Proceedings of the 17th World Congress
The International Federation of Automatic Control
Seoul, Korea, July 6-11, 2008

Adaptive Visual Servoing of Robot Manipulators without Measuring the Image Velocity ⋆

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Abstract: The direct adaptive control of planar robot manipulators through visual servoing is considered. A solution is developed for image-based visual systems to allow tracking of a desired trajectory, when both camera calibration and robot dynamics are uncertain. In order to solve the MIMO parameter adaptive problem without using image velocity information, the adaptive camera calibration is formulated as a relative degree two MIMO adaptive control problem. A recently proposed Lyapunov/passivity-based adaptive control for relative degree two MIMO system based on SDU factorization is applied. The resulting adaptive calibration is then combined with an adaptive motion controller for the manipulator, which takes into account its uncertain nonlinear dynamics. The overall stability of the adaptive visual servoing system can be proved thanks to the explicit Lyapunov-like functions of both adaptation schemes.

Keywords: visual servoing, adaptive control, robot control, Lyapunov-based design, passivity.

1. INTRODUCTION

The problem of controlling robotic systems through visual feedback has still received considerable attention in the control literature. For many years, visual servoing techniques have been studied as potential tools for relevant industrial applications (Hutchinson et al. (1996)).

Several adaptive schemes have been proposed to circumvent the performance degradation due to modelling uncertainty, particularly with respect to the camera calibration and robot parameters (Papanikolopoulos and Khosla (1993); Kelly (1996); Nasisi and Carelli (2003)). However, most of the above cited works have not considered the nonlinear robot dynamics in the controller design. These controllers may result in unsatisfactory performance when high-speed tasks or direct-drive actuator are required. Exceptions can be found in recent papers like (Kelly (1996); Kelly et al. (1999); Hsu and Aquino (1999); Zergeroglu et al. (2001); Nasisi and Carelli (2003); Zachi et al. (2006)). In these papers the robot motion control requires on the velocity of the end-effector image.

It is well known that the measurement of the velocity is impaired by noisy image data (Kano et al. (2001)). This motivates the development of an alternative adaptive scheme free of image velocity measurement. In (Zergeroglu et al. (2000)) a globally asymptotic stable adaptive camera calibration scheme was proposed, however the author assume exact knowledge of the mechanical parameters.

In this paper, we propose a solution for the direct adaptive visual tracking of planar manipulators using a fixed camera, when both camera calibration and robot dynamics are uncertain. The proposed strategy is developed for image-based look-and-move visual servoing systems. In order to solve the MIMO parameter adaptive problem related to adaptive camera calibration scheme, without using direct image velocity information, an uncertain linear plant with relative degree two has to be considered. A recently proposed model reference adaptive control (MRAC) for relative degree 2 MIMO systems (Hsu et al. (2007)) using SDU factorization (Costa et al. (2003)) is considered. This new solution is Lyapunov-based in the sense that an explicit Lyapunov function exists for the complete state of the adaptive system. The importance of having an explicit Lyapunov for the adaptive camera calibration part is that it can be easily combined with a well known adaptive manipulator motion controller, which takes into account its uncertain nonlinear dynamics, leading to an overall globally stable adaptive system. Simulation results are also presented to illustrate the effectiveness of the proposed scheme.

2. ROBOT SYSTEM MODEL

Consider the problem of tracking a desired image trajectory with a planar manipulator using a fixed and uncalibrated camera. The camera image coordinate frame can be related to the robot coordinate frame by the following transformation:

$$y_c = K_p y + y_{c_0}\,, \tag{1}$$

$$K_p = \frac{f}{Z}\begin{bmatrix} -\alpha_1 & 0 \\ 0 & \alpha_2 \end{bmatrix}\begin{bmatrix} cos(\phi) & sin(\phi) \\ -sin(\phi) & cos(\phi) \end{bmatrix}, \tag{2}$$

where $y_c \in \mathbb{R}^2$ is the end-effector position in the image coordinate frame, $y \in \mathbb{R}^2$ is the end-effector position in the robot coordinate frame given by the direct kinematic map $y = k(q)$, $q \in \mathbb{R}^2$ of the manipulator joint angle vector, $y_{c_0} \in \mathbb{R}^2$ is a bias vector, K_p is the camera/workspace transformation (uncertain) matrix, Z is the total depth

⋆ This work was supported in part by CNPq and FAPERJ, Brazil.

between the camera focal point and the working plane, f is the camera focal length (in general $f << Z$), α_1, α_2 are (positive) scaling factors in y_{c1} and y_{c2} directions, respectively, and $\phi \in (-\pi/2; \pi/2)$ is the angle between the camera and robot frames. Here, we assume that the camera and robot frames have the same orientation with affine Z-axis.

Now, we recall the manipulator dynamic model. The nonlinear dynamic model of the manipulator can be expressed in cartesian coordinates y by (Sciavicco and Siciliano (2000))

$$\bar{M}(q)\ddot{y} + \bar{C}(q,\dot{q})\dot{y} + \bar{g}(q) = Y(q,\dot{q},\dot{y},\ddot{y})a = F \qquad (3)$$

where $\bar{M}$, $\bar{C}$, $\bar{g}$ are defined in terms of the joint coordinates and velocities, namely: $\bar{M}(q) = J^{-T}(q)M(q)J^{-1}(q)$, $\bar{C}(q,\dot{q}) = J^{-T}[C(q,\dot{q}) - M(q)J^{-1}\dot{J}(q,\dot{q})]J^{-1}$, $\bar{g}(q) = J^{-T}g(q)$ and $F = J^{-T}\tau$, where $J(q) = \frac{\partial k(q)}{\partial q} \in \mathbb{R}^{2\times 2}$ is the manipulator Jacobian. It is well known that the left hand of (3) can be linearly parameterized by $Y(q,\dot{q},\dot{y},\ddot{y})a$ where $a \in \mathbb{R}^m$ is the constant system parameters and $Y \in \mathbb{R}^{2\times m}$ is a regressor matrix.

It is worth mentioning that, in joint space, $M(q)$ represents the inertia matrix, $C(q,\dot{q})\dot{q}$ represents the centripetal and Coriolis torques, $g(q)$ represents the gravity torques, and τ is the vector of applied joint torques.

The properties of $\bar{M}$ and $\bar{C}$ are similar to those of the corresponding joint-space matrices (Sciavicco and Siciliano (2000)). However, one should note that the validity of the cartesian model is restricted to motions which do not lead to a singular Jacobian matrix.

3. VISUAL SERVO CONTROL STRATEGY

In this section, we describe the control strategy using visual information. Since Z is constant in the planar case, the cartesian control problem can be described from (1):

$$\dot{y}_c = K_p \; v_k \, , \qquad (4)$$

where $v_k = \dot{y}$ with kinematic control law $\dot{q} = J^{-1}(q)v_k$.

Defining the desired trajectory $y_{cd} \in \mathbb{R}^2$ in the image frame, the tracking problem is formulated as designing v in (4) so that the image tracking error $e_c = y_c - y_{cd}$ tends asymptotically to zero. To this end, two basic assumptions are considered:

(A1) The desired image trajectory y_{cd} is defined within the robot workspace, and the desired image velocity $\dot{y}_{cd}$ is known and bounded.
(A2) Manipulator motions are away from Jacobian singularities.

If K_p is known, one can obtain the desired trajectory in the robot coordinate frame by

$$y_m = K_p^{-1} \; (y_{cd} - y_{c0})$$

and apply an adaptive or robust control strategy for (3) (Slotine and Li (1991)).

However, in this work, we consider the unknown robot dynamic parameters a and uncalibrated camera case, i.e. K_p is unknown, thus y_m cannot be calculated.

Note from (1) and (3), that the dynamic model in camera coordinate frame is given by:

$$\bar{M}_c(q)\ddot{y}_c + \bar{C}_c(q,\dot{q})\dot{y}_c + \bar{g}_c(q) = Y_c(q,\dot{q},\dot{y}_c,\ddot{y}_c)a = K_p^{-T}F$$

where $\bar{M}_c = K_p^{-T}\bar{M}K_p^{-1}$, $\bar{C}_c = K_p^{-T}\bar{C}K_p^{-1}$ and $\bar{g}_c = K_p^{-T}\bar{g}$.

In the case of uncertain a and K_p, a standard adaptive solution (Ioannou and Sun, 1996, p.742) adapts a and K_p^{-1} separately. Interestingly, this is exactly what has been usually done in the robotics literature (Hsu and Aquino (1999); Zergeroglu et al. (2001)), i.e., the robot dynamic control and the adaptive camera calibration scheme are designed separately. Note that, the robot is passive from $K_p^{-T}F \mapsto \dot{y}_c$ but not necessarily from $F \mapsto \dot{y}_c$.

3.1 Cascade Strategy

The main idea here is to introduce a cascade control structure (Guenther and Hsu (1993)). To this end, consider there exists a control law $F = f(y, \dot{y}, y_m, \dot{y}_m, \ddot{y}_m)$ which solves the tracking control problem for robot (3), i.e., F is such that $e(t) = y(t) - y_m(t) \to 0$ for $t \to \infty$, for a given desired trajectory in robot coordinate frame $y_m(t)$.

Now, from Figure 1, suppose we can define the desired trajectory y_m and its derivatives $\dot{y}_m, \ddot{y}_m$ in terms of a cartesian control signal v.

Some intuition can be gained if the parameters of the robot dynamic model (3) are assumed to be exactly known. A standard Computed Torque strategy could be used to solve the tracking problem, i.e. $F = \bar{M}(q)[\ddot{y}_m + K_d\dot{e} + K_p e] + \bar{C}\dot{y} + \bar{g}$ yields a stable closed loop error system. Thus, defining y_m through $\dot{y}_m = v$, one has that $\dot{y}_c = K_p v + K_p \dot{e}$, where $\dot{e}$ satisfies the stable closed loop equation $\ddot{e} + K_d\dot{e} + K_p e = 0$. Thus, with positive gains K_d and K_p, this implies $e(t), \dot{e}(t) \to 0$ or equivalently, that we only differ from the kinematic control case (4) by a vanishing signal $\dot{e}(t)$.

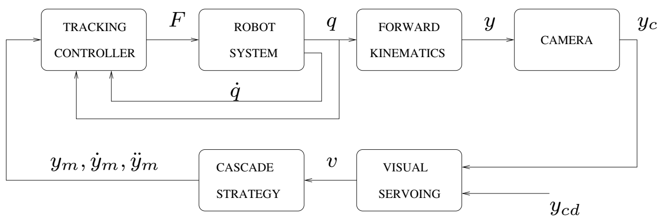

Fig. 1. Block diagram of the visual servoing cascade structure.

In (Hsu and Aquino (1999); Zachi et al. (2006)), the cascade strategy is such that instead of (4) one has

$$\dot{y}_c = K_p \; [v + G(s) \; e] \qquad (5)$$

where $G(s)$ is a linear operator (possibly non-causal) with s being the differential operator. Under this formulation, adaptive visual servo schemes were proposed in previous works (Hsu and Aquino (1999); Zergeroglu et al. (2001); Zachi et al. (2006)). Such methods were intended to cope with the uncertainties of intrinsic and extrinsic parameters of the camera, namely the scaling factors and the camera orientation with respect to the robot workspace. They could also include the uncertainties of the robot dynamic parameters. However, the robot motion adaptive control involved a regressor matrix which depends on the velocity of the end-effector image.

In (Hsu and Aquino (1999); Zachi et al. (2006)), a linear visual system with relative degree one from v to y_c is obtained by defining $\dot{y}_m = v + \lambda e$. As a result, the computation of $\ddot{y}_m$ requires $\dot{v}$ and, consequently, the derivative of y_c. It is well known that the measurement of the velocity is impaired by noisy image data.

This motivates the development of an alternative adaptive scheme free of image velocity measurement. If we set $\dot{y}_m = H^{-1}(s)v$, for some first order Hurwitz polynomial $H(s)$, the resulting visual system has relative degree $n^* = 2$,

$$\ddot{y}_c = K_p\ [v + G(s)\ e], \tag{6}$$

and therefore can be controlled using the adaptive control scheme proposed in this paper, with the advantage that $\ddot{y}_m$ no longer depends on the derivative of v, and thus, on the image velocity.

Furthermore, for the stability analysis of the proposed cascade scheme, the passivity framework derives simple rules to describe combinations of subsystems expressed in a Lyapunov formalism. Notably, it is commonly applied in several control problems of mechanical systems such as robot manipulator control (Ortega and Spong (1989)), underwater vehicles and dynamic ship positioning.

For cascaded passive systems the following general result can be stated.

Theorem 1. Consider the following interconnected systems:

$$\Sigma_1 : \begin{cases} \dot{x}_1 = f_1(x,t) + g_1(x,t)y_2\,, \\ y_1 = h_1(x_1)\,, \end{cases}$$
$$\Sigma_2 : \begin{cases} \dot{x}_2 = f_2(x,t) + u_2\,, \\ y_2 = h_2(x_2)\,, \end{cases} \tag{7}$$

where Σ_1 is the driven system and Σ_2 is the driving system. Assume that $\|g_1(x,t)\| \leq c, \forall x, t$ and for some $c > 0$.

If system Σ_1 is output strictly passive from $y_2 \mapsto y_1$ with positive definite storage function $V_1(x_1)$ such that

$$\dot{V}_1 \leq -\lambda_1 \|y_1\|^2 + c_1 y_2^T y_1; \quad \lambda_1 > 0$$

and system Σ_2 is output strictly passive from $u \mapsto y_2$ with positive definite storage function $V_2(x_2)$ such that

$$\dot{V}_2 \leq -\lambda_2 \|y_2\|^2 + c_2 u_2^T y_2; \quad \lambda_1 > 0\,,$$

then, for $u_2 = 0$, $x_1, x_2 \in L_\infty$ and $y_1, y_2 \to 0$ as $t \to \infty$. (for a proof see (Hsu et al. (2007))) □

The passivity properties of the proposed adaptive strategy will be explored in the following section using Theorem 1.

4. ADAPTIVE ROBOT CONTROL

It is well known from (Slotine and Li (1991)) that an adaptive control law F exists such that y will asymptotically follow $y_m(t)$. In what follows, we will show that parameter adaptive control of the robot can be used for simply cascading with a visual servoing scheme.

First, the virtual error $\sigma \in \mathbb{R}^2$ is defined as:

$$\sigma = \dot{e} + \lambda e = \dot{y} - \dot{y}_r\,; \quad e = y - y_m\,; \quad \dot{y}_r := \dot{y}_m - \lambda e\,. \tag{8}$$

The control law is given by

$$F = Y(q, \dot{q}, \dot{y}_r, \ddot{y}_r)\hat{a} - K_D\sigma + u_2\,, \tag{9}$$

where $Y(\cdot)$ is defined in (3), K_D is positive definite gain matrix, u_2 is a fictitious external input which drives the closed loop system, and $\hat{a}$, an estimation of parameter vector a in (3), is updated by the gradient law

$$\dot{\hat{a}} = -\Gamma Y^T(q, \dot{q}, \dot{y}_r, \ddot{y}_r)\ \sigma\,, \tag{10}$$

where Γ is a positive definite adaptation gain.

Remark 1. It is important to notice that with known kinematics and measurable $q\,, \dot{q}$ all signals needed to evaluate Y are available.

Thus, the passivity properties of the closed loop system can be establish in the following theorem:

Theorem 2. Consider the robot dynamic model (3), control law (9) and adaptation law (10). Then, the map $u_2 \mapsto \sigma$ is output strictly passive with positive definite storage function

$$2V_r(\sigma, \tilde{a}) = \sigma^T \bar{M}(q)\sigma + \tilde{a}^T\Gamma^{-1}\tilde{a}\,, \tag{11}$$

with $\tilde{a} = \hat{a} - a$. Furthermore, for $u_2 = 0$, all signals are bounded and $\sigma, e, \dot{e}$ tend to zero as $t \to \infty$. □

Proof: from (3), (8), (9), the closed-loop robot tracking error dynamics is given by:

$$\bar{M}\dot{\sigma} + (\bar{C}(q, \dot{q}) + K_D)\ \sigma = Y\tilde{a} + u_2\,. \tag{12}$$

Now, considering (11), the closed-loop dynamics (12), resorting to the skew-symmetry property of $\dot{\bar{M}}(q) - 2\bar{C}(q, \dot{q})$, and considering adaptation law (10), we finally reach

$$\dot{V}_r(\sigma, \tilde{a}) = -\sigma^T K_D \sigma + \sigma^T u_2\ \ . \tag{13}$$

Then, we can conclude that the system is output strictly passive from $u_2 \mapsto \sigma$. For $u_2 = 0$, $\dot{V}_r \leq 0$, then using *Barbalat's Lemma*, one can show that all signals are bounded and $\sigma, e, \dot{e}$ tend to zero as $t \to \infty$. □

Now we can apply the cascade control strategy presented in the previous section. Based on the cascade strategy proposed in section 3.1, and from (8), considering that $\dot{y} = \sigma + \dot{y}_r$, we can define

$$\dot{y}_r = G^{-1}(s)\ v + \lambda G^{-1}(s)\ \dot{y}\,, \tag{14}$$

where $G(s) = s + \lambda$, such that the end-effector image motion $y_c(t) = K_p y(t)$ is governed by

$$\ddot{y}_c = K_p\ [v + G(s)\ \sigma]\,, \tag{15}$$

where σ can be considered as a vanishing disturbance since, from Theorem 2, it tends asymptotically to zero.

Thus, the cascade strategy is obtained by simply setting

$$\dot{y}_m = \dot{y}_r + \lambda e\,, \quad \text{and} \quad \ddot{y}_m = \ddot{y}_r + \lambda\dot{e}\,, \tag{16}$$

where $\ddot{y}_m$ depends on v (and not on $\dot{v}$) since $\ddot{y}_r = -\lambda\dot{y}_r + v + \lambda\dot{y} = v + \lambda\sigma$.

It is worth noting that the proposed cascade structure can be also performed using a robust robot motion control with similar passivity properties (Slotine and Li (1991)).

5. ADAPTIVE VISUAL SERVOING

For the control design, we can obtain the following state space realization for (15):

$$\dot{x}_c = Ax_c + BK_p\,v + B_\sigma\ \sigma\,, \qquad y_c = Cx_c\,, \tag{17}$$

where

$$A = \begin{bmatrix} 0 & I \\ 0 & 0 \end{bmatrix}; \quad B = \begin{bmatrix} 0 \\ I \end{bmatrix}; \quad B_\sigma = \begin{bmatrix} K_p \\ \lambda K_p \end{bmatrix}; \quad C = [I \;\; 0]$$

Defining y_{cd} as the desired trajectory in the image frame, the tracking problem is then formulated as designing v so that the tracking error $e_c = y_c - y_{cd}$ tends to zero.

Let us define the desired trajectory by means of a model reference:

$$y_{cd} = G_m(s)\ r, \qquad G_m(s) = \frac{\lambda_c^2}{(s+\lambda_c)^2}\ I \tag{18}$$

where $r(t)$ is piecewise continuous and uniformly bounded and λ_c is a free positive parameter.

The MRAC approach could lead us to the matching control by output feedback. Here, we are able to adopt a simpler approach by taking into account that the plant is essentially a double integrator, except for the matrix gain K_p. Indeed, we can first solve the problem for a unit (matrix) gain double integrator, *by output feedback*, determining a control law, say, $u := K_p v$. Then the matching control law u^* for (15) would simply be $v^* = K_p^{-1} u^*$. Then we define the control parameterization in terms of u which can be regarded as a regressor vector which is available from only the output and input signals.

Thus, a model matching control law u^* is given by:

$$u^* = -2\lambda_c \hat{\dot{y}}_c - \lambda_c^2 y_c + \lambda_c^2 r \tag{19}$$

$$\dot{z}_1 = -\lambda_0 z_1 + u, \tag{20}$$

$$\dot{z}_2 = -\lambda_0 z_2 + y_c \tag{21}$$

$$\hat{\dot{y}}_c = z_1 - \lambda_0^2 z_2 + \lambda_0 y_c \tag{22}$$

where $\lambda_0 > 0$ is a free parameter. In term of variable $z = z_1 - \lambda_0^2 z_2$, the last three equations correspond to a reduced order observer of $\dot{y}$. Note however that u is not measurable since K_p is unknown. The model matching control law for v is $v^* = K_p^{-1} u^*$, which can be written:

$$v^* = \theta^{*T}\ \omega - \frac{2\lambda_c}{\Lambda(s)}\ v, \tag{23}$$

with

$$\omega = \frac{2\lambda_c \lambda_0^2}{\Lambda(s)}\ y_c - (\lambda_c^2 + 2\lambda_c\lambda_0)\ y_c + \lambda_c^2\ r\,, \tag{24}$$

where $\theta^{*T} = K_p^{-1}$ and $\Lambda(s) = s + \lambda_0$.

5.1 Image Error System

Now, we can express the image error system in terms of the augmented state $z_c = [x_c^T,\ z_1^T,\ z_2^T]^T$ by combining (17), (20) and (21), and defining $u = K_p v$:

$$\dot{z}_c = A_1 z_c + B_m K_p v + B_{cs}\sigma\,, \qquad y_c = C_m z_c \tag{25}$$

where $C_m = [C \;\; 0 \;\; 0]$,

$$A_1 = \begin{bmatrix} A & 0 & 0 \\ 0 & -\lambda_0 & 0 \\ C & 0 & -\lambda_0 \end{bmatrix}; \quad B_m = \begin{bmatrix} B \\ I \\ 0 \end{bmatrix}; \quad B_{cs} = \begin{bmatrix} B_\sigma \\ 0 \\ 0 \end{bmatrix}.$$

By adding and subtracting v^* to v, and using the fact that v^* is a model matching control, one has that

$$\dot{z}_c = A_m z_c + B_m r + B_m K_p (v - v^*) + B_{cs}\,\sigma \tag{26}$$

$$y_c = C_m z_c \tag{27}$$

where the triple $\{A_m, B_m, C_m\}$ corresponds to a non-minimal realization of the reference model (18), where the relative degree from r to y_{cd} is two and consequently $C_m B_m = 0$.

Then, we can obtain the error system in terms of the error state $z_e := z_c - z_{cd}$ and the tracking error $e_c = y_c - y_{cd}$:

$$\dot{z}_e = A_m z_e + B_m K_p (v - v^*) + B_{cs}\sigma\,, \quad e_c = C_m z_e$$

Then defining

$$v = \hat{v} - \frac{2\lambda_c}{\Lambda(s)}\ v \tag{28}$$

and considering (23) one has that:

$$\dot{z}_e = A_m z_e + B_m K_p (\hat{v} - \theta^{*T}\ \omega) + B_{cs}\sigma \tag{29}$$

$$e_c = C_m z_e \tag{30}$$

We can reduce this (multivariable) relative degree two problem to a relative degree one according to (Ioannou and Sun (1996)) by defining the signals

$$\hat{v}_f = L^{-1}(s)\ \hat{v}; \quad \omega_f = L^{-1}(s)\omega \tag{31}$$

with $L(s) = s + \lambda_c$ and rewriting (28) as

$$\dot{z}_e = A_m z_e + B_m K_p L(s)(\hat{v}_f - \theta^{*T}\omega_f) + B_{cs}\sigma \tag{32}$$

$$e_c = C_m z_e \tag{33}$$

For simplicity we introduce the notation $\tilde{v}_f = \hat{v}_f - \theta^{*T}\omega_f$. Then, performing the change of variable

$$\bar{z}_e = z_e - B_m K_p \tilde{v}_f \tag{34}$$

we get

$$\dot{\bar{z}}_e = A_m \bar{z}_e + B_{m1} K_p \tilde{v}_f + B_{cs}\sigma\,, \qquad e_c = C_m \bar{z}_e \tag{35}$$

where $B_{m1} = A_m B_m + \lambda_c B_m$. To arrive at the system (35), we have taken into account that $C_m B_m = 0$. According to the SDU factorization approach for designing MIMO adaptive control (Costa et al. (2003)), we consider the factorization $K_p = SDU$, where S is symmetric, D is diagonal, and U is unit upper triangular. Such a factorization is nonunique and can be chosen such that $\{A_m,\, B_{m1}S,\, C_m\}$ is SPR (Costa et al. (2003)), i.e., there exist positive definite matrices P and Q such that

$$A_m^T P + P A_m = -2Q, \qquad S B_{m1}^T P = C_m\,. \tag{36}$$

Thus, the error equation has been brought to a new form:

$$\dot{\bar{z}}_e = A_m \bar{z}_e + B_{m1} SD(\hat{v}_f - \hat{v}_f^*) + B_{cs}\sigma, \quad e_c = C_m \bar{z}_e \tag{37}$$

where $\hat{v}_f^* = U\theta^{*T}\omega_f + (I - U)\hat{v}_f$. The key feature of (37) is that the diagonal matrix D appears in the place of K_p, and an assumption can now be made about the signs of its entries d_1, d_2.

5.2 Controller Structure

Now we formulate the adaptive controller parameterization for $\hat{v}_f = [\hat{v}_{f1},\ \hat{v}_{f2}]^T$. According to the SDU factorization approach (Costa et al. (2003); Hsu et al. (2007)), a model matching control is expressed as

$$\hat{v}_f^* = \begin{bmatrix} \theta_1^{*T}\Psi_1 \\ \theta_2^{*T}\Psi_2 \end{bmatrix} \tag{38}$$

where $\theta_1^* \in \mathbb{R}^3$, $\theta_2^* \in \mathbb{R}^2$ and

$$\Psi_1^T := [\omega_f^T \quad \hat{v}_{f2}] , \qquad \Psi_2 := \omega_f \tag{39}$$

Accordingly, the (filtered) control parameterization is defined by

$$\hat{v}_f = \begin{bmatrix} \theta_1^T \Psi_1 \\ \theta_2^T \Psi_2 \end{bmatrix} \tag{40}$$

and the adaptation law is given by (i=1,2)

$$\dot{\theta}_i = -\gamma_i \; sgn(d_i) \; e_{ci} \Psi_i \, . \tag{41}$$

where d_i are the entries of matrix D.

Now, in order to recover v in (28) we have from (31)

$$\hat{v} = \begin{bmatrix} \hat{v}_1 \\ \hat{v}_2 \end{bmatrix} = \begin{bmatrix} \dot{\theta}_1^T \Psi_1 + \theta_1^T \Omega_1 \\ \dot{\theta}_2^T \Psi_2 + \theta_2^T \Omega_2 \end{bmatrix} \tag{42}$$

where $\dot{\theta}_i$ is given by (41) and

$$\Omega_1^T := [\omega^T \quad \hat{v}_2]^T , \qquad \Omega_2 := \omega \tag{43}$$

The corresponding algorithm is presented in Table 1.

5.3 Stability Analysis

Following (Ioannou and Sun (1996)), we consider the state representation (35). As a matter of fact, we can obtain a true Lyapunov function for the error system (i.e. with complete error state) by considering $\omega_f = L(s)^{-1}\omega$.

The error vector $\tilde{\omega}_f := L^{-1}(s)(\omega - \omega_M)$, where ω_M corresponds to the model reference realization defined to achieve (29), can be expressed as the output of a stable and proper filter with input e (hence of z) (similarly as in (Ioannou and Sun, 1996, p.358))

$$\dot{\varepsilon} = H\varepsilon + K\bar{z}_e \, , \qquad \tilde{\omega}_f = L\varepsilon + M\bar{z}_e \, , \tag{44}$$

with ε of appropriate dimension and H being a strictly Hurwitz matrix.

The passivity properties of the proposed adaptive visual servoing system is stated in the following theorem:

Theorem 3. Consider systems (35) and (44), with adaptive control (28)(42) and update law (41). Then, for P satisfying (36), the map $\sigma \mapsto B_{cs}^T P \bar{z}_e$ is output strictly passive with positive definite storage function given by:

$$2V_L(\bar{z}_e, \varepsilon, \tilde{\theta}_1, \tilde{\theta}_2) = \bar{z}_e^T P \bar{z}_e + \gamma_1^{-1} \tilde{\theta}_1^T \tilde{\theta}_1 + \gamma_2^{-1} \tilde{\theta}_2^T \tilde{\theta}_2 + \alpha \, \varepsilon^T P_1 \varepsilon \tag{45}$$

where P_1 is a positive definite matrix satisfying $H^T P_1 + P_1 H = -Q_1$ for positive definite matrix Q_1. □

Proof: Considering (45), for sufficiently small α (using Schur's complement), we have that: $\dot{V}_L \leq -\bar{z}_e^T Q \bar{z}_e + \bar{z}_e^T P B_{cs} \sigma$, which defines an output strictly passive maps $\sigma \mapsto B_{cs}^T P \bar{z}_e$ (Hsu et al. (2007)). □

Thus, considering also the passivity properties of the adaptive robot control (Theorem 2), we can apply Theorem 1 where the cascaded subsystems are identified by the corresponding states as

$$\Sigma_1 : \quad x_1^T = \left[\bar{z}_e^T \; \varepsilon^T \; \theta_1^T \; \theta_2^T\right] ; \quad y_1 = B_{cs}^T P \bar{z}_e \, ,$$
$$\Sigma_2 : \quad x_2^T = \left[e^T \; \dot{e}^T \; \tilde{a}^T\right] , \qquad y_2 = \sigma,$$

Thus, from Theorem 1, all signals of the system are L_∞ and, $\sigma(t)$ and $\bar{z}_e(t)$ tend to zero asymptotically. This implies that tracking errors $e(t)$ and $e_c(t) \to 0$ as $t \to \infty$.

6. SIMULATION RESULTS

Here we consider the nonlinear robot dynamic model (3). Uncertainty of the robot parameters is compensated by the adaptive control approach developed in this paper. We consider that the planar two-link manipulator is moving on a horizontal plane with forward kinematics given by:

$$y_1 = l_1 cos(q_1) + l_2 cos(q_1 + q_2) \tag{46}$$
$$y_2 = l_1 sin(q_1) + l_2 sin(q_1 + q_2) \tag{47}$$

where l_1, l_2 stands for link lengths, then we have that the components of matrices M, C, g are: $M_{11} = a_1 + 2a_2 cos(q_2)$; $M_{12} = M_{21} = a_3 + a_2 cos(q_2)$; $M_{22} = a_3$; $h_2 = a_2 sin(q_2)$; $C_{11} = -h_2 \dot{q}_2$; $C_{12} = -h_2(\dot{q}_1 + \dot{q}_2)$; $C_{21} = h_2 \dot{q}_1$; $C_{22} = 0$; $g_1 = a_4 sin(q_1) + a_5 sin(q_1 + q_2)$; $g_2 = a_5 sin(q_1 + q_2)$, with $a_1 = I_1 + m_1 l_{c1}^2 + I_2 + m_2 l_{c2}^2 + m_2 l_1^2$; $a_3 = I_2 + m_2 l_{c2}^2$; $a_2 = m_2 l_1 l_{c2}$; $a_4 = g(m_1 l_{c1} + m_2 l_1)$; $a_5 = g m_2 l_{c2}$.

The parameter values were chosen to be the ones in (Kelly (1996)), say: $m_1 = 23.902 \; kg$; $l_1 = 0.45 \; m$; $m_2 = 3.88 \; kg$; $I_1 = 1.266 \; kg \; m^2$; $I_2 = 0.093 \; kg \; m^2$; $l_{c1} = 0.091 \; m$; $l_{c2} = 0.048 \; m$; $l_2 = 0.55 \; m$; $g = 9.8 \; m/s^2$.

The desired trajectory y_{cd} was designed to be the output of the model $G_m(s) = 100/(s + 10)^2$ in response to the external reference signals

$$r_1 = c_1 \; sin(w_r t) + c_2 + c_4 \; sin(1.5 w_r t) \tag{48}$$
$$r_2 = c_1 \; sin(w_r t + c_5) + c_3 + c_4 \; sin(1.5 w_r t + c_5) \tag{49}$$

The parameters used in the simulations were $K_D = diag\{200, 20\}$; $\lambda_c = 10$; $\Gamma = 20I$; $\phi = 1 \; rad$; $\gamma_1 = \gamma_2 = 10$; $w_r = 1 \; rad/s$; $c_5 = 1.6 \; rad$; $c_1 = c_4 = 50$; $c_2 = 300$; $c_3 = 200$; $\lambda = 10$; $\lambda_0 = 10$; $f = 0.008 \; m$, $Z = -0.632 \; m$; $\alpha_1 = \alpha_2 = 72727 \; pixels/m$.

The states initial conditions are $q(0) = [-\pi/20, \; \pi/2]^T$, $y_{cd}(0) = [400.3, \; 355.7]^T$, $\theta_1(0) = [10^{-3}, \; 0, \; 0]^T$; $\theta_2(0) = [0, \; -10^{-3}]^T$; and $\hat{a}(0) = 0.9[a_1, \; a_2, \; a_3, \; a_4, \; a_5]^T$ (all other initial states are nulls).

In order to avoid involved calculations to derive the regressor vector Y of the robot dynamic model in cartesian space (3), we have designed the robot dynamic adaptive control in joint space (Slotine and Li (1991)). In joint space, σ and e in (8) are defined in terms of joint angles q and desired joint trajectory q_m. Then, the cascade strategy (14) should be redefined as $v = \frac{d}{dt}(J(q)\dot{q}_r) - \lambda\sigma$, where $\dot{q}_r = \dot{q}_m - \lambda e$.

Simulation results are presented in Figures 2-4. Tracking error are shown in Figure 2. The image space trajectories are depicted in Figure 3. Stable and convergent behavior of the output error $e_c(t)$ is apparent. Thus, this full example of planar robot visual servoing, including the uncertainty of the robot dynamics, confirms the theoretical results.

7. CONCLUSIONS

The problem of controlling robots with non neglegible dynamics through adaptive visual servoing was presented. The proposed scheme was developed taking into account the uncertainties of both camera and robot parameters. The kinematic control solution for the MIMO adaptive visual servoing case without using image velocity information, is formulated as a relative degree two multivari-

Table 1. Algorithm for Adaptive Visual Servoing without image velocity measurement

Regressor vector	$\omega = \frac{2\lambda_c \lambda_0^2}{\Lambda(s)}\ y_c - (\lambda_c^2 + 2\lambda_c\lambda_0)\ y_c + \lambda_c^2\ r$
	$\Omega_2^T = \omega^T, \quad \Omega_1^T = [\omega^T\ \hat{v}_2]$
Filtered signals	$\omega_f = L^{-1}(s)\ \omega, \quad \hat{v}_{fi} = \theta_i^T \Psi_i, \qquad L(s) = s + \lambda_c$
	$\Psi_2 = \omega_f, \quad \Psi_1^T = [w_f^T\ \hat{v}_{f2}]$
Output error	$e_c = y_c - y_{cd} \quad ; \quad y_{cd} = G_m(s) r$
Robot Control law	$F = Y(q, \dot{q}, \dot{y}_r, \ddot{y}_r)\ \hat{a} - K_D \sigma \quad ; \quad K_D = K_D^T > 0$
	$\sigma = \dot{e} + \lambda e = \dot{y} - \dot{y}_r\ ; \quad e = y - y_m\ ; \quad \dot{y}_r := \dot{y}_m - \lambda e$
Cascade Strategy	$\dot{y}_r = G^{-1}(s)\ v + \lambda G^{-1}(s)\ \dot{y} \quad ; \quad G(s) = s + \lambda$
Visual Servoing law	$v_i = \hat{v}_i - 2\lambda_c \Lambda^{-1}(s)\ v_i \quad ; \quad \hat{v}_i = \dot{\theta}_i^T \Psi_i + \theta_i^T \Omega_i \quad ; \quad \Lambda(s) = s + \lambda_0$
Adaptation law	$\dot{\hat{a}} = -\Gamma Y^T \sigma \quad ; \quad \Gamma = \Gamma^T > 0$
	$\dot{\theta}_i = -\gamma_i e_{ci} \Psi_i \quad ; \quad \gamma_i > 0$

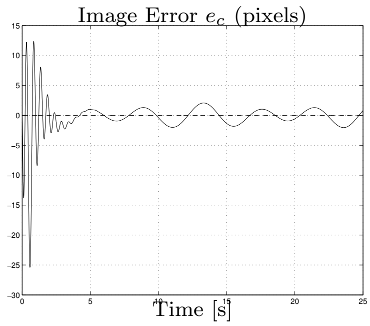

Fig. 2. Tracking errors e_{c1} (-·-), e_{c2} (–).

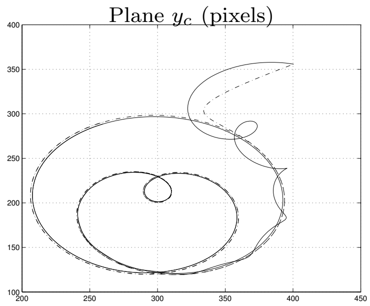

Fig. 3. Camera plane trajectories y_c (–), y_{cd} (-·-).

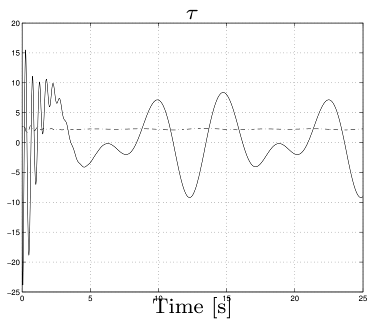

Fig. 4. Control Signal: τ_1 (–), τ_2 (-·-).

able adaptive control problem. The combination of the kinematic controller with the adaptive motion control was achieved by a cascade structure, resulting on an overall stable adaptive visual system. Simulation results illustrate the performance of the proposed strategies.

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