A Visual Servoing Based Path Following Controller*

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Abstract-Visual servoing has been well explored in the literature for task specification and planning in image space. Planning tasks and paths in image space can be especially useful in unstructured environments, as a 3D reconstruction is not needed. However, few works have discussed following arbitrary image paths with visual servoing for robotic arms. This paper presents a path following controller for robotic arms based on image based visual servoing that can follow arbitrary paths in image space. The controller uses visual error to generate velocities that smoothly approach the path along the tangent. Additionally, the controller can optionally follow the orientation of the path, and can be applied to both eve-in-hand and eye-to-hand setups. Experiments are conducted on a Kinova Gen3 7DOF arm to evaluate the controller. Benefits of the path following controller over a trajectory-tracking approach are shown. Specifically, our path following controller displays smooth responses to physical disturbances and forced pauses.

I. INTRODUCTION

In many robotic applications, a robot must act with limited or no prior information about its environment. For example, when sanding down surface imperfections during manufacturing, the robot must be able to handle a variety of imperfections, where the position may not be known ahead of time. In such cases, vision based control systems can be used to guide robot motion using geometric information received from cameras. One method of specifying motion visually is through visual servoing [1], which maps motion in the image space to motion in the robot's frame of reference. Visual servoing can be done without calibration [2], making it flexible and easy to apply, while other methods such as reinforcement learning require more data or a training process [3]. Visual servoing is typically divided into position based visual servoing (PBVS) which minimizes an error between the 3D positions of the target location and end effector, and image based visual servoing (IBVS), which minimizes an error vector between the visual features of the end effector and target position.

To complete tasks, we often need to specify a path that the robot should follow, either to move through free space or to apply a tool in a certain way. This is necessary as with only a target position, we may run into obstacles or undesirable joint configurations [4]. Often, this is done through planning a path in 3D space, such as in [5]. However, to do this accurately, we need an understanding of the 3D structure of the environment, which can be expensive or impossible to obtain [6]. Planning a path in image space is thus appealing as we

can do so without any 3D information from the environment. It also allows for paths to be visually extracted from the environment, which can be coupled naturally with computer vision methods such as edge detection for automated task planning [7]. The ability to follow arbitrary paths is important as it allows for more flexible task specification, which is especially important when working in image space.

Once a path has been specified, control methods can be divided into path following controllers (PFC), which set the current target as the closest state on the path to the current state, and trajectory tracking controllers (TTC), which follow a series of timed references [8]. A TTC is the more common selection, and its use has been explored many times in relation to visual servoing, especially in mobile robots [9], [10], [11], [12], [13], [14]. However, these TTCbased methods have drawbacks, as they can have undesirable behavior responding to disturbances, as they may act poorly when catching up to a timed reference [15]. As such, a PFC is preferred, as they are more robust to disturbances and tend to respond more smoothly. A PFC is also beneficial as it affords a smooth approach tangent to the path. However, fewer works have discussed a visual servoing based PFC, and those that do tend to either plan in 3D space [16], require camera intrinsic parameters [17], or lack orientation following [18].

In our controller design, we improve upon these PFC controllers in terms of flexibility by decreasing the amount of scene and setup information required, and by including orientation following. Our image based path following controller can follow arbitrary paths in image space, both in the eye-tohand and eye-in-hand case. An extension of the controller is presented that is can additionally follow path orientation. We assume that the target path is achievable by the robot, and that the robot will not leave the field of view of the camera while following the path. Additionally, we assume the robot has a known kinematic model, and that the camera position is known relative to the robot. Our controller is evaluated with experiments in simulation and on a real robot arm. Controller performance is compared with a TTC implementation.

II. RELATED WORKS

Many existing works discuss the problem of planning valid paths in image space for visual servoing, such as Mezouar et al [19], where potential fields are used, Chaumette et al [20] where path planning and trajectory tracking are combined, and Krishnan et al [13], where a sliding mode controller is used to assist the visual servoing control law. While these works have been shown to be effective, they have the drawbacks of a trajectory tracking approach, specifically a

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poor response to disturbances due to the use of a timed reference.

Several existing works discuss the path following problem with visual servoing for mobile robots. In Cherubini et al [21], both image based and pose based controllers are presented for non-holonomic mobile robots, while Safia et al [22] presents a controller based on landmarks.

In Dahroug et al [16], path following through visual servoing is introduced in a medical robotics setting. The path following task is projected on the null space of a remote center of motion constraint. The control design consists of two weighted terms, one bringing the end effector to the path and one bringing it along the path. However, the path is planned in 3D space, rather than in image space.

A similar problem of contour following is discussed in Duy Cong et al [17] and Chang et al [18], where the former uses a combination of a 3D shortest path visual servoing controller and image based visual servoing to first move parallel to the contour plane. However, this requires the camera intrinsic parameters. The latter uses a SCARA robot alongside PH splines to incorporate a feedforward term into the control law to reduce tracking error.

III. METHODOLOGY

Given a path in image space with a defined start and end point, our objective is to generate end effector velocities that minimize the error between the current position and the path, and then move the end effector along the path.

A. Path Definition

First, we define the path to be used in our controller. We are looking for an equational curve or function that defines the path in image space. This function can be defined in several ways. One way is through projective geometry, which can be particularly useful in the case of paths that can be represented as lines or conics. In this case, line paths are described as $\mathbf{p} = {\mathbf{x} | \mathbf{x}^T l = 0}$, while conic paths are described as $\mathbf{p} = {\mathbf{x} | \mathbf{x}^T C \mathbf{x} = 0}$ [23]. Alternatively, for arbitrary curves, it can be convenient to parameterize the curve as $\mathbf{p}(t) = [x(t), y(t)]$, typically with $t \in [0, 1]$ or $t \in [0, \infty)$. Examples of these types of paths are shown in Fig. 1 along with attractive fields of the paths.

Once we have a path function, we define the error between the current end-effector position in image space, $\mathbf{x} = [x, y] \in \mathbb{R}^2$, and the path, **p**. To do this, we define a function $\theta(\mathbf{p}, \mathbf{x}) \to \mathbb{R}^2$ which determines the point on the path closest to the current state, and set $\mathbf{x}^* = \theta(\mathbf{p}, \mathbf{x})$. Path error is then defined as $\mathbf{e} = \mathbf{x} - \mathbf{x}^*$

In the case of a parameterized path, one can choose $\theta(\mathbf{p}, \mathbf{x})$ as [24]:

$$\theta(\mathbf{p}, \mathbf{x}) := \mathbf{p}(\operatorname*{arg\,min}_{t \in T} ||\mathbf{p}(t) - \mathbf{x}||). \tag{1}$$

While in the case of a projective conic, $\theta(\mathbf{p}, \mathbf{x})$ is the function that finds the point that minimizes the orthogonal distance to the conic. One method of doing this is described in Wijewickrema et al [25]. In general, the path can be



Fig. 1: Path Attractive Vector Fields

described by any function in image space, so long as it is possible to define $\theta(\mathbf{p}, \mathbf{x})$ and we can determine \mathbf{p}' .

Note that the difference here that distinguishes our PFC from a TTC is that a TTC would define $\mathbf{x}^* = r(t)$, where r(t) is a function that gives a reference target on the path for a given time.

B. Visual Servoing Control Law

We start with the visual servoing controller described in "Visual Servo Control Part I: Basic Approaches" by F. Chaumette and S. Hutchinson [26]. In this section, we assume an eye-to-hand camera configuration. The interaction matrix that relates end effector velocity to feature velocity is given by:

$$\mathbf{L}_{x_c} = \begin{bmatrix} \frac{-f}{Z} & 0 & \frac{x}{Z} & \frac{xy}{f} & \frac{-(f^2 + x^2)}{f} & y\\ 0 & \frac{-f}{Z} & \frac{y}{Z} & \frac{f^2 + y^2}{f} & \frac{-xy}{f} & -x \end{bmatrix}.$$
 (2)

Where f is camera focal length, and Z is the depth of the point relative to the camera frame and should be approximated or estimated. As this matrix describes the interaction between camera motion and feature motion, we then apply a transformation to the frame in which we control the robot. In practice, a rough approximation of this transformation is usually sufficient [20]. Assuming we control the robot from the base frame:

$$\mathbf{L}_{x_b} = -\mathbf{L}_{x_c}{}^c \mathbf{V}_b. \tag{3}$$

Where ${}^{c}\mathbf{V}_{b}$ is the adjoint representation [27] of the transformation between camera frame and base frame of the robot, $(\mathbf{R}, \mathbf{t}) \in SE3$, given by:

$${}^{c}\mathbf{V}_{b} = \begin{bmatrix} \mathbf{R} & [\mathbf{t}]_{\times}\mathbf{R} \\ \mathbf{0} & \mathbf{R} \end{bmatrix}.$$
 (4)

Since we typically do not have an exact measurement of Z, we do not have the true value of the interaction matrix. As such, we use an approximation of \mathbf{L}_{x_b} . In our work, we choose the approximation presented in [28]:

$$\mathbf{L}_{x_b} = \begin{bmatrix} \alpha_1 \bar{\mathbf{L}}_{x_b} + \alpha_2 \mathbf{L}_{x_b}^* \\ \beta_1 \bar{\mathbf{L}}_{x_b} + \beta_2 \mathbf{L}_{x_b}^* \end{bmatrix},$$
(5)

where $\hat{\mathbf{L}}$ is the interaction matrix at the current point with an approximated depth (Z) value, and \mathbf{L}^* is the interaction matrix at the desired position. $\alpha_1, \alpha_2, \beta_1, \beta_2$ are constants we set to 0.75, 0.25, 0.25, and 0.75 respectively. As we have doubled the rows of the interaction matrix, we also modify the error vector as follows:

$$\mathbf{e}_{new} = \begin{bmatrix} (\alpha_1 + \alpha_2)\mathbf{e} \\ (\beta_1 + \beta_2)\mathbf{e} \end{bmatrix}.$$
 (6)

Note that in practice, our choices of $\alpha_1, \alpha_2, \beta_1, \beta_2$ do not affect the magnitude of the error vector as $\alpha_1 + \alpha_2 = 1.0$ and $\beta_1 + \beta_2 = 1.0$.

We now apply the standard control law for IBVS from [26] to drive the arm to the closest point on the path, setting $\dot{\mathbf{e}} = -\lambda \mathbf{e}$:

$$\mathbf{v} = -\lambda \mathbf{L}_{x_h}^+ \mathbf{e},\tag{7}$$

where $\mathbf{v} = [v_x, v_y, v_z, \omega_x, \omega_y, \omega_z]$ is an end effector twist expressed in base frame, λ is a constant, and $\mathbf{L}_{x_b}^+$ indicates the pseudo-inverse of \mathbf{L}_{x_b} .

C. Base Path Following Scheme

Now that we have a control that moves us to the path, we introduce a second term that moves the arm smoothly along the path. As the interaction matrix relates image velocities and the end effector twist, if we have a desired image feature velocity, denoted $\dot{\mathbf{x}}^*$, we can obtain a twist by passing it through the same interaction matrix.

$$\mathbf{v}_{des} = \mathbf{L}_{x_b}^+ \dot{\mathbf{x}}^* \tag{8}$$

To obtain $\dot{\mathbf{x}}^*$, we take the derivative of \mathbf{p} at \mathbf{x}^* . We can then influence the speed at which we move along the path by setting $\dot{\mathbf{x}}^*$ to be a scaled unit vector of the derivative:

$$\dot{\mathbf{x}}^* = s \frac{\mathbf{p}'}{||\mathbf{p}'||}.\tag{9}$$

Since the units of \mathbf{p}' is pixels, the actual end effector speed that a specific value of s corresponds to depends on the distance from the path to the camera.

This target would suffice for most simple paths. However, for paths with tight turns and curves, we can improve our target by taking into account path curvature and the second derivative if they are non-zero. For a parameterized path, curvature can be calculated as:

$$\kappa = \frac{|x'(t)y''(t) - y'(t)x''(t)|}{(x'(t)^2 + y'(t)^2)^{3/2}},$$
(10)

which describes the rotation of the unit tangent vector at t. This can be used to rotate the tangent vector to anticipate the curve. Alternatively, the value of \mathbf{p}'' can be added at some scale to our tangent vector to act as an acceleration compensation.

To include the second term in our control law, we weigh the term bringing the arm to the path from (7) and the term bringing the arm along the path. The former decreases in magnitude as $||\mathbf{e}||$ decreases, and so we need to weigh the latter to increase as $||\mathbf{e}||$ decreases. We do this with an exponential function, giving the following control law:

$$\mathbf{v} = -\lambda \mathbf{L}_{x_b}^+ \mathbf{e} + \frac{\mathbf{L}_{x_b}^+ \dot{\mathbf{x}}^*}{\exp\left(||\mathbf{e}||/d\right)},\tag{11}$$

where d is a constant that affects the rate at which the second term decays as **e** increases. The second term also improves the approach to the path, as once $||\mathbf{e}||$ becomes small, the second term begins to move along the tangent line, causing a smooth approach in the tangent direction.

D. Orientation Path Following Scheme

For certain tasks, the orientation along the path is important. Therefore, we also provide a second control law that matches the path orientation as the arm follows the path. To do this, we will modify our control law using the ideas from a 2-1/2d visual servoing control law. [9]

Specifically, we want to control our orientation with the PBVS control law for orientation from [20]:

$$\boldsymbol{\omega} = -\lambda_{\omega} \boldsymbol{\theta} \boldsymbol{u}, \qquad (12)$$

where θu is the angle axis representation of the difference between our current and target orientations. To get a target orientation, we consider the rotation matrix in the camera frame created by the angle of the tangent vector of our current target point, $\mathbf{R}_{cam-path}$. Using the rotation $\mathbf{R}_{base-cam} \in SO3$ from the camera frame to base frame to convert $\mathbf{R}_{cam-path}$ to base frame ($\mathbf{R}_{base-path} =$ $\mathbf{R}_{base-cam}\mathbf{R}_{cam-path}$), we obtain a rotation that we can convert to angle-axis form to obtain θu . In this way, we obtain a 3D orientation for the path without any knowledge of the 3D position of the path.

Now, if we consider the linear and angular components of an interaction matrix separately:

$$\dot{\mathbf{e}} = \mathbf{L}\mathbf{v}$$

$$= \begin{bmatrix} \mathbf{L}_v & \mathbf{L}_\omega \end{bmatrix} \begin{bmatrix} \mathbf{v} \\ \mathbf{\omega} \end{bmatrix}$$

$$= \mathbf{L}_v \mathbf{v} + \mathbf{L}_\omega \mathbf{\omega}.$$

Then, by once again setting $\dot{\mathbf{e}} = -\lambda \mathbf{e}$, we can solve for linear velocity:

$$\mathbf{v} = -\mathbf{L}_{v}^{+} (\lambda \mathbf{e} + \mathbf{L}_{\omega} \boldsymbol{\omega}). \tag{13}$$

In this control law, the $L_{\omega}\omega$ attempts to compensate for the error created by our angular velocity. However, in our experiments, we found that it is better to drop this term, as in practice we found it caused poor path following behavior. This was due to the magnitude of the orientation compensation combining poorly with the path following velocities. As such, to obtain our new control law, we drop the $L_{\omega}\omega$ and apply the remainder of (13) to our existing path following control law in (11):

$$\boldsymbol{\nu} = -\mathbf{L}_{v_b}^+(\lambda_v \mathbf{e}) + \frac{\mathbf{L}_{v_b}^+ \dot{\mathbf{x}}^*}{\exp\left(\left(||\mathbf{e}|| + ||\boldsymbol{\theta}\boldsymbol{u}||\right)/d\right)}, \quad (14)$$

Note that we have also updated the decay term to include θu to slow down our movement along the path our orientation error increases. This θu can also be scaled in the exponential to change the priority of orientation. Finally, note that we split λ into $\lambda_v, \lambda_\omega$ so that we may choose different constants for our linear and angular convergence.

E. The Eye-In-Hand Case

The control laws described here can also be applied to an eye-in-hand camera setup. The main difference is with tracking, as now the path must be tracked, while the end effector point, \mathbf{x} , is now a constant point.

However, orientation following in this scenario is more challenging. In most cases, any rotation of the camera will result in a large change in the image. This can greatly increase the path error and also change the path target point, which changes the orientation target.

One way to reduce the effect of this issue is to set \mathbf{x} to always be the center of the image. Since our orientation target attempts to keep the camera frame aligned to the path, a change in direction of the path will primarily cause a change in the rotation around the camera's Z axis. If the point we are moving to the center of the path is the center of the camera image, then rotating about the Z axis of the camera will cause little to no movement of this point, assuming our X and Y axes are aligned. This allows the control law to function as normal, at the cost of being able to choose the alignment point in the image freely.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In our experiments, we aim to evaluate the flexibility of the controller by testing a variety of paths with different camera setups. Additionally, we evaluate the performance of our PFC controller in comparison to a TTC when faced with a disturbance. Finally, we test the controller under a variety of values for λ , d, and s to discuss how to tune the control law.

A. Controller Performance

First, we evaluate the performance of the controller on a real robot arm on a variety of paths. For the experiment, we use a Kinova Gen3 7DOF arm. A RealSense D435i camera is used as an overhead camera, and its depth map is used to approximate the value of Z in the interaction matrix. A RealSense D405 is used as the eye-in-hand camera. The camera pose is roughly estimated relative to the robot. A marker is placed on the arm for tracking.

To start, we test paths without orientation matching. Experiments were run with $\lambda = 1.5$, d = 5.0, s = 40.0. The paths followed are b-splines that give a smooth parameterized path. The control loop is run at a rate of 30 Hz. Results can be seen in Fig 2. We see that path error can be held below 5 pixels on both paths.

Next, to evaluate the controller with orientation following, two curved paths were evaluated with the same parameters as above. Results can be seen in Fig. 3. Fig. 4 shows the velocity profiles for the second curved path. We see that as angular velocity increases to reduce the orientation error, the linear velocities decrease as the second term is decayed to allow the controller to catch up its orientation. This leads to the peaks and valleys in the velocity profile. It is important to note that the path orientation is not followed as strictly as the path itself. This is because even if we have error in our orientation, we still continue moving along the path unless d is set very low. Thus, orientation sometimes lags behind the path.

Finally, the eye-in-hand case of the controller is evaluated on a contour following problem. Fig. 5 shows the extracted contour and the error following the contour, with the path being tracked and updated at each iteration. The end effector point is selected as the center of the image.



Fig. 2: Controller performance on straight line and square paths

B. Manufacturing Example

We show the use of the controller in a manufacturing example. The end effector of the robot is given a sanding block, and the last joint is spun continuously to act as an automatic sanding tool. The controller is used to sand along a path obtained from the image. The experimental setup is shown in Fig. 6

For this task, a visual contour was placed in the view of the camera next to the robot's target workspace. The contour is extracted using edge detection, rescaled, and send as a path target in the robot's work area. This illustrates one way that paths can be generated from visual information in the environment. Path following control is then applied. Results from this task can be seen in Fig. 7. Despite the additional friction from the sanding, the controller is still able to follow the path with low error.



Fig. 3: Controller performance with orientation matching on two curved paths.



Fig. 4: Velocity profile for the second curved path.

C. Comparison with a Trajectory Tracking Controller

Next, we analyze the choice of a path following controller (PFC) by comparing it to a simple trajectory tracking controller (TTC). The TTC uses the standard IBVS control law to follow a series of timed targets. To compare the controllers, we consider a situation where the robot being forced to temporarily stop along the path. This is shown in Fig. 8, where the diamond shows the location of a forced pause. We can see that the TTC has undesirable performance due to falling behind the timed reference, while the PFC is unaffected and behaves as normal. Fig. 9 shows a similar result in responding to a disturbance. The TTC has undesirable behavior and cuts across the path while catching



Fig. 5: Controller performance on an eye-in-hand contour following task.



Fig. 6: Setup for sanding task.



Fig. 7: Sanding path followed for semicircle and triangle contours.

up to the timed reference, while the PFC reapproaches the path smoothly along the tangent direction. In both cases, we can see that the use of a PFC leads to a better response.

D. Analysis of Parameters

To discuss the design of the controller, we analyze the effect of the 3 main parameters in our control law: λ , d, and s. Recall that λ affects the gain that brings us to the path, d affects the decay of the term moving us along the path as **e** changes, and s affects the speed we move along the path.

To run hundreds of experiments, a simulation environment was created using Robosuite [29] with a Kinova Gen3 arm. The Robotics Toolbox for Python [30] is also used to obtain additional kinematic information from the simulation.

Fig. 10 shows that increasing s and decreasing d both increase the average path error, while decreasing the total number of iterations. Increasing speed generally leads to less



Fig. 8: TTC and PFC Performance on circular path after a forced pause



Fig. 9: TTC and PFC Performance on zigzag path after a disturbance

reaction time for the controller, leading to overshooting on curves or turns. This can be partially compensated for by decreasing d, as a lower d will lead to a more accurate path approach, and will reduce the effect of overshooting by slowing down if we leave the path.

Fig. 11 shows the relationship between λ , d, and error. Note that in this data, the robot starts on the path. A higher λ decreases path following error as it increases the strength the term that pulls us to the path. However, if λ is set too high, it can lead to undesirable behavior when approaching the path, as it will increase approach speed and may lead to overshooting the path or higher than desired velocities.

In general, path error can be kept low if s is low, as the controller will have more reaction time to update velocities as the path changes. Thus, when it comes to choosing values for these parameters, one should first determine the desired s value, and then tune λ and d until path error is sufficiently low. Note that since s and d are measured in image pixels, parameter values will be different depending on how close the camera is to the path.

V. CONCLUSION AND FUTURE WORK

This paper presented a solution to the problem of following a path defined in image space. The PFC framework chosen is used to follow the path with a configurable speed parameter. The results show the controller is able to follow a variety of paths with pixel error under 5 pixels. Future research include investigating alternate methods of controlling orientation in a non-decoupled way. Use of other scene features may allow for more effective orientation following schemes. Incorporating a method for projecting a desired 3D velocity profile into image space could allow for



Fig. 10: Effect of decay and speed on control performance



Fig. 11: Effect of lambda and speed on average error

more precise specification for path following speed. Finally, combining this controller with path planning methods that ensure a visibility constraint could lead to a complete system for path following task specification.

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