial position of micro gripper is (0.0, 0.0) and the moving target initial position is (x, y) = (0.8, -0.3) with the velocity of about 4mm/s. The task is done at the time of 10s with the tracking error between the target and the micro-gripper about 25 pixels. Fig.8 gives the trajectory of target and gripper of in vertical direction camera (left) and in horizontal direction camera (right).
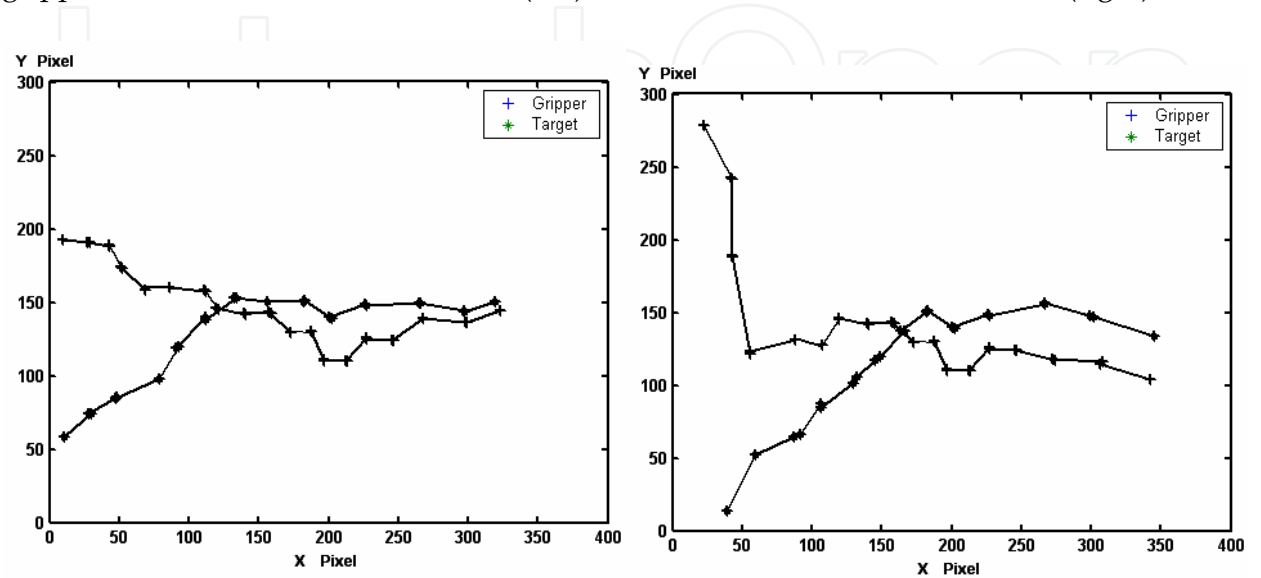
Fig. 8. Trajectory of target and gripper in vertical direction camera in horizontal direction camera

As shown in Fig.8, we can find that micro-gripper and the target have a large tracking error at initial stages. The reason for the large error is that there are a lot of noises and a small control output to step motor. With the progression of time, the error decreases to 25 pixels, it satisfies the tracking task requirement.
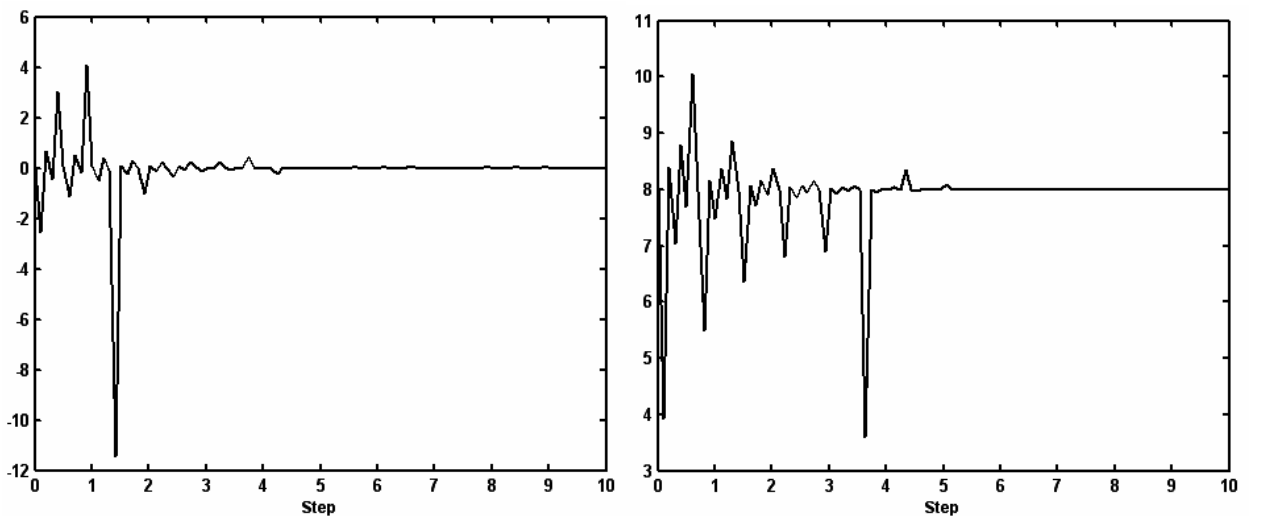
Fig. 9. Convergence speed of chebyshev algorithm (left) and Convergence speed of RLS (right)

Then, we have finished the experiment using chebyshev polynomial and RLS as cost function to estimate image jacobian matrix. The comparisons of convergence speed of two cost functions are shown in Fig.9. Clearly, compared with the RLS algorithm, it achieves a good performance in speed and stability when we apply chebyshev polynomial as a cost function.

Automatic position test

To accomplish micromanipulator positioning and girpping small parts, we must firstly obtain the centre of object and the centre of the end of endeffector. The centre of object and the end of endeffector can be accessed by a series of image processing (gray, de-noising, filter, canny operator, edge extraction, fuzzy c-means clustering). Fig.10 shows the original microscopic image of object and the endeffector in vertical and horizontal view fields. Fig.11 shows the object centre image and the end centre of the endeffector after processing in vertical and horizontal view fields. In Fig.11, the XY image plane coordinates of the center of the object is (147,99) and the centre of the end of the endeffector is (343,77).
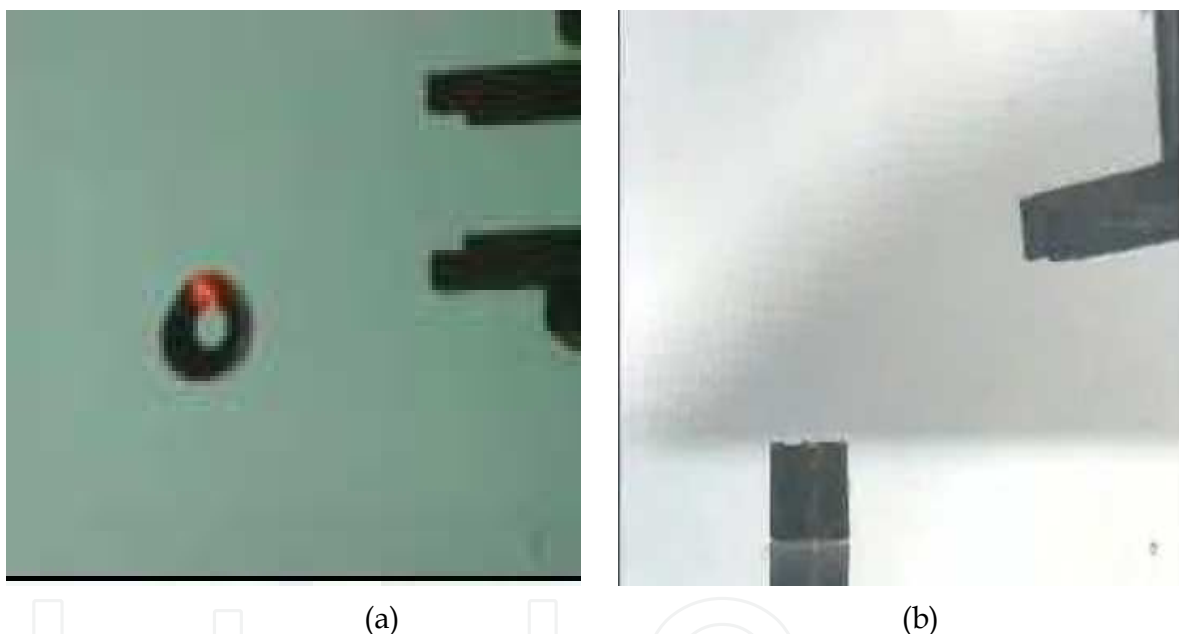
(a)   (b)

(a) Microscopic images in vertical view field (b) Microscopic images in horizontal view field

Fig. 10. The original microscopic image of object and the endeffector in vertical (a) and horizontal (b) view fields

Assuming that the initial parameters of PD controller Kp is 10 and Kd is 0, that is, only joined proportional control, control effect is shown in Fig.12. we can see the implementation of automatic positioning objects to the target center, a greater oscillation and overshoot. When Kp is 10 and Kd is 1.5, which incorporates proportional and differential control, control result is shown in Fig.13. Differential joined inhibits apparently the system overshoot, and the system meets the rapid and smooth. Finally, the implementation of micro-manipulator positioning and automatic gripping operations is given, it can be obtained the satisfied implementation with the results to the system application requirements.
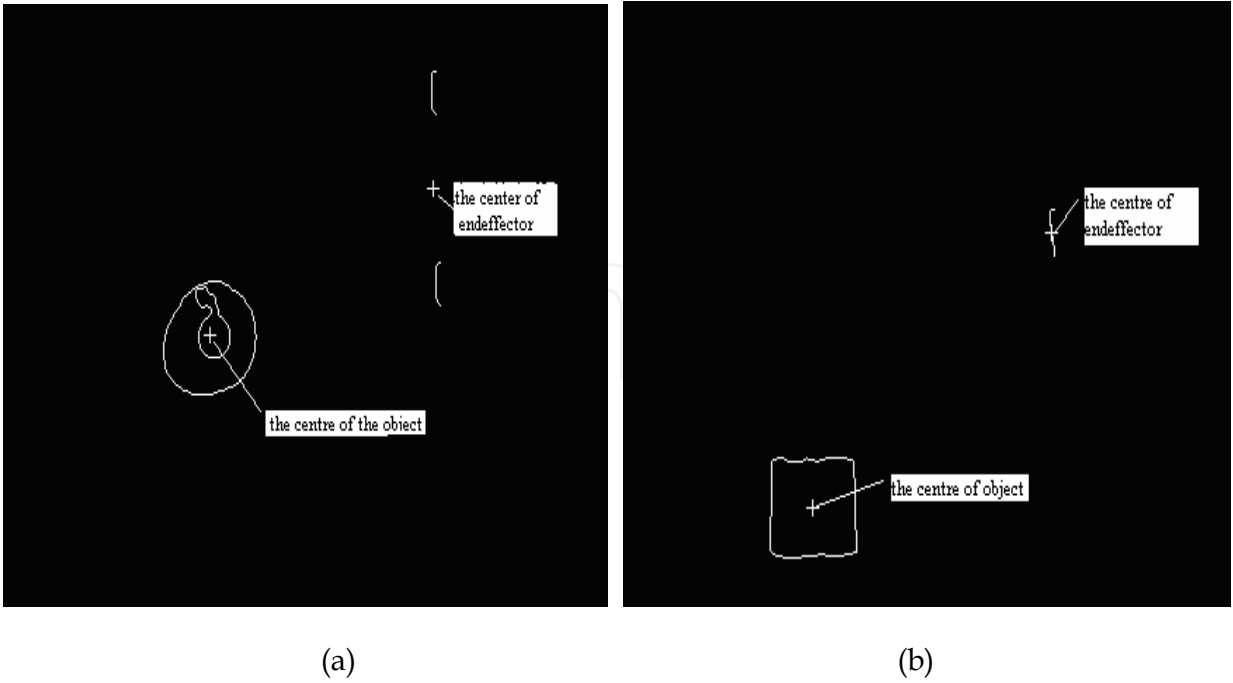
(a)   (b)

(a) Microscopic images in vertical view field (b) Microscopic images in horizontal view field

Fig. 11. The object centre image and the end centre of the endeffector after processing in vertical (a) and horizontal (b) view fields
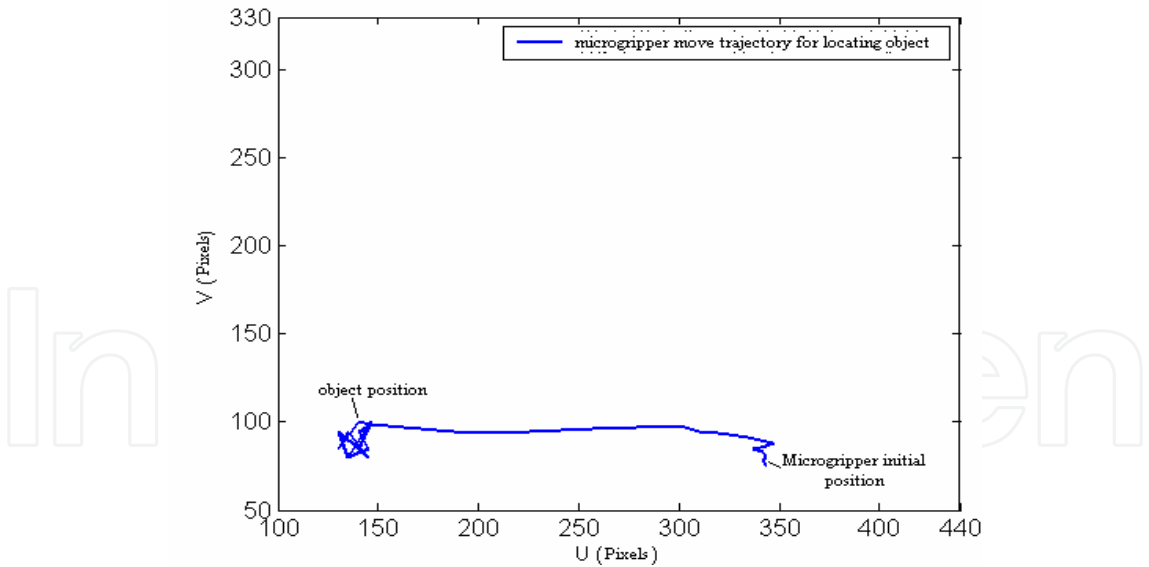

Fig. 12. The trajectories of micromanipulator approaching goal objects with only proportional control (XY plane)

Finally, In order to verify the effective of uncalibrated visual servoing method, we test the experiments of single microgripper hand to position automatic and grip micro objects. The flow chart of single microgripper hand to position automatic and grip micro objects is shown in Fig.14.
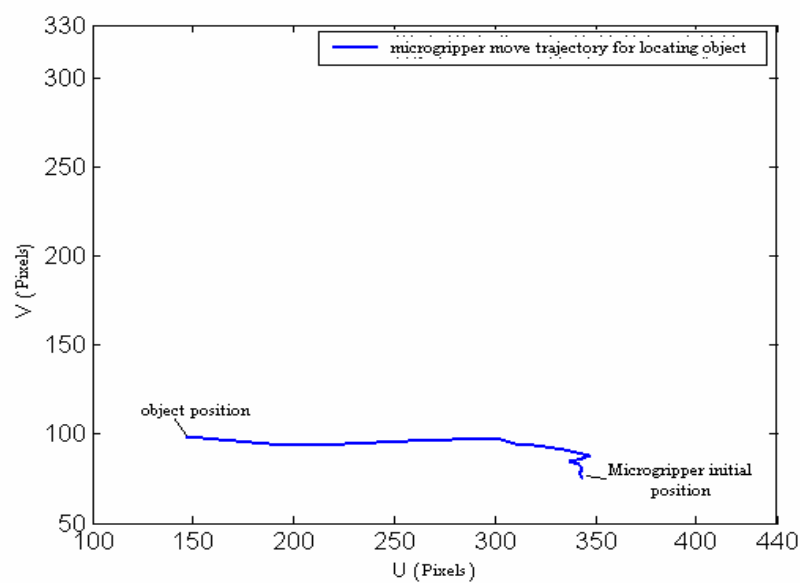
Fig. 13. The trajectories of micromanipulator approaching goal objects with proportional and differential control (XY plane)
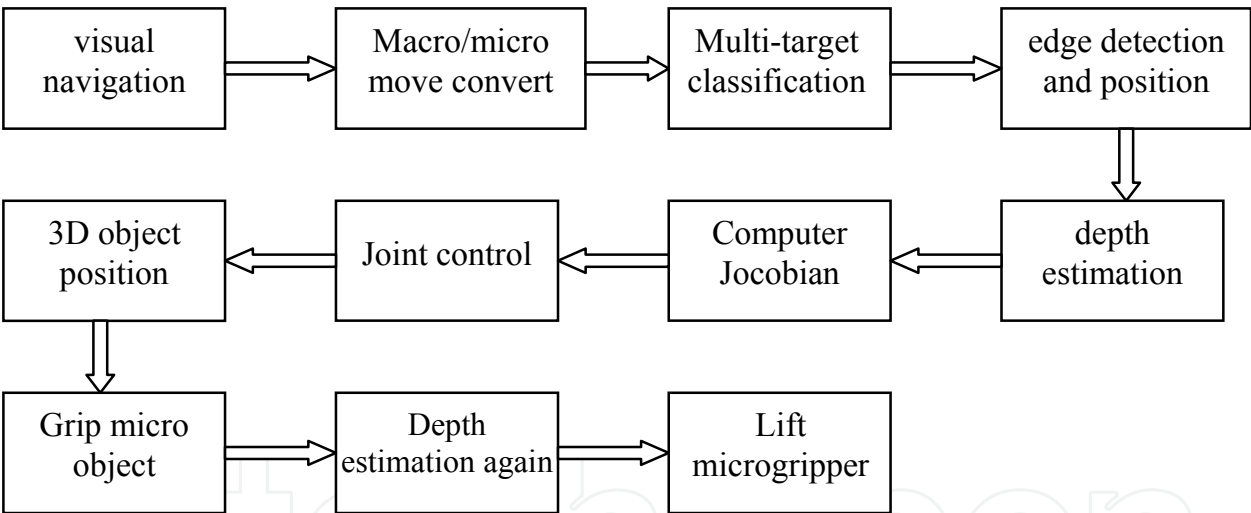

Fig. 14. The flow chart of single microgripper hand to position automatic and grip micro objects under microscope visual information

Fig.15 shows the process of the piezoelectric microgripper automatically locating and gripping the micro-target in the vertical view field. The time-consuming of process is about one minute:

(a) to (c) is the process of piezoelectric microgripper close to the target micro-target;

(d) is the process of the end of piezoelectric microgripper positioning the center of the micro target;

(e) is the process of the piezoelectric microgripper gripping the micro target;

(f) is the process of the piezoelectric microgripper lifting the designated height for follow-up of the micro-target assembly.

(a)   (b)

(c)   (d)

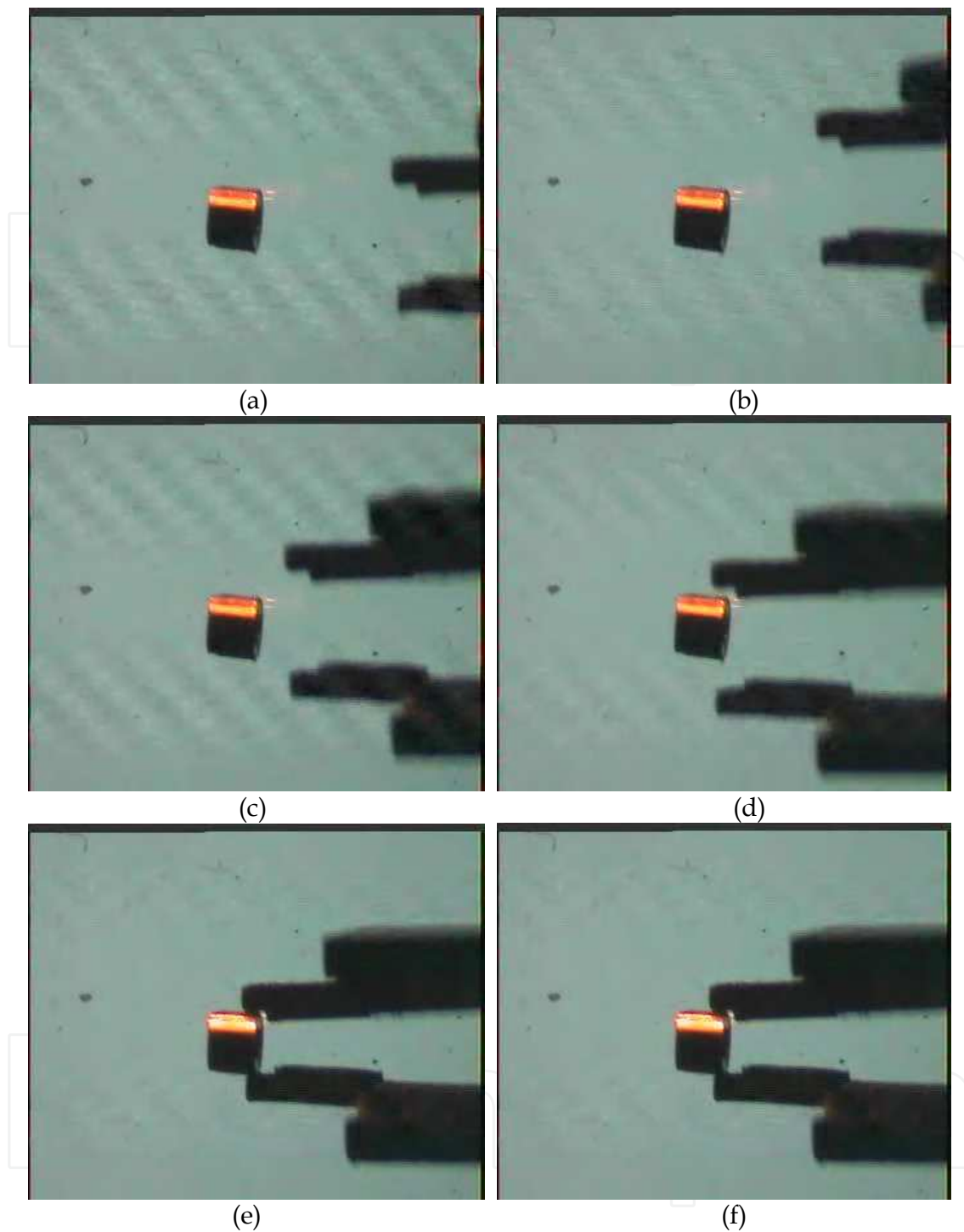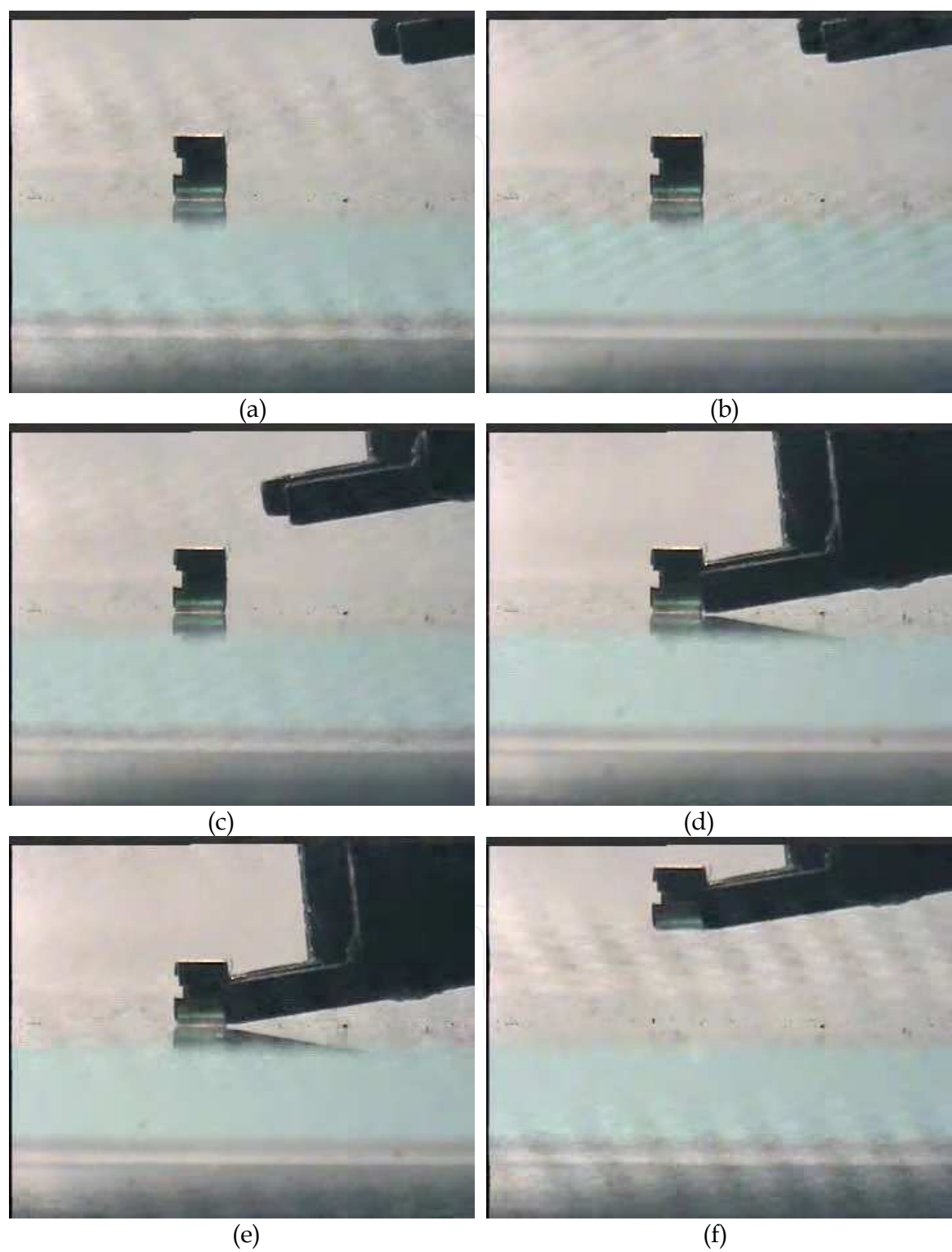(e)   (f)

Fig. 15. The process of the piezoelectric microgripper automatically locateing and gripping the micro-target in the vertical view field

Fig.16 shows the process of the piezoelectric microgripper automatically locating and gripping the micro-target in the horizontal view field. The time-consuming of process is about one minute:

(a) to (c) is the process of piezoelectric microgripper close to the target micro-target;

(d) is the process of the end of piezoelectric microgripper positioning the center of the micro target;

(e) is the process of the piezoelectric microgripper gripping the micro target;
(f) is the process of the piezoelectric microgripper lifting the designated height for follow-up of the micro-target assembly.

(a) (b)

(c) (d)

(e) (f)

Fig. 16. The process of the piezoelectric microgripper automatically locateing and gripping the micro-target in the horizontal view field

7. Conclusion

For the completion of three-dimensional micro-sized components assembly, an improved support vector machine algorithm is presented, which is employed to identify multi micro objects. Then apply an improved broyden's method to estimate the image jacobian matrix on line. Classical RLS algorithm can provide an optimal estimate to a well-prior knowleage in image jacobian model for uncalibrated visual servoing. However the method has a strict requirement on the prior knowledge and shows a poor adaptability on convergence speed and stability to unknown dynamic applications. A novel improved broyden's method using chebyshev polynomial approximation algorithm for jacobian matrix estimation has been presented. Finally, design a PD controller to control micro-robot. In the microscopic visual environment, the visual servo task of micromanipulator positioning and automatic gripping micro-parts are completed. The experiment results show that the proposed method can meet the requirements of micro-assembly tasks.

8. Future work

Micro-objects and end-effectors can not be shown and controlled at the same time with a single zoom threshold or focus ratio because of the non-uniform light intensity. Therefore, the study of multi-scale's multi-objects classification algorithm is important and effective for improving the accuracy of micro-assembly tasks. Besides, Research on the micro-assembly control strategy based on multi-sensor data fusion is an important technique to improve the micro-robot system performance.

9. Acknowledgments

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Visual Servoing

Edited by Rong-Fong Fung

The goal of this book is to introduce the visional application by excellent researchers in the world currently and offer the knowledge that can also be applied to another field widely. This book collects the main studies about machine vision currently in the world, and has a powerful persuasion in the applications employed in the machine vision. The contents, which demonstrate that the machine vision theory, are realized in different field. For the beginner, it is easy to understand the development in the vision servoing. For engineer, professor and researcher, they can study and learn the chapters, and then employ another application method.

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