Implementation of Object Grasping Control for a Robot Arm Using Fuzzy Control and Two-CCD Imaging Measurements

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Abstract—**An implementation of an object grasping control system for a robot arm is presented in this paper. The hardware of the system contains a fabricated robot arm with a gripper, a pair of charge-coupled device (CCD) cameras, and a computer as the control center. The two CCD cameras are used to "see" the target object and the two-eye imaging geometry is used to calculate the target's position in 3-D space. In the control process, the inverse-kinematics (IK) concept is utilized to drive the robot arm. First let the robot arm reach a point round the target object such that the target object locates inside the effective grasping region. A fuzzy based object approaching control is proposed then to adjust the gripper position such that the position error between the target object and gripper positions is reduced until the target object position is reached. Thus, the gripper can grasp the target object precisely. Two experimental cases are conducted to demonstrate the effectiveness of the proposed control, in which the target objects are an egg and a bottle, respectively.**

Index Terms—**3-D Position Measurement, Charge-Coupled Device (CCD) Geometry, Fuzzy Control, Inverse Kinematics (IK), Object Grasping Control, Robot Arm**

I. INTRODUCTION

Robot arms are usually expected to perform repeated and servant tasks which are in need of precise motion controls. In this study, the robot arm with a gripper (shown in Fig. 1) is designed to execute the object grasping behavior. Building an appropriate sensory feedback control system is mandatory to achieve the specific control purpose.

Previous literatures regarding to the robot arm motion control are reviewed in the following paragraphs. Furuta *et al.* [1] proposed the dynamic equation of a robot arm; based on the laser beam sensory feedback, a PID controller is designed to achieve the trajectory tracking for a robot arm. White *et al.* [2] developed a graphics simulator for a robot arm to compute the coordinates of each joint such that the robot arm can be controlled to track an assigned trajectory. Munasinghe *et al.* [3] presented an off-line trajectory generation algorithm to solve the contouring problem of industrial robot arms. Using the Mitsubishi PA-10 robot arm platform, Kennedy and Desai [4] proposed a harmonic drive transmission model to investigate the gravity and material influence to the robot arm. Then the robot arm can be controlled to track a desired trajectory and the motion error can be analyzed. In [5], a two-link robot arm was controlled by a fuzzy sliding mode controller in which parameters are adjusted by fuzzy-neural methods.

Furthermore, the inverse kinematics (IK) is a well-known concept and has been widely applied in robot arm motion control. Shen *et al.* [6] applied a self-configuration fuzzy system to find the IK solutions for a robot arm. Feliu *et al.* [7] employed the IK-based two-nested control-loop scheme to control the tip position by using joint position and tip acceleration feedbacks. The paper [8] proposed an on-line algorithm based on a second-order IK to ensure the path tracking capability under joint limits of a robot arm. Shimizu *et al.* [9] proposed an analytical methodology of IK computation for a 7-DOF redundant robot arm with joint limits.

Based on Riemannian geometry, the paper [10] proposed an optimal extended Jacobian IK algorithm for robot arms. Using the IK technique, the robot arm in [11] was designed to push the buttons of an elevator.

Recently, a vision-based sensory technique for constructing a 3-D measurement (or called stereo measurement) is getting popular in estimating the 3-D coordinates of objects for robotics applications. Nilsson and Holmberg [12] combined a 2-D vision camera and an ultrasonic range sensor together for the robot gripper to estimate the object position. Baek and Lee [13] used two cameras and one laser to recognize the elevator door and to determine its depth distance. Okada *et al.* [14] designed and implemented a knowledge based visual 3-D object recognition system with multi-cue integration and particle filter technique. Moreover, the photogrammetric methods were proposed in [15]–[17], which utilize objects' features to measure their distances. Gao *et al.* [18] presented a signal processing pipeline for 3-D stereoscopic cameras to do camera calibration and depth estimation. Using an RGB color histogram, the paper [19] effectively applied color images to achieve the 3-D measurement. Hsu *et al.* [20] proposed an image-based 3-D measuring system to measure distance and area by using a single charge-coupled device (CCD) camera and two laser projectors. In [21] and [22], distance and angle measurements for objects were made based on pixel variation in CCD images. Das and Ahuja [23] compared the performances of the binocular cues of stereo and vergence, and the monocular cue of focus to improve the accuracy of range estimation. The paper [24] adopted two cameras and a laser projector to measure the edge of an object regardless of its position.

Object grasping control for a robot arm is the main objective of this paper. A two-CCD vision system with the imaging geometry is presented to measure the objects and the gripper positions in 3-D space. To manipulate the robot arm, the IK technique [6] is utilized to achieve the motion control. Based on the practical position error between the gripper and the target object, this paper proposes a fuzzy object approaching control to drive the gripper to reach the target object precisely. This is performed such that the gripper can firmly grasp the object. With the object picked up by the robot, grasping control is complete. Finally, two real experiments are implemented to verify the feasibility of the proposed control scheme.

The rest of this paper is organized as follows; Section II briefly introduces the real robot arm system, while Section III presents the two-CCD vision system with its two-eye imaging geometry to calculate the target position in 3-D space. In Section IV, the object grasping control based on the IK technique and the fuzzy object approaching control are proposed. Practical experiments are given in Section V to evaluate the proposed control scheme and Section VI provides conclusions on the techniques and experiments.

II. DESCRIPTION OF THE ROBOT ARM SYSTEM

This section introduces the robot arm system, which is designed to implement the object grasping behavior in 3-D space. Figure 1(a) shows a photograph of the robot arm system and Fig. 1(b) depicts the framework of the system. The system is comprised of a fabricated robot arm with a gripper, a set of two-CCD vision device, and a computer as the control center. Referring to Fig. 1, the hardware of the system is precisely described as follows.

A. Robot Arm

The robot arm consists of several servo motors with metal connections. There are three joints (joints 1, 2, and 3) in the robot arm for the gesture motion in 3-D space (see Fig. 1). Joints 1, 2, and 3 are designed for the shoulder rotation, lifting movement, and elbow bending, respectively. At the end of the robot arm, a two-palm gripper driven by two small servo motors is used for the object grasping. Two pieces of skidproof mats are pasted inside the gripper palms to increase the grasping friction, while two green patterns are pasted outside the palm to aid the gripper image detection. Each servo motor is combined with a speed-reducer gearbox to increase the rotary torque, and is controlled by serial recommended standard-232 (RS-232) command signals from the computer.

B. Two-CCD Vision Device

Sensory feedback for the robot arm object grasping control depends on the vision capability which is provided through use of two CCD cameras (Logitech C905 USB cameras) that are mounted in parallel on the top platform (see Fig. 1). Both the gripper and the target object are generally captured by the two CCDs with this setup. The 3-D positions of the gripper or the target object can now be calculated by the two-eye imaging geometry. According to the specifications of the CCD cameras, the camera resolution is 640 x 320 pixels and the capturing rate is 30 frames per second.

C. Control Center

The control center of the robot arm system is a laptop computer with an Intel Core 2 Duo 2.4 GHz CPU and 2 GB random-access memory (RAM). The computer is employed to execute the two-eye image processing, pattern recognition, imaging geometry calculation, 3-D position measurement, and the motion control for the robot arm. Borland C++ Builder is the integrated development environment (IDE) used to develop the control software.

III. TWO-CCD IMAGING MEASUREMENTS

The main objective in this paper is to control the robot arm to reach the accurate position such that the robot gripper can grasp the target object successfully. Hence, the first task is to measure the 3-D positions of the robot gripper and the target object by using the two-CCD vision device. Before the geometric analysis, three 3-D coordinate systems in the working space are defined (see Fig. 1). The first is the world coordinate $[\mathrm{X}, \mathrm{Y}, \mathrm{Z}]_{\mathrm{W}}^{T}$ as the main coordinate, and the second is the vision coordinate $[\mathrm{X_v}, \mathrm{Y_v}, \mathrm{Z_v}]_{\mathrm{V}}^{T}$ for the CCD measurement. Notably, the above two coordinates have the same origin $\mathrm{O}(0,0,0)_{\mathrm{W}} = \mathrm{O_v}(0,0,0)_{\mathrm{V}}$ locating at the center position of the vision device (see Fig. 1), where O and $\mathrm{O_v}$ represent the world and the vision origins, respectively. Furthermore, the last is the kinematics coordinate $[\mathrm{X_k}, \mathrm{Y_k}, \mathrm{Z_k}]_{\mathrm{K}}^{T}$ for the motion control of the robot arm, where the kinematics origin $\mathrm{O_k}(0,0,0)_{\mathrm{K}}$ locates at the shoulder position.

A. Single-CCD Imaging Geometry

Let the imaging geometry for a single CCD be firstly discussed. Suppose that the view plane of a target 3-D position is perpendicular to the optical axis of a fixed CCD camera, and the captured image can be projected onto a 2-D imaging frame. Figure 2 shows the schematic diagram of a single CCD camera capturing a spatial image based on a pinhole camera model, in which f represents the CCD focal length and y_v represents the photographic distance between the CCD and the view plane. The center of the pixel-based imaging frame is denoted by $\mathrm{C_p}$, $\mathrm{C_v}$ is the CCD optical point on the view plane, and the vision origin $\mathrm{O_v}$ is at the CCD lens. Furthermore, $(x_v, y_v, z_v)_{\mathrm{V}}$ represents the position of the robot gripper or the target object on the view plane and (x_p, z_p) represents the reflected coordinates on the imaging frame. Once the 2-D vector (x_p, z_p) is found by the pixel computation, the values of x_v and z_v are derived from (1) based on the similar triangle concepts.

$$
\begin{cases}
x_v = \dfrac{x_p}{f} \cdot y_v \\
z_v = \dfrac{z_p}{f} \cdot y_v
\end{cases}
\tag{1}
$$

However, since the photographic distance can not be measured from an image captured by the single CCD, the value of y_v can not be exactly measured. That means a single CCD is difficult to measure the 3-D position $(x_v, y_v, z_v)_{\mathrm{V}}$. Therefore, by expanding the single CCD measuring method to a two-CCD vision system, a 3-D position measurement is obtained. A two-CCD system is suggested in this paper.

B. Two-CCD Imaging Geometry

Two CCD cameras are set up in parallel and at the same height to capture a perpendicular view plane. Pair of different imaging frames can be obtained from the cameras for further geometric analysis. Figure 3 illustrates the schematic diagram of the two-eye imaging geometry for the 3-D position measurement, in which f_1 and f_2 are focal lengths of CCD1 and CCD2, respectively, and D is the separated distance between CCD1 and CCD2. Moreover, $\mathrm{C_{p1}}$ and $\mathrm{C_{p2}}$ are the centers of pixel-based imaging frames 1 and 2, respectively. Then $\mathrm{C_{v1}}$ and $\mathrm{C_{v2}}$ denote two CCDs' optical points on the view plane, respectively, and the vision origin $\mathrm{O_v}$ is the midpoint between CCD1 and CCD2.

As shown in Fig. 3, the 3-D position measurement obtains $(x_v, y_v, z_v)_{\mathrm{V}}$ using the two 2-D pixel vectors (x_{p1}, z_{p1}) and (x_{p2}, z_{p2}), which are the reflected coordinates on the imaging frames 1 and 2, respectively. Referring to Fig. 3(b), the separated distance D provides a method to measure the photographic distance.

$$D = |x_{v1}| + |x_{v2}| = \frac{|x_{p1}|}{f_1} \cdot y_v + \frac{|x_{p2}|}{f_2} \cdot y_v \tag{2}$$

From (2), the distance y_v is firstly obtained in (3a). Then the values of x_v and z_v are obtained from (3b) and (3c), respectively.

$$y_v = \frac{D}{\frac{|x_{p1}|}{f_1} + \frac{|x_{p2}|}{f_2}} \tag{3a}$$

$$x_v = \frac{1}{2}\left(\frac{x_{p1}}{f_1} + \frac{x_{p2}}{f_2}\right) \cdot y_v \tag{3b}$$

$$z_v = \frac{z_{p1}}{f_1} \cdot y_v \quad \left(\text{or } z_v = \frac{z_{p2}}{f_2} \cdot y_v\right) \tag{3c}$$

Consequently, the measurement of 3-D position $(x_v, y_v, z_v)_{\mathrm{V}}$ for the robot gripper or the target object is achieved.

C. Coordinate Transformation

In the working space, the vision origin $\mathrm{O_v}$ is equally assigned as the world origin, i.e., $\mathrm{O_v = O}$. However, the vision device is capable to rotate its visual direction. There exists a three-phase difference in angle between the vision and the world coordinates, which can be divided into a pitch angle ψ_x, a roll angle ψ_y, and a yaw angle ψ_z, as depicted in Fig. 4. Herein, the three-phase rotation matrices in [12], [25] can be used to transform the vision coordinate $[\mathrm{X_v, Y_v, Z_v}]_{\mathrm{V}}^T$ to the world coordinate $[\mathrm{X, Y, Z}]_{\mathrm{W}}^T$.

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \begin{bmatrix} \cos\psi_z & \sin\psi_z & 0 \\ -\sin\psi_z & \cos\psi_z & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos\psi_y & 0 & \sin\psi_y \\ 0 & 1 & 0 \\ -\sin\psi_y & 0 & \cos\psi_y \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\psi_x & \sin\psi_x \\ 0 & -\sin\psi_x & \cos\psi_x \end{bmatrix} \cdot \begin{bmatrix} x_v \\ y_v \\ z_v \end{bmatrix} \tag{4}$$

Consequently, a desired 3-D position $(x_v, y_v, z_v)_{\mathrm{V}}$ in vision coordinate can be described as a calibrated world coordinate $(x, y, z)_{\mathrm{W}}$.

IV. OBJECT GRASPING CONTROL DESIGN

A. Inverse Kinematics Based Motion Control

Recall to the fabricated robot arm (shown in Fig.1), this paper applies the IK technique to manipulate the robot arm such that the robot gripper can reach the acceptably accurate position and grasp the object. Figure 5 shows the IK concept which is a mapping from the working space to the joint space [6]. With the current position of the robot gripper is $(x_k, y_k, z_k)_{\mathrm{K}}$ in the kinematics coordinate, the mapping joint angles $(\theta_1, \theta_2, \theta_3)$ for the robot arm can be obtained by geometric derivations using IK. Figure 6 illustrates the kinematics coordinate of the robot arm, where $\mathrm{O_k}$ is the kinematics origin, Q is the elbow node, and $\mathrm{G}_{IK}(x_k, y_k, z_k)_{\mathrm{K}}$ is the gripper position. The lengths of the links 1 and 2 are denoted as d_1 and d_2, respectively. Thus, the two links with the three joints $(\theta_1, \theta_2, \theta_3)$ are established so that the robot arm can have flexibility in 3-D space (see Fig. 1 and Fig. 6). For further geometric derivations, a projective robot arm can be found on the $\mathrm{Y_k}$-$\mathrm{Z_k}$ plane, where R and S represent the projective points of G_{IK} and Q, respectively. Additionally, the W axis represents the direction along θ_1 and $\theta_2 = 0$ on the $\mathrm{Y_k}$-$\mathrm{Z_k}$ plane. The G' is the projective point of G_{IK} along the link 1 direction, and the G'' is the projective point of G' along the W axis.

Let us provide three figures (Fig. 7(a)–(c)) to introduce the deviations of the rigid kinematics of the robot arm. Figure 7(a) shows the two-link arm plane, where $L = \sqrt{x_k^2 + y_k^2 + z_k^2}$ is the distance between the gripper G_{IK} and the kinematics origin $\mathrm{O_k}$. The elbow bending joint angle θ_3 is obtained as follows.

$$\begin{aligned}\theta_3 &= \pi - \alpha \\ &= \pi - \cos^{-1}\left(\frac{d_1^2 + d_2^2 - L^2}{2d_1 d_2}\right), \text{ where } 0 \le \theta_3 \le \pi/2\end{aligned} \tag{5}$$

In the $\mathrm{X_k}$-W plane shown in Fig. 7(b), the lifting movement joint angle θ_2 can be derived as

$$\theta_2 = \sin^{-1}\left(\frac{x_k}{d_1 + d_2\cos\theta_3}\right), \text{ where } 0 \le \theta_2 \le \pi/2\,. \tag{6}$$

Furthermore, Fig. 7(c) depicts the projected arm on the $\mathrm{Y_k}$-$\mathrm{Z_k}$ plane where $L_{yz} = \sqrt{y_k^2 + z_k^2}$. Consequently, the shoulder rotation joint angle θ_1 is obtained.

$$\begin{aligned}\theta_1 &= \beta + \gamma \\ &= \cos^{-1}\left(\frac{L_{yz}^2 + \left((d_1 + d_2\cos\theta_3)\cos\theta_2\right)^2 - (d_2\sin\theta_2)^2}{2L_{yz}\left((d_1 + d_2\cos\theta_3)\cos\theta_2\right)}\right) + \sin^{-1}\left(\frac{z_k}{L_{yz}}\right), \text{ where } 0 \le \theta_1 \le \pi/2\end{aligned} \tag{7}$$

With the transform of $(\theta_1, \theta_2, \theta_3)$ in (5)–(7) into the motor control signals, the robot gripper can be excepted to reach the desired position $\mathrm{G}_{IK}(x_k, y_k, z_k)_{\mathrm{K}}$. Moreover, since the kinematics origin $\mathrm{O_k}$ locates at the shoulder position which has a shifting distance $\left(\mathrm{O_k} - \mathrm{O_v}\right)$ away from the vision origin $\mathrm{O_v}$, the shifting relationship between the kinematics coordinate $[\mathrm{X_k},\ \mathrm{Y_k},\ \mathrm{Z_k}]_{\mathrm{K}}^T$ and the world coordinate $[\mathrm{X},\ \mathrm{Y},\ \mathrm{Z}]_{\mathrm{W}}^T$ is as follows.

$$(x, y, z) = \left(\mathrm{O_k} - \mathrm{O_v}\right)_{\mathrm{W}} + (x_k, y_k, z_k) \tag{8}$$

Therefore, a gripper position $\mathrm{G}_{IK}(x_k, y_k, z_k)_{\mathrm{K}}$ can yield the corresponding $\mathrm{G}_{IK}(x, y, z)_{\mathrm{W}}$ in the world coordinate.

Remark 1: Practically, the motor backlash problems and the hardware uncertainties may affect the 3-D position accuracy of the IK technique, i.e., the robot gripper can not accurately approach a desired position by only using the IK method. Hence, the two-CCD device is suggested to provide a vision-based sensory feedback to improve the open-loop IK technique, as the two-eye imaging measurement can be utilized to determine the position error. To reduce the position error and to achieve the object grasping motion, an object approaching strategy is further proposed in the following subsection.

B. Object Approaching Strategy

This paper presents a specific object approaching method for the two-palm gripper (see Fig. 1) to guarantee a successful grasping behavior. Figure 8 shows an effective grasping region for the gripper. First, the gripper reaches a preset point around the target object such that the target object is inside the front region of the gripper. Next, the gripper is controlled to approach and grasp the target object.

In the approaching process, this paper must highlight three 3-D points. The first is the desired IK point G_{IK} for the gripper, which is assigned to manipulate the robot arm. The remaining two are G_{VD} and T_{VD}, which are the practical positions of the gripper and the target object, respectively. Notably, G_{VD} and T_{VD} can be recognized and measured by the two-CCD vision device. Furthermore, let the position error be defined as

$$\begin{aligned} \boldsymbol{e} &= (\mathrm{G}_{VD} - \mathrm{T}_{VD}) \\ &= (e_x, e_y, e_z), \end{aligned} \tag{9}$$

where e_s denotes the error on the s-axis, where $s = x, y, z$.

The approaching control uses a fuzzy rule base (FRB) (10) in which the antecedent is e_s and the consequent is the step parameter σ_s for adjusting the desired IK point G_{IK}. Both are decomposed into five fuzzy sets, including NB (negative big), NS (negative small), ZO (zero), PS (positive small), and PB (positive big).

$$
\text{FRB}: \begin{cases} \text{Rule 1: If } e_s \text{ is NB, then } \sigma_s \text{ is NB;} \\ \text{Rule 2: If } e_s \text{ is NS, then } \sigma_s \text{ is NS;} \\ \text{Rule 3: If } e_s \text{ is ZO, then } \sigma_s \text{ is ZO;} \quad (s = x, y, z) \\ \text{Rule 4: If } e_s \text{ is PS, then } \sigma_s \text{ is PS;} \\ \text{Rule 5: If } e_s \text{ is PB, then } \sigma_s \text{ is PB;} \end{cases} \tag{10}
$$

Figure 9 shows the membership functions of e_s and σ_s, where $s = x, y, z$. The defuzzification strategy is implemented by the weighted average method [26], [27].

$$
\sigma_s = \sum_{r=1}^{5} \omega^r(e_s) \cdot u_s^r \,, \quad (s = x, y, z) \tag{11}
$$

where $\omega^r(e_s)$ is the fired weight of e_s and u_s^r is the support of the consequent fuzzy set in the *r*th rule, and $\sum_{r=1}^{5} \omega^r(e_s) = 1$.

C. Object Grasping Control Design

Referring to Fig. 8, the IK technique and the fuzzy based approaching control are summarized, and the complete object grasping control procedures are presented as the following:

● Step 1: Recognition and measurement of the target object point T_{VD}.

● Step 2: Let the initial IK position be a shifting point around the target object, i.e., $\mathrm{G}_{IK}^{(0)} = (\mathrm{T}_{VD} + \Delta\mathrm{T})_{\mathrm{W}}$, where $\Delta\mathrm{T}$ is a preset shifting vector. By using the IK method, the robot gripper is controlled and expected to approach $\mathrm{G}_{IK}^{(0)}$ and have the target object be located inside the effective grasping region.

● Step 3: Use the two-CCD vision system to measure the practical position $\mathrm{G}_{VD}^{(i)}$ of the gripper. Then the position error can be evaluated as $\boldsymbol{e}^{(i)} = (\mathrm{G}_{VD}^{(i)} - \mathrm{T}_{VD})_{\mathrm{W}}$. If the position error $\boldsymbol{e}^{(i)}$ satisfies the accurate conditions

$$
\left| e_s^{(i)} \right| \le \rho_s \text{, for all } s = x, y, z \tag{12}
$$

the control is terminated. That means, within this small position error, the gripper can grasp the target object. Here, ρ_s represents the error threshold on the *s*-axis, where $s = x, y, z$. Otherwise, continue to Step 4.

- Step 4: Use the FRB (10) and the defuzzification (11) to determine the approaching step parameter σ_s, $(s = x, y, z)$. The adjusting step is computed as $\sigma_s \cdot e_s^{(i)}$ on the *s*-axis, where $s = x, y, z$. Then the next IK position can be updated as follows.

$$\mathrm{G}_{IK}^{(i+1)} = \mathrm{G}_{IK}^{(i)} + (\sigma_x \cdot e_x^{(i)}, \sigma_y \cdot e_y^{(i)}, \sigma_z \cdot e_z^{(i)})_{\mathrm{W}} \tag{13}$$

- Step 5: Based on the change of the IK position, the robot gripper is controlled to take motion and keep approaching target object. Repeat Step 3.

Overall, i denotes the control iteration count. According to the above five steps, the object grasping control is completed, i.e., the target object can be grasped successfully.

V. EXPERIMENTAL RESULTS

Two experimental cases are performed to verify the feasibility of the proposed object grasping control for the robot arm (shown in Fig. 1). In the robot arm, the two links are represented by the lengths $d_1 = 17$ cm and $d_2 = 26$ cm. The target objects to be grasped in the experiments are an egg and a metal drinking bottle.

The two-CCD vision device is set as Fig. 3 (recall Section III.B). The separated distance $D = 3$ cm exists between CCD1 and CCD2. The focal lengths of CCD1 and CCD2 are set the same as $f_1 = f_2 = 265$ pixel. Moreover, the rotation difference between $[\mathrm{X_v}, \mathrm{Y_v}, \mathrm{Z_v}]_{\mathrm{V}}^T$ and $[\mathrm{X}, \mathrm{Y}, \mathrm{Z}]_{\mathrm{W}}^T$ is $(\psi_x, \psi_y, \psi_z) = (27°, 0°, 60°)$ (recall Section III.C and Fig. 4).

Figure 10 is a series of frames to demonstrate that the robot arm achieves an egg grasping behavior in the first experiment. Initially, two CCDs capture an egg and its position is measured by the two-eye imaging geometry as $\mathrm{T}_{VD} = (5.37, 39.42, -15)_{\mathrm{W}}$ (see the iteration $i = 0$ in Fig. 10). The shifting vector is given as $\Delta\mathrm{T} = (0, 0, 10)$, and the initial IK point is $\mathrm{G}_{IK}^{(0)} = (\mathrm{T}_{\mathrm{V}} + \Delta\mathrm{T})_{\mathrm{W}} = (5.37, 39.42, -5)_{\mathrm{W}}$. Then the robot gripper is firstly manipulated to reach the point $\mathrm{G}_{VD}^{(1)} = (7.71, 37.81, -6.97)_{\mathrm{W}}$ where the coordinate values are obtained by the two-eye measurement (see the iteration $i = 1$ in Fig. 10). Moreover, the position error is calculated as $\boldsymbol{e}^{(1)} = (\mathrm{G}_{VD}^{(1)} - \mathrm{T}_{VD})_{\mathrm{W}} = (2.34, -1.61, 8.02)_{\mathrm{W}}$, where the error thresholds are predefined as $\rho_x = 2.5$, $\rho_y = 1.5$, and $\rho_z = 1.5$. Since the position error $\boldsymbol{e}^{(1)}$ does not satisfy the accurate requirement (due to $\left|e_y^{(1)}\right| = 1.61 > \rho_y$ and $\left|e_z^{(1)}\right| = 8.02 > \rho_z$), a new IK position is generated as $\mathrm{G}_{IK}^{(1)} = (4.77, 40.24, -10.21)_{\mathrm{W}}$ by (13) using the fuzzy object approaching control (10)–(11). Therefore the robot arm is controlled again to adjust the gripper's position to approach the target object. After three iterations (movements), the robot gripper reaches the position $\mathrm{G}_{VD}^{(3)} = (7.17, 40.62, -15.19)_{\mathrm{W}}$ such that the position error is shortened to meet the accurate request (see the iterations $i = 1$ to $i = 3$ in Fig. 10). Then the object approaching control is terminated, since the gripper position $\mathrm{G}_{VD}^{(3)}$ is close enough to the target position T_{VD}. Finally, the robot gripper can firmly grasp the egg and lift it (see images after the iteration $i = 3$ in Fig. 10).

Figure 11 shows the second experiment that the robot arm performs the bottle grasping task. In this case, the shifting vector is given as $\Delta\mathrm{T} = (1.5, -5, 3)$. The error thresholds are again defined as $\rho_x = 2.5$, $\rho_y = 1.5$, and $\rho_z = 1.5$. Similar to the control process of the first experiment, the bottle position is measured as $\mathrm{T}_{VD} = (11.52, 41.98, -8.5)_{\mathrm{W}}$ (see the iteration

$i = 0$ in Fig. 11). Based on the IK motion control and the object grasping control, the gripper is controlled to reach and grasp the bottle successfully (see Fig. 11).

The two experiments conducted show that with the IK technique, two-eye measurement, and fuzzy object approaching controller, the robot arm can successfully achieve the object grasping task.

VI. CONCLUSION

This paper has presented a two-eye vision-based method for the target object grasping with a robot arm. The adopted techniques contain the IK motion control, two-eye imaging measurement, and fuzzy object approaching control. The completed control scheme has been implemented into a laptop computer to manipulate the robot arm for achieving the desired behavior. The experimental results have indeed verified that the proposed control scheme is useful and effective for the real robot arm.

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