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ROBOTIC ADAPTIVE IMPEDANCE CONTROL BASED ON VISUAL GUIDANCE

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Abstract- Uncalibrated visual servoing based on SVR-Jacobian estimator is proposed in unknown environment. Multiple support vector regression (SVR) machines are used to estimate the Jacobian matrix of images，and the nonlinear mapping between the image features of the curved line and the robot joint angle is constructed, uncalibrated robot impedance control can be carried out．Image Jacobian matrix expression with Gaussian kernel is put forward, the effectiveness of the presented approach is verified by using a 6 DOF robot with a CCD camera and a force/torque sensor installed in its end effector.

Index terms*:* robot, vision, impedance control, support vector regression, Jacobian matrix.

I. INTRODUCTION

A large number of industrial robots work in a structured environment, when the product size, structure and process is adjusted, the robot must be programmed and calibrated to adapt to the new operation task. How to improve the robotic autonomous ability and reduce the dependence of the robot on the structure environment is a problem to be solved urgently.

In the uncertain environment, the visual information is the important information for robot control[1-3]. However, when the robot end contacts with the environment, the force and torque information generated by the force sensor cannot get by vision. Visual information and force sensor information are complementary, often used in the actual work. From improve the robot's adaptability to the environment and rapid response capability perspective, in recent years, many researchers have explored the machine vision as a feedback control source for servo control to form visual servo feedback control system[4,5].

Tsuji applicate visual impedance control to realize robotic obstacle avoidance, joint impedance is introduced to reflect the effect of compliant control[6]. Wen shuangquan presents a method for unknown objects grasping using six-axis force/torque sensors, the position of the contact point and corresponding normal direction on the object can be calculated from the sensor information once contact occurs, the robotic hand is a touching sensor and capable of exploration the shape of unknown objects through continual contact to find suitable force-closure grasp configurations[7]. Koh Hosoda presents an adaptive robot controller which is proposed to achieve a contacting task with an unknown environment, while the robot is visually guided, in the visual servo control, the method uses the least square method to estimate the Jacobi matrix, and does not require the accurate calibration of the visual sensor, at the same time, the normal direction of the constrained environment is estimated by using the force feedback data, but its disadvantage is that the robotic Jacobi matrix should be precisely known, and the camera should be fixed, which limits the working range of the robot arm[8].Vincenzo Lippiello presents an algorithm which the environment is a rigid object of known geometry but of unknown and possibly time varying position and orientation, the estimation accuracy is improved during the interaction by using force and joint position measurements. The proposed method can be exploited to implement any kind of interaction control strategy[9]. Ruben Smits shows how multi sensor fusion with position, force and vision sensors can help to improve robot control[10]. C. C. Cheah propose a visually servoed adaptive controller for motion and force tracking with uncertainties in the constraint surface, kinematics, dynamics, and camera model, the robot can track the desired trajectories with the uncertain internal and external parameters updated online[11]. J. POMARES describes an adaptive and auto-calibrated method to track surfaces, the method fuses visual and force information to track a given trajectory maintaining the contact with the surface, the main contribution of the visual servoing approach employed by the impedance control system is the possibility of carrying out the tracking of the trajectory, avoiding time restrictions and without previous knowledge of the intrinsic parameters employed[12]. Antonio C. Leite considers a hybrid force and vision control system for robotic manipulators using a force sensor and a fixed uncalibrated camera, the method is proposed to combine direct force control and adaptive visual servoing to perform tasks on unknown smooth surfaces, in the presence of uncertainties in the camera-robot system parameters, simulation results are presented to illustrate the performance of the proposed scheme [13].Hui Zhang developed a practical 6 DOF robot path generation method using hybrid force and visual servoing methodology, the force servoing keeps the robot tool continuously contacting with the wheel surface and the visual servoing controls the robot tool to follow a marked tool path on the wheel while the position and orientation are controlled and recorded, a robot path is then generated from the recorded data [14]. Nobutaka Tsujiuchi propose two newly developed methods, one is the angle detection of the inclined plane by perspective, and the second is the universal force controller that contains of variable stiffness impedance controller and sliding mode controller, angle detection and contact task were carried out using the proposed control system and the practicability of this method was verified[15]. Sang-Wook Jeon presents object contour following task based on integrated information of both vision and force sensor, the distance to the contour from the center of the image and the angle of the contour is detected by the relative area method that measures the image features of interest directly from the thresholded image without any intermediate steps, a set of contour edge points is detected by canny edge detector[16]. Alkkiomaki, O present a method which fuses force and vision in an extended Kalman filter (EKF), a hybrid force controller is then set up to follow a trajectory based on the estimate from the EKF, the estimate allows a simple proportional force control to track a continuous trajectory reliably, where an unfiltered visual measurement becomes unstable [17]. Isela Bonilla presents a control strategy for industrial robot manipulators which consists of the combination of a calibration-free, vision-based control method with an impedance control approach, the vision-based, robot control method known as camera-space manipulation is used to generate a given trajectory over an arbitrary surface, a kinematic posture-based impedance controller is implemented in order to regulate the interaction forces generated by the contact between the robot end-effector and the work surface where the trajectory is traced[18]. QIU Lian-kui present an force & vision based control scheme for industrial robot arm to track the curve in the uncertain plane and to keep the contact force constant at the same time, with the stereo vision eye -to -hand configuration, the image based vision servoing, with PID controller, is employed to control the end-effector's motions which are parallel to the plane surface, a force sensor is used to acquire the contact force information between the end -effector and the environment and the PD controller is used to control the end -effector's motion component which is vertical to the ground surface[19].

Contact tasks is one of the typical tasks for industrial robot. Contact tasks, such as socket also has been able to use the robot to achieve. However, grinding and polishing task for a robot, with considerable difficulty, it is necessary to control the contact force between the manipulator and the environment[20]. To accomplish complex tasks, multi-sensor are often required. Nelson,B.J[21]give the visual/force feedback sensor fusion architecture, a management layer process different sensing information, the structure is simple, but its shortcoming is to precise calibrate for vision sensor, force sensor and environment. The uncalibrated visual servoing based on image does not require complex camera calibration and robot kinematics model[22]. For uncalibrated visual servoing, the first thing is to solve the Jacobi matrix model estimation problem of image features relative to the robot joint angle, both the traditional Broyden estimator for image Jacobi matrix estimation[23], or neural network to achieve the nonlinear mapping relationship between target feature and the robot joint angle[24], in the actual performance may be unsatisfactory, how to use small samples to build robots visual mapping model has important practical significance.

This paper presents a new visual/force hybrid control method according to the literature [25,26], in the visual servo control, use SVR-Jacobian estimator to approximate the mapping relationship of tracking curve image feature and the robot joint angle, at the same time, use adaptive impedance control to normal side force control for constrained environments. The experimental results show that the hybrid control improves the flexibility, adaptability.

II. VISUAL MAPPING MODEL BASED ON SVR-JACOBIAN ESTIMATOR

The performances of visual servoing depend on image features used in the control circuit. Especially for the visual servo structure based on image, selection and extraction of image features is becoming more and more important, it will directly determine the stability and robustness of the control law and the performance of the final system[27].

Robotic visual servo control for six freedom degree, it is necessary to have six joints of six independent image features and the corresponding robot angle. The selected image features $\xi^{(j)}=[\xi_1^{(j)},\xi_2^{(j)},\cdots\xi_6^{(j)}]^T$ is shown in Figure 1, j on behalf of a window j, L and W as the window j length and width [28].

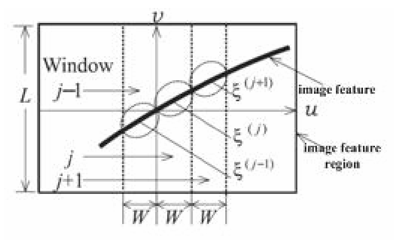

Fig.1 Definition of image feature parameter vector

In the j window, definite $g_{qr}^{(j)}=\begin{cases}0 & \text{(white pixels)}\\ 1 & \text{(black pixels)}\end{cases}$ (1a)

Then you can define independent image features of $\xi^{(j)}$. barycentric coordinates:

$$\xi_1^{(j)}=\frac{\sum_{q=1}^{L}\sum_{r=1}^{W}g_{qr}^{(j)}\cdot q}{\sum_{q=1}^{L}\sum_{r=1}^{W}g_{qr}^{(j)}} \quad (1b) \qquad \xi_2^{(j)}=\frac{\sum_{q=1}^{L}\sum_{r=1}^{W}g_{qr}^{(j)}\cdot r}{\sum_{q=1}^{L}\sum_{r=1}^{W}g_{qr}^{(j)}} \quad (1c)$$

Area: $\xi_3^{(j)}=\sum_{q=1}^{L}\sum_{r=1}^{W}g_{qr}^{(j)}$ (1d)

the long axis and short axis of the equivalent ellipse:

$$\xi_4^{(j)}=\frac{\lambda_{20}^{(j)}+\lambda_{02}^{(j)}+\sqrt{(\lambda_{20}^{(j)}-\lambda_{02}^{(j)})^2+4(\lambda_{11}^{(j)})^2}}{2\xi_3^{(j)}} \quad (1e)$$

$$\xi_5^{(j)}=\frac{\lambda_{20}^{(j)}+\lambda_{02}^{(j)}-\sqrt{(\lambda_{20}^{(j)}-\lambda_{02}^{(j)})^2+4(\lambda_{11}^{(j)})^2}}{2\xi_3^{(j)}} \quad (1f)$$

the direction: $\xi_6^{(j)} = \frac{1}{2}\tan^{-1}\frac{\lambda_{11}^{(j)}}{\lambda_{20}^{(j)} - \lambda_{02}^{(j)}}$ (1g)

Where, $\lambda_{11}^{(j)} = \sum_{q=1}^{L}\sum_{r=1}^{W} g_{qr}^{(j)} \cdot [q - \xi_1^{(j)}][r - \xi_2^{(j)}]$ (1h) $\lambda_{20}^{(j)} = \sum_{q=1}^{L}\sum_{r=1}^{W} g_{qr}^{(j)} \cdot [q - \xi_1^{(j)}]^2$ (1i)

$\lambda_{02}^{(j)} = \sum_{q=1}^{L}\sum_{r=1}^{W} g_{qr}^{(j)} \cdot [r - \xi_2^{(j)}]^2$ (1j)

Robotic six joint angle vector are $\theta = [\theta_1, \theta_2, \cdots \theta_6]^T$, In most cases, between the joint angle and the image feature vector is a complex nonlinear relationship, where use support vector regression to establish the model of the relationship. In general, support vector regression process multi input single output nonlinear mapping, but between the joint angle and the image feature vector is multi input multi output relationship, so need for each component of the feature vector to construct a support vector regression machine.

When use LS-SVR to establish the regression modeling, firstly input samples are mapped from the original space to high dimensional feature space $\psi(x) = [\varphi(x_1), \varphi(x_2), \cdots, \varphi(x_n)]$ by nonlinear mapping function $\phi(\cdot)$. Construct optimal linear regression function in the high dimensional feature space

$$f(x) = \sum_{i=1}^{n} \omega_i \varphi_i(x) + b \qquad (2)$$

Where, $\varphi(\cdot)$ is a nonlinear mapping function, ω is the weight vector, b is a bias. The function estimation problem can be viewed as solving optimization problems as follows:

$$\begin{aligned} &\min J(\omega,\xi) = \frac{1}{2}\omega^{\mathrm{T}}\omega + \frac{1}{2}\gamma\sum_{i=1}^{n}\xi_i^2 \\ &\text{s.t.} \quad y_i = \omega^{\mathrm{T}}\varphi(x_i) + b + \xi_i, i = 1,2,\cdots,n \end{aligned} \qquad (3)$$

Where, $\varphi(\cdot)$, ω and b are the same meaning as above， ξ_i is the error variables, constant γ called the penalty coefficient, $\gamma > 0$. In order to solve the optimization problem of type (3), the Lagrange function as follows is introduced:

$$\mathrm{L}(\omega, b, \xi, \alpha) = J(\omega, \xi) - \sum_{i=1}^{n} \alpha_i \omega^{\mathrm{T}} \varphi(x_i) + b + \xi_i - y_i \qquad (4)$$

Where, α_i is the Lagrange multiplier.

According to KKT (Karush-Kuhn-Tucker) optimal conditions:

$$\frac{\partial \mathrm{L}}{\partial \omega}=0\,,\quad \frac{\partial \mathrm{L}}{\partial b}=0\,,\quad \frac{\partial \mathrm{L}}{\partial \xi_i}=0\,,\quad \frac{\partial \mathrm{L}}{\partial \alpha_i}=0 \qquad (5)$$

We can get:

$$\omega=\sum_{i=1}^{n}\alpha_i\varphi(x_i)\,,\quad \sum_{i=1}^{n}\alpha_i=0\,,\quad \alpha_i=\gamma\xi_i\,,\quad \omega^{\mathrm{T}}\varphi(x_i)+b+\xi_i-y_i=0 \qquad (6)$$

For $i=1,2,\cdots,n$, the following matrix equation can get through simplification:

$$\begin{bmatrix} 0 & I^{\mathrm{T}} \\ I & \Omega+\frac{1}{\gamma} \end{bmatrix}\begin{bmatrix} b \\ \alpha \end{bmatrix}=\begin{bmatrix} 0 \\ y \end{bmatrix} \qquad (7)$$

Where, $y=[y_1,y_2,\cdots y_n]$, $I=[1,1,\cdots 1]^{\mathrm{T}}$, $\alpha=[\alpha_1,\alpha_2,\cdots\alpha_n]^{\mathrm{T}}$, the element $\Omega_{ij}=\varphi(x_i)\varphi(x_j)$ in the Ω, $i,j=1,2,\cdots,n$.

Use the least squares method, α and b can be obtained by type (7). Finally get the expressions for estimating function:

$$f(x)=\sum_{i=1}^{n}\alpha_i K(x,x_i)+b \qquad (8)$$

Where, $K(x,x_i)$ is the kernel function, it makes the function solution around the feature space, obtained directly in the input space.

After determine the image features, LS-SVR network structure can be set up according to the corresponding visual servoing tasks, direct learn the mapping between image feature tracked curve and robot joint angle. Image features of the tracked curve are $\xi^{(j)}=[\xi_1^{(j)},\xi_2^{(j)},\cdots\xi_6^{(j)}]^T$, the robotic six joint angle vector are $\theta=[\theta_1,\theta_2,\cdots\theta_6]^T$, in most cases, between the two is a complex nonlinear relationship, where use support vector regression to model the relationship. Because the image processing time more than the robot servo control time-consuming, let T be the robotic servo control cycle time. Image feature extraction time depend on the specific hardware and software. The image feature extraction time is assumed mT, M is times. In time $t=imT$, the curve image feature is $\xi=\xi^{(j)}(im)$.

The mapping of each feature component $\xi_k^{(j)}$ $(k=1,2,\cdots 6)$ for the robot joint angle can be expressed as type (8):

$$\xi_k^{(j)}(\theta)=\sum_{i=1}^{n}\alpha_{ki}K(\theta,\theta_i)+b_k \qquad (9)$$

The kernel function is Gauss radial basis function, there are

$$\xi_k^{(j)}(\theta) = \sum_{i=1}^{n} \alpha_{ki} \exp(-\|\theta - \theta_i\|^2 / 2\sigma^2) + b_k \qquad (10)$$

Respectively derivative the joint angle component to obtain characteristic components of the Jacobi matrix component on the robot joint angle:

$$\begin{cases} \dfrac{\partial \xi_i^{(j)}}{\partial \theta_1} = \dfrac{1}{\sigma^2} \sum_{i=1}^{n} \alpha_{ki} (\theta_{1i} - \theta_1) \exp \dfrac{-(\theta_1 - \theta_{1i})^2}{2\sigma^2} \\ \dfrac{\partial \xi_i^{(j)}}{\partial \theta_2} = \dfrac{1}{\sigma^2} \sum_{i=1}^{n} \alpha_{ki} (\theta_{2i} - \theta_2) \exp \dfrac{-(\theta_2 - \theta_{2i})^2}{2\sigma^2} \\ \qquad \vdots \\ \dfrac{\partial \xi_i^{(j)}}{\partial \theta_6} = \dfrac{1}{\sigma^2} \sum_{i=1}^{n} \alpha_{ki} (\theta_{6i} - \theta_6) \exp \dfrac{-(\theta_6 - \theta_{6i})^2}{2\sigma^2} \end{cases} \qquad (11)$$

Jacobi matrix component on the joint angle can be written as:

$$J(\theta) = \begin{bmatrix} \dfrac{\partial \xi_1^{(j)}}{\partial \theta_1} & \dfrac{\partial \xi_1^{(j)}}{\partial \theta_2} & \cdots & \dfrac{\partial \xi_1^{(j)}}{\partial \theta_6} \\ \dfrac{\partial \xi_2^{(j)}}{\partial \theta_1} & \dfrac{\partial \xi_2^{(j)}}{\partial \theta_2} & \cdots & \dfrac{\partial \xi_2^{(j)}}{\partial \theta_6} \\ \vdots & \vdots & & \vdots \\ \dfrac{\partial \xi_6^{(j)}}{\partial \theta_1} & \dfrac{\partial \xi_6^{(j)}}{\partial \theta_2} & \cdots & \dfrac{\partial \xi_6^{(j)}}{\partial \theta_6} \end{bmatrix} \qquad (12)$$

Each line of type (12) is decided by equation (11).

The image feature vector $\xi^{(j)}$ of the tracked curves and joint angle vector θ satisfy the equation:

$$\dot{\xi}^{(j)}(\theta) = J(\theta)\dot{\theta} \qquad (13)$$

Generally use the incremental form, in this paper, curve image feature increment is $\Delta\xi = \xi^{(j+1)}(im) - \xi^{(j)}(im)$, then,

$$\Delta\xi(\theta) = J(\theta)\Delta\theta \qquad (14)$$

Equation (13) and (14) are important equations based on image visual servo, different visual servo methods mainly depends on the Jacobi matrix $J(\theta)$ how is produced, here use support vector regression method to estimate the Jacobi matrix. In the robotic visual servo, usually for the inverse operation of type (13), according to the characteristics change determine joint angle.

III. FUZZY ADAPTIVE IMPEDANCE CONTROL

Impedance control is through the adjustment the target impedance model set by the user, the robot terminal reach compliant motion. The target impedance models commonly used such as (15) are shown.

$$M[\ddot{x}_d(k)-\ddot{x}(k))]+D[\dot{x}_d(k)-\dot{x}(k)]+K[x_d(k)-x(k)]=f_d(k)-f(k) \qquad (15)$$

M, D, K are symmetric and positive definite matrices which specify the inertia, damping and stiffness of the robot respectively; $x_d(k), x(k)$ are the reference position trajectory and the actual position trajectory of end-effector respectively; $f(k)$ is the sensed contact force； $f_d(k)$ is the desired contact force that is usually a vector with a constant magnitude.

Dynamic equations of the robot work space coordinates $x(k)$ and the robot joint $\theta(k)$ is

$$\dot{x}(k)=J(\theta(k))\dot{\theta}(k) \qquad (16)$$

Where, J is the robot Jacobi matrix. Assume $x_{d3}(k)$ is the environmental vertical normal component of $x_d(k)$, the remaining components

$$\ddot{x}_{di}(k)=\ddot{x}_i(k), \quad \dot{x}_{di}(k)=\dot{x}_i(k), \quad x_{di}(k)=x_i(k) \ i=1,2,4,5,6 \qquad (17)$$

$f_{d3}(k)$ is the environment vertical force component of $f_d(k)$, the remaining components $f_{di}(k)=0$, $i=1,2,4,5,6$. Assume $x_{c3}(k)$ is the work space position of end effector when in contact with the environment, $x_{d3}(k)$ can be obtained by using the normal component $x_{c3}(k)$:

$$m_{d3}\ddot{x}_{d3}(k)+d_{d3}\dot{x}_{d3}(k)+k_{d3}[x_{d3}(k)-x_{c3}(k)]=f_{d3}(k) \qquad (18)$$

Obtained $x_{d3}(k)$, can be calculated by

$$\dot{x}_{d3}(\mathrm{k})=[x_{d3}(k+1)-x_{d3}(k)]/T, \quad \ddot{x}_{d3}(\mathrm{k})=[\dot{x}_{d3}(k+1)-\dot{x}_{d3}(k)]/T \qquad (19)$$

Then, the impedance control of environment normal direction closed loop system can be written in the following form:

$$f_{d3}(k)-f_3(k)=m_{d3}\ddot{e}_3(k)+d_{d3}\dot{e}_3(k)+k_{d3}e_3(k) \qquad (20)$$

By formula (20) can be obtained, by adjusting the weight m_{d3}, d_{d3} and k_{d3} respectively to determine the contact force influence of $\ddot{e}_3$, $\dot{e}_3$ and $\ddot{e}_3$, the acceleration, velocity, position and force errors trend can be used to decide how to adjust these parameters. In other parameters invariant case, increase inertia parameters m_{d3}, the stability of the contact force is greater, and vice versa. The increase or decrease of the damping parameter d_{d3} generally does not affect the steady state of the contact force, but it will change the contact process between the manipulator and the environment. In general, increase damping parameter d_{d3}, the overshoot is decreased, the vibration is weakened, the force peak decreases significantly, but the large damping parameter will make the force response reach the steady state is longer. The stiffness parameter k_{d3} is the change amount of the mechanical hand and the environment, its size directly reflects the mechanical hand in contact with the environment is rendered rigid or flexible, generally speaking, in force control direction reduces the stiffness parameters will make the contact force of the manipulator and the environment becomes smaller, and the value of the position control direction is greater, the accuracy is higher. The adjustment of the stiffness parameters should make the system in the critical damping or the damping state, in order to guarantee the system stability. But in actual practice because it is difficult to obtain the acceleration, so m_{d3} cannot be adjusted, this case m_{d3} can take a very small value to reduce the error of acceleration effect on the controller.

Tsuji T presents a method that uses neural networks to regulate impedance parameters of the manipulator while identifying environmental characteristics through on-line learning, four kinds of neural networks are used: three for the position, velocity and force control of the end-effector, and one for the identification of environments, the neural networks for the position and velocity control are trained during free movements, the neural networks for the force control and identification of environments are trained during contact movements[29]. Wim Meeussen presents the Compliant Task Generator: a new approach for the automatic conversion of a geometric contact path into a force based task specification, a contact path planner generates a sequence of six-dimensional poses and corresponding contact formations, while a hybrid robot controller expects a desired wrench, twist and the local wrench and twist subspaces, the approach applies to all contact motions between known polyhedral objects, and is verified in real world experiments[30].

In this paper, fuzzy variable stiffness controller and fuzzy variable damping controller are designed respectively by introducing the fuzzy inference technology to adjust d_{d3} and k_{d3}, impedance parameters requirements are different according to different stages, impedance parameter are adjusted real time using fuzzy rules, the transition process stability is ensured while reducing the impact force.

Fuzzy variable stiffness controller input variables are position error $e_3(k)$ and contact force error $e_{f3}(k)$, output variable are the target stiffness coefficient correction Δk_{d3}, fuzzy variable damping controller input variables are speed error $\Delta e_3(k) = e_3(k) - e_3(k-1)$ and the contact force error $e_{f3}(k)$, the output variables are the target damping coefficient correction Δd_{d3}. Fuzzy inference uses Mamdani algorithm, after all input variables and output variables are normalized and divided into seven fuzzy subset, the membership function of each fuzzy set are selected for the Gaussian function, fuzzy inference rules use max min composition operation, fuzzy inference results use center of gravity method. When $e_3(k)$ is PB, $e_{f3}(k)$ is PB, the actual contact force does not reach the setting value, and the impedance parameter k_{d3} is need to be increased, and other fuzzy control rules are shown in Table 1.

Table 1 Fuzzy control rules

Δk_{d3}、 Δd_{d3}		$e_{f3}(k)$						
		NB	*NM*	*NS*	*ZO*	*PS*	*PM*	*PB*
$e_3(k)$、 $\Delta e_3(k)$	*NB*	*NB*	*NB*	*NB*	*NB*	*NM*	*NS*	*ZO*
	NM	*NB*	*NB*	*NB*	*NM*	*NS*	*ZO*	*PS*
	NS	*NB*	*NB*	*NM*	*NS*	*ZO*	*PS*	*PM*
	ZO	*NB*	*NM*	*NS*	*ZO*	*PS*	*PM*	*PB*
	PS	*NM*	*NS*	*ZO*	*PS*	*PM*	*PB*	*PB*
	PM	*NS*	*ZO*	*PS*	*PM*	*PB*	*PB*	*PB*
	PB	*ZO*	*PS*	*PM*	*PB*	*PB*	*PB*	*PB*

IV. EXPERIMENTAL STUDY

The proposed control strategy is verified by experimental research, tracking unknown trajectories by Adept-3 robot, robot control parameters see[31], SAFMS-11 six dimension wrist force/torque sensor developed by Chinese Academy of Sciences Hefei Intelligent Machinery Research Institute is used. Window of camera image size is $256[\text{pixel}] \times 256[\text{pixel}]$ used in this paper, $L = 256$, $W = 10$. Sampling time of visual servo and force servo are respectively 150ms and 6ms.

In the visual mapping modeling process, generate a set of joint angles by the computer control the robot, through real-time CCD camera is rigid connected with the end of the robot collect the tracked curve image features, to obtain the training data set. The robot end is required to move along the unknown trajectory, maintain contact force 40*N*. The variables domain of the fuzzy impedance control algorithm is respectively: $e_3(k) \in [-0.8, 0.8]$, $\Delta e_3(k) \in [-1,1]$, $e_{f3}(k) \in [-1,1]$, $\Delta d_{d3}(k) \in [-6,6]$, $\Delta k_{d3}(k) \in [-6,6]$. The initial value d_{d3} is 27 and the initial value k_{d3} is 120. Figure 2,3 is the experimental results, which f_x, f_y respectively is the contact force along the X,Y direction component.

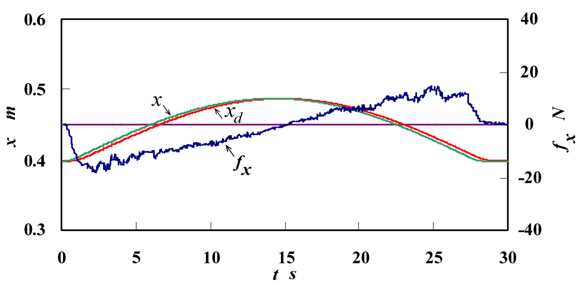

Fig.2 position/force of *X* direction

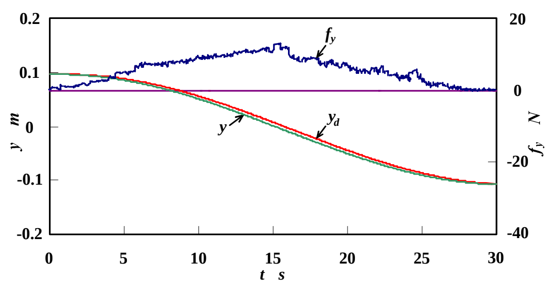

Fig.3 position/force of *Y* direction

The experiment requires the robot terminal contact rod along the unknown trajectory motion, normal tracking process to achieve variable force tracking. There are two kinds of different materials - steel and rubber track process (at thirteenth seconds as the dividing line).

$$f_{d3} = \begin{cases} 15, \ 3 < t < 8.5 \\ 20, 8.5 < t < 15 \\ 15, 15 < t < 25 \end{cases} \tag{21}$$

Figure 4, figure 5 is the result of the experiment, can be seen from Figure 4, curve tracking error is very small.

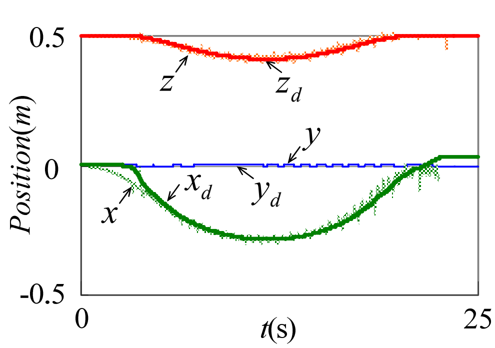

Fig.4 Unknown curve tracking

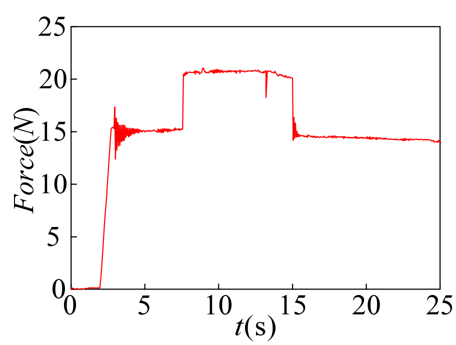

Fig.5 Tracking of variable force

From the workpiece edge tracking and force tracking curve can be seen, the hybrid control strategy is proposed in this paper can basically meet the control requirements.

V. CONCLUSION

In the contact type practical task, due to external constraints uncertainty, it is difficult to get ideal control results of conventional force control method, the hybrid control of multi sensors is studied. In the visual servo control, use multiple support vector regression(SVR) machines to mapping relation between image features tracked curve and the robot joint angle, at the same time using adaptive impedance control to the constraint environment for force control. From the experimental results, the control strategy with high control precision and force tracking capability, is robust to changes in environmental contact parameters.

VI. ACKNOWLEDGEMENT

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