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Surveying the Application of Iterative Learning Strategy in Uncalibrated Vision-Based Robot Manipulators Control

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***Abstract* – This article presents an iterative learning scheme for studying the problem of vision guided robot trajectory tracking. Traditionally visual sensing and manipulation are combined in an open-loop fashion, 'looking' then 'moving'. The accuracy of the operation depends directly on the correctness of the visual sensor, manipulator and robot controller. An alternative to increasing the accuracy of these subsystems is to use a visual-feedback control loop, which will increase the overall accuracy of the system, a principle concern in any application.**

In this paper, the problem visual servoing is studied with a more general point of view under one aspect. It will consist of proposing an uncalibrated visual servoing, which can deal with unknown environment without using a-prior knowledge based on iterative learning method.

To show the practical applicability of the proposed method it has been applied to PUMA560 manipulators using a simulation model to confirm that the method can work properly.

***Keywords* – Itrative Learning Control (ILC), Visual Servoing, Robot Manipulators, Uncalibrated Vision-Based Control.**

I. INTRODUCTION

Visual servoing is a closed-loop control of a robot system where vision is used as the underlying sensor [1], usually consists of two intertwined processes: tracking and control. Tracking provides a continuous updating of features during the robot/object motion.

The task in visual servoing is to control the *pose* of robot's end-effector using visual information extracted from the image. More precisely in visual servoing task, image information is used to measure the error between the current location of the robot and desired location. Image information can be in 2-dimensional, expressed by image plane coordinate or 3-dimensional where camera model is employed to retrieve pose information respect to world/robot coordinate system. Thus the robot is controlled using either 2 or 3 dimensional information of captured image. This is one of the major classifications of visual systems that distinguish position-based control from image-based control [2]. The primary disadvantage of position-based control is that it is often highly calibration dependent [2].

In image-based visual servoing (IBVS), an error signal is measured in the image and is mapped directly to actuator command. IBVS systems have several advantages over PBVS systems. They are robust to calibration errors and do not require a full 3D reconstruction of the environment [3]. It is also reduce computational delay, eliminate errors in sensor modeling and camera calibration.

The subject of controlling the iterative processes has taken into consideration a lot by investigators since these two recent decades, it has achieved good improvements in both theoretical field, and utilization field as it is became one of the specialty majors of control science. Iterative learning control (ILC) is a method to control the systems which are doing a specific task repetitively in a restricted and constant time interval. As long as the iterative learning control issue was introduced [4], many methods have been considered. Rogers et al. [5] firstly proposed the 2-D forms of the ILC system and investigate the convergence of the ILC systems via the stability criterion for the 2-D system. Geng et al. [6] introduces a 2-D system for designing an ILC system. By using a 2-D Roesser model, Kurek et al. [7] and Fang et al. [8] proposed feedback feed-forward ILC methods for repetitive dynamics. In this paper, the problem of image based visual servoing is considered as an ILC case. As a result, an update formula will be presented to address the tracking problem and finally the simulation results are shown the efficiency of the method. The paper is structured as follows: First a brief overview of Iterative learning Method for Nonlinear Systems. In Sections II the Application of Iterative Learning strategy in Uncalibrated Vision-Based Robot Manipulators Control shown .In Sections III, simulation results are used to show the efficiency of the presented method. Finally, concluding observations are discussed in Section IV.

II. ITERATIVE LEARNING METHOD FOR NONLINEAR SYSTEMS

The iterative learning control (ILC) method has been proposed by Arimoto et al. [4] for the control systems which can perform the same task repetitively. Recently, most of the proposed learning algorithms have been used in applications on robot control where the robot system is required to execute the same motion repetitively, with a certain periodicity. The basic learning controller for generating the present control input is based on the previous control history and a learning mechanism. For the ILC of continuous-time systems, a well known design [4], [9], [10] is the so called D-type ILC. Since the derivative action destroys the noise reduction of the control system, a

P-type ILC has been studied recently for the control of robotic motion [11], [12] and for a class of nonlinear systems [13]–[15].

For real application of an iterative learning controller, it is of great importance to discretize the systems and store the sampled-data of desired output, system output, and control input in memory. Consequently, it is more practical to design and analyze the ILC systems in discrete-time domain.

In this regard, a class of discrete-time nonlinear systems described by the following difference equation is studied.

$$z^{(n)} = f(Z) + g(Z)u \qquad (1)$$

where in the above relation $Z = [z, \dot z, \dots, z^{(n-1)}]$. The relation (1) is also can be shown in the following form:

$$\begin{cases} \dot z_1 = z_2 \\ \dot z_2 = z_3 \\ \vdots \\ \dot z_n = f(Z) + g(Z)u \end{cases} \qquad (2)$$

Furthermore, $z(t)$ is output of system and $z^{(i)}$ denotes the derivative of order *i* of the $z(t)$ and also $u(t)$ is input of the system. Also, it is assumed that the function *f* is a continuous and uniform one with respect to *z*. Moreover, it is assumed that $f(0,t) = 0$.

For the system (1) a controller with the following equation can be used

$$u_{k+1}(t) = u_k(t) + q\Delta e_k(t) \qquad (3)$$

Where *t* denotes time and the subscript *k* is used to show the trial number. Also, *u* is the controller and $\Delta e_k(t)$ is as follows:

$$\Delta e_k(t) = \dot z_{n,k+1} - (-\alpha_1 z_{1,k} - \alpha_2 z_{2,k} - \cdots - \alpha_n z_{n,k}) \qquad (4)$$

As it is obvious this ILC is D-type and the α parameters are the elements of a specific matrix which is determined by controller designer and in some cases are called learning factors.

$$q = \begin{bmatrix} 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & & & & \vdots \\ -\alpha_1 & -\alpha_2 & & \dots & -\alpha_n \end{bmatrix} \qquad (5)$$

III. ITERATIVE CONTROL OF ROBOT MANIPULATORS USING VISUAL METHODS

In the problem of visual servoing the movements of a robot is controlled based on visual features extracted from images. These features are categorized into an n dimensional vector *y*. The main purpose in image-based visual servoing is to move the end effecter of robot from its current position, *y*, to the visual desired position y_d. The visual features, *y*, and robot actions, *x*, are related by a visual-motor function, *f*, which is unknown in initializing and this relation can be written as $y = f(x)$ [16]. The visual motor function *f*, is non-linear and cross-coupled. In general an unknown function can be written in Taylor expansion. Therefore the visual motor function can be written as:

$$f(x) \approx f(x_k) + J(x_k)(x - x_k) \qquad (6)$$

Where $J(x_k)$ is the "image" or visual-motor Jacobian defined as:

$$(J_{j,i})(x_k) = \frac{\partial f_j(x_k)}{\partial x_i} \qquad (7)$$

As it was mentioned before it is very significant in practical problems to discretize the systems and other related parameters.

In every iterative learning problem and mainly in tracking problems the main task is to optimize or minimize a specific error function. In this case, the problem is viewed as an optimization of the error function defied as:

$$E = \frac{1}{2}(f - y_d)^T (f - y_d) \qquad (8)$$

As an iterative strategy in the first place we should compute the distance between desired position, y_d, and the real position of end-effecter, *y*, which is extracted from images. As a result the movement of end-effecter is computed as follows:

$$\Delta x_k = -J_k^{+}(x_k)(y_k - y_d) \qquad (9)$$

Where J^{+} denotes the generalized matrix inverse, i.e., simple matrix inverse when *J* is invertible, and the pseudo-inverse, $(J^T J)^{-1} J^T$ when it is not. This term, Δx, is also called correction term.

For more accuracy and as a high order iterative learning method the relation (9) can be extended to the following term.

$$\Delta x_k = -J_k^{+}(x_k)(y_k - y_d) - J_{k-1}^{+}(x_{k-1})(y_{k-1} - y_d) - \cdots$$

After computing correction term, this should be executed

$$x_{k+1} = x_k + \alpha \Delta x_k \qquad (10)$$

One approach to estimate the Jacobian is based on the information obtained from performing the task. By simultaneously tracking changes in visual feature values and changes in motor joint angles we can learn about the derivatives of *f* in the direction of joint space where the robot has moved. This method has several advantages. It does not need any a-prior knowledge. It is able to estimate the Jacobian by just observing the process, without introducing any extra "calibration" movements. More precisely, after making the movement Δx_k and observing the change $\Delta y_{measured}$ in the feature values, we have a secant approximation to the directional derivative along Δx_k. Now we wish to update the Jacobian in order to satisfy the most recent observation:

$$\Delta y_{measured} = J\Delta x \qquad (11)$$

Which can be done using the rank one Broyden's updating formula and several methods exist for finding approximate solutions Δx , e.g., normal equations or SVD based methods.

$$J_{k+1} = J_k + \frac{(\Delta y_{measured} - J_k \Delta x)\Delta x^T}{\Delta x^T \Delta x} \qquad (12)$$

The first Jacobian could be a raw estimation such as random number and it will get updated along the dimensions spanned by $\{\Delta x\}$.

IV. SIMULATION RESULT

In this section, the proposed method will be evaluated using a simulation model of PUMA560 built in Matlab robotics toolbox. The PUMA560 is a six DOF robot manipulator and configured similarly to the human arm

(Fig. 1). This gives 3 redundant freedoms for positioning one point, and 0 redundant freedoms for general (full) rigid pose. For simplicity in setting up the simulation orthographic cameras were placed along the x and y axes and used for the visual measurements. (Note that however because the visual-motor Jacobian is estimated, any camera can be used.)

The simulation program is written in Matlab and the results of this simulation are shown in the following figures. The end-effecter of manipulator robot (Puma560) can be in any position in the first iteration. Figure 2 shows the pose of robot's end-effecter in the first iteration of each run of the simulator. It is for more simplicity and to provide useful results which can be compared with each other. As a result, in the first iteration the end-effecter is assumed to be located in the position of [45.21 -15 43.18] (in the Cartesian space).

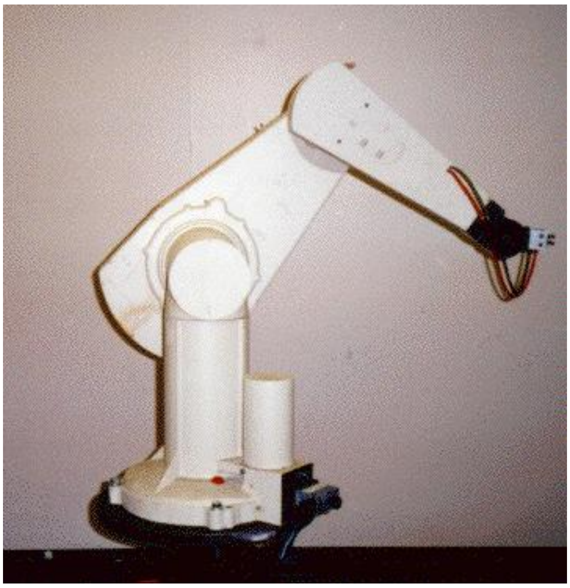

Fig.1. PUMA560 manipulator

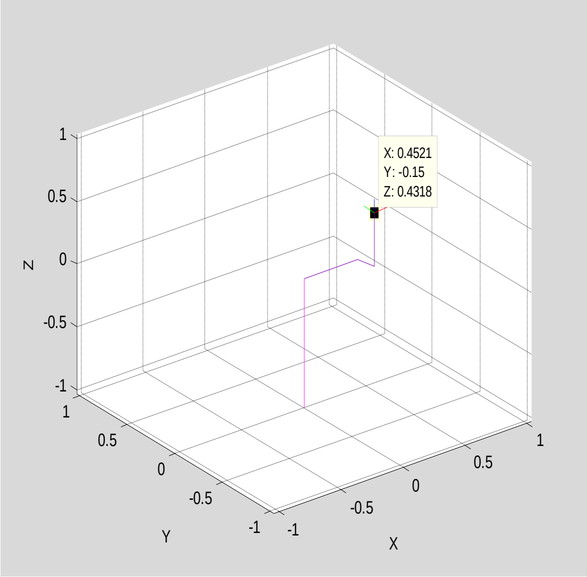

Fig.2. The pose of robot's end-effecter in the first iteration

In the first example, it is assumed the y_d is [-20 -40 40]. Consequently, robot's end-effecter should be moved from start position [45.21 -15 43.18] to [-20 -40 40]. As it can be seen in figures 4, 5 the tracking error's L_2-norm is reduced until it approaches to zero. The convergence rate is in proportion to the parameter α in Eq. 10. On the other hand, by increasing this parameter the convergence rate increases. Despite this improvement in the convergence rate, this parameter can increase to a value that is the threshold of divergence of the tracking error's L_2 *norm.*

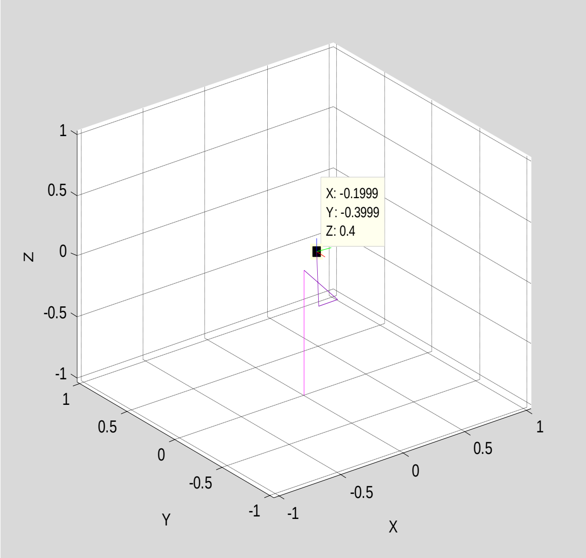

Fig.3. The final pose of robot's end-effecter in the configuration space for y_d=[-20 -40 40].

As it is obvious in the figures 4 and 5, when α is equal to 0.6 the convergence rate of the tracking error is much more than when that is equal to 0.1.

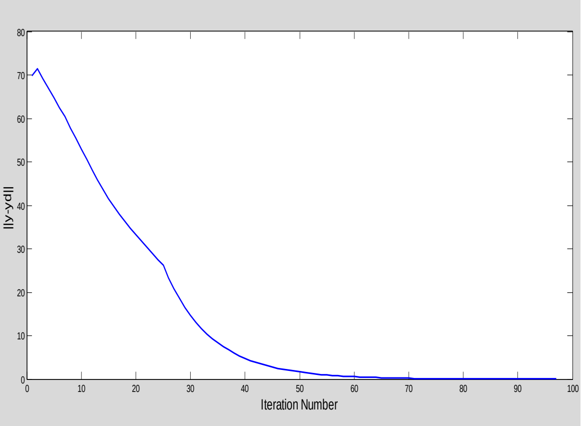

Fig.4. The tracking error's L_2-*norm* during manipulation with $\alpha = 0.1$

As another example we choose y_d = [40 20 35]. The pose of end-effecter in the configuration space and the tracking error's L_2-*norm* can be seen respectively in figures 6 and 7.

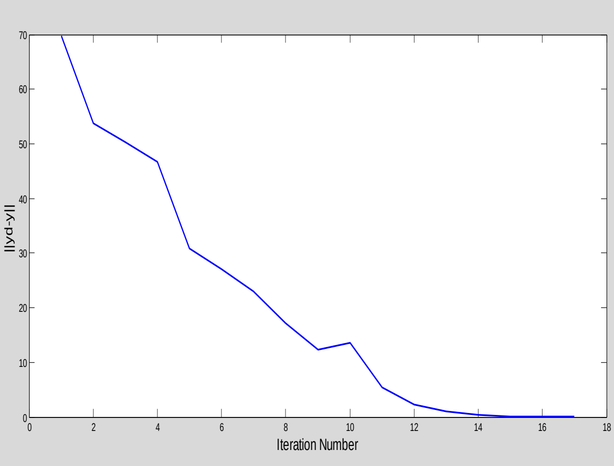

Fig.5. The tracking error's L_2-*norm* during manipulation with $\alpha = 0.6$

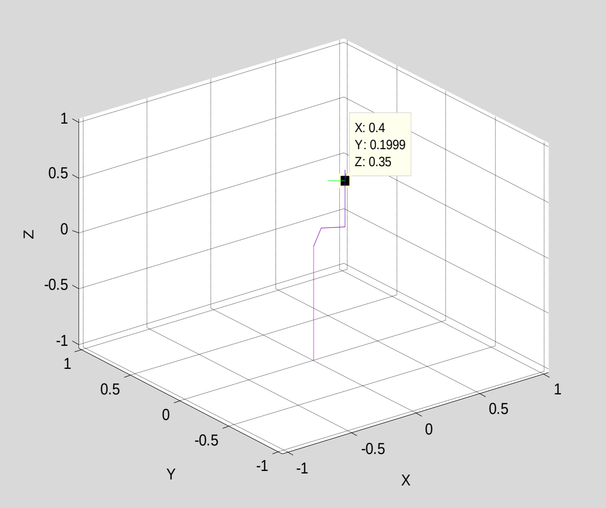

Fig.6. The final pose of robot's end-effecter in the configuration space for y_d = [40 20 35].

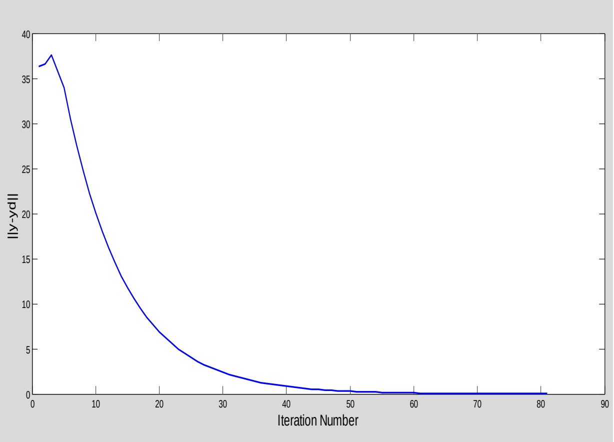

Fig.7. The tracking error's L_2-*norm* during manipulation with $\alpha = 0.1$

V. CONCLUSION

The purpose of the method is to make robotic manipulation possible outside of carefully engineered manufacturing applications. A potential application of visual servo control system is telerobotics. Telerobotics has important application especially in the environments which is inhospitable to humans such as deep ocean, inside nuclear reactors, and in deep space. In telerobotics, robots are controlled by remote links to human operators who may be close by or thousands of miles away. To control robot manipulators, in this paper, a method is considered using visual sensors and iterative learning methods. Furthermore, the convergence rate of tracking error is also considered.

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