An Experimental Study of Stabilizing Receding Horizon Control of Visual Feedback System with Planar Manipulators

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This paper investigates vision based robot control based on a receding horizon control strategy. The stability of the receding horizon control scheme is guaranteed by using the terminal cost derived from an energy function of the visual feedback system. By applying the proposed control scheme to a two-link direct drive manipulator with a CCD camera, it is shown that the stabilizing receding horizon control nicely works for a planar visual feedback system. Furthermore, actual nonlinear experimental results are assessed with respect to the stability and the performance.

1 Introduction

Robotics and intelligent machines need sensory information to behave autonomously in dynamical environments. Visual information is particularly suited to recognize unknown surroundings. In this sense, vision is one of the highest sensing modalities that currently exist. Vision based control of robotic systems involves the fusion of robot kinematics, dynamics, and computer vision to control the motion of the robot in an efficient manner. The combination of mechanical control with visual information, so-called visual feedback control or visual servoing, is important when we consider a mechanical system working in dynamical environments [1].

In previous works, Kelly [2] considered the set-point problem with a static target for a dynamic visual feedback system that includes the manipulator dynamics which is not be negligible for high speed tasks. The authors discussed passivity based control of the eye-in-hand system [3, 4]. However, the control law proposed in [3] is not based on optimization, the desired control performance cannot be guaranteed explicitly.

Receding horizon control, also recognized as model predictive control is a well-known control strategy in which the current control action is computed

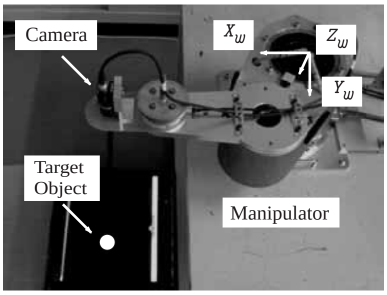

Fig. 1. Planar visual feedback system

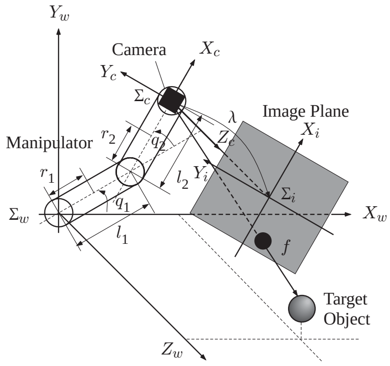

Fig. 2. Schematic diagram

by solving, a finite horizon optimal control problem on-line [5]. A large number of industrial applications using model predictive control can be found in chemical industries where the processes have relatively slow dynamics. On the contrary, for nonlinear and relatively fast systems such as in robotics, few implementations of the receding horizon control have been reported. For the receding horizon control, many researchers have tackled the problem of stability guarantees. An approach proposed by Parisini *et al.* [6] is based on using a quadratic endpoint penalty of the form $ax^T(t+T)Px(t+T)$ for some $a > 0$, some positive definite matrix P and a terminal state $x(t+T)$. Jadbabaie *et al.* [7] showed that closed-loop stability is ensured through the use of a terminal cost consisting of a control Lyapunov function. Moreover, these results were applied to the Caltech Ducted Fan to perform aggressive maneuvers [8, 9]. Visual feedback, however, is not considered here. Predictive control could be of significant benefit when used in conjunction with visual servoing. With the incorporation of visual information, the system could anticipate the target's future position and be waiting there to intercept it [10].

In this paper, stabilizing receding horizon control is applied to the planar visual feedback system in [3], a highly nonlinear and relatively fast system. This represents a first step towards high performance visual servoing targeting more aggressive maneuvers. The main idea is the use of the terminal cost derived from an energy function of the visual feedback system. By applying the proposed control scheme to a two-link direct drive manipulator with a CCD camera, it is shown that the stabilizing receding horizon control nicely works for the planar visual feedback system. Furthermore, the experimental results are assessed with respect to performance.

First, passivity-based control of a planar visual feedback system is reviewed. Next, a stabilizing receding horizon control for a planar visual feedback system using a control Lyapunov function is proposed. Then, the control performance of the stabilizing receding horizon control scheme is evaluated through experiments with a two-link direct drive manipulator with a camera as shown in Fig. 1.

2 Visual Feedback System with Planar Manipulator

The dynamics of n-link rigid robot manipulators can be written as

$$M(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q) = \tau \tag{1}$$

where q, $\dot{q}$ and $\ddot{q}$ are the joint angle, velocity and acceleration, respectively, τ is the vector of the input torque [11]. We assume that the robot evolves in a plane of $n = 2$, referring to Figs. 1 and 2.

The objective of visual feedback control is to bring the camera which is mounted on the end-effector of the manipulator to the position of the target object, i.e., to bring a image feature parameter vector $f = [f_x \ f_y]^T$ to the origin. The image feature parameter vector f is obtained from a perspective transformation. Although details are omitted for lack of space, the planar visual feedback system is given as follows [3, 12].

$$\begin{bmatrix} \dot{\xi} \\ \dot{f} \end{bmatrix} = \begin{bmatrix} -M(q)^{-1}C(q,\dot{q})\xi + w_f M(q)^{-1} J_p^T R_{wc} f \\ -\frac{s\lambda}{z_{wo}} R_{wc}^T J_p \xi - R_{wc}^T \dot{R}_{wc} f \end{bmatrix} + \begin{bmatrix} M(q)^{-1} & 0 \\ 0 & -\frac{s\lambda}{z_{wo}} R_{wc}^T J_p \end{bmatrix} u \tag{2}$$

where $u := [u_\xi^T \ u_d^T]^T$ is the control input, $\xi := \dot{q} - u_d$ is the error vector with respect to the joint velocity, the scalar $w_f > 0$ is a weight for the input torque, R_{wc} is a rotation matrix and J_p is the manipulator Jacobian. A scalar $s > 0$ is the scale factor in pixel/m, λ is the focal length of the camera and z_{wo} is a constant depth parameter. We define the state of the visual feedback system as $x := [\xi^T \ f^T]^T$. The purpose of this paper is to control this planar visual feedback system (2) by using stabilizing receding horizon control.

In previous work [3], the passivity of the visual feedback system (2) is derived by using the following energy function $V(x)$

$$V(x) = \frac{1}{2}\xi^T M(q)\xi + \frac{w_f z_{wo}}{2s\lambda} f^T f. \tag{3}$$

Here, we consider the following control input

$$u = -K\nu := u_k, \quad K := \begin{bmatrix} K_\xi & 0 \\ 0 & K_d \end{bmatrix}, \quad \nu := Nx := \begin{bmatrix} I & 0 \\ 0 & -w_f J_p^T R_{wc} \end{bmatrix} x, \tag{4}$$

where $K_\xi := \mathrm{diag}\{k_{\xi 1}, k_{\xi 2}\} \in \mathcal{R}^{2\times 2}$ and $K_d := \mathrm{diag}\{k_{d1}, k_{d2}\} \in \mathcal{R}^{2\times 2}$ are positive gain matrices. Differentiating $V(x)$ along the trajectory of the system and using the control input u_k, the next equation is derived.

$$\dot{V} = \nu^T u = -x^T N^T K N x. \tag{5}$$

Therefore, the equilibrium point $x = 0$ for the closed-loop system (2) and (4) is asymptotic stable, i.e., u_k is a stabilizing control law for the system.

3 Stabilizing Receding Horizon Control

In this section, the finite horizon optimal control problem for the visual feedback system (2) is considered. Receding horizon schemes are often based on the following cost function.

$$J(u,t) = \int_t^{t+T} l(x(\tau),u(\tau))d\tau + F(x(t+T)), \quad F(x(t+T)) \geq 0 \tag{6}$$

$$l(x(t),u(t)) = x^T(t)Q(t)x(t) + u^T(t)R(t)u(t), \quad Q(t) \geq 0,\ R(t) > 0. \tag{7}$$

The resulting open loop optimal control input u^* is implemented until a new state update occurs, usually at pre-specified sampling intervals. Repeating these calculations yields a feedback control law.

The following lemma concerning a control Lyapunov function is important to prove a stabilizing receding horizon control. The definition for a control Lyapunov function $M(x)$ is given by

$$\inf_u \left[\dot{M}(x) + l(x,u) \right] \leq 0, \tag{8}$$

where $l(x,u)$ is a positive definite function [7].

Lemma 1. *Suppose that the following matrix P is positive semi definite.*

$$P := \rho N^T K N - Q - N^T K^T R K N, \quad \rho > 0. \tag{9}$$

Then, the energy function $\rho V(x)$ of the visual feedback system (2) can be regarded as a control Lyapunov function.

The proof is straightforward using a positive definite function $l(x(t),u(t))$ (7) and the stabilizing control law u_k (4) for the system. Suppose that the terminal cost is the control Lyapunov function $\rho V(x)$, the following theorem concerning the stability of the receding horizon control holds.

Theorem 1. *Consider the following cost function for the visual feedback system (2).*

$$J(u,t) = \int_t^{t+T} l(x(\tau),u(\tau))d\tau + F(x(t+T)) \tag{10}$$

$$l(x(t),u(t)) = x^T(t)Q(t)x(t) + u^T(t)R(t)u(t), \quad Q(t) \geq 0,\ R(t) > 0 \tag{11}$$

$$F(x) = \rho V(x), \quad \rho > 0. \tag{12}$$

Suppose that P (9) is positive semi definite, then the receding horizon control for the visual feedback system is asymptotically stabilizing.

This theorem is proven by using a similar method as in [7], details are omitted due to lack of space. Theorem 1 guarantees the stability of the receding horizon control using a control Lyapunov function for the planar visual feedback system (2) which is a highly nonlinear and relatively fast system. Since the stabilizing receding horizon control design is based on optimal control theory, the control performance should be improved compared to the simple passivity-based control [3], under the condition of adequate gain assignment in the cost function. In this paper, as a first step, we propose unconstrained stabilizing receding horizon control schemes. In the near future, we will consider constraints which represent one of the advantages of receding horizon control, and develop it using level set, see [7].

Moreover, focused on the inverse optimality approach [12], the following corollary is derived.

Corollary 1. *Consider the following weights of the cost function (10)-(12).*

$$Q(t) = qN^T(t)KN(t), \quad q \geq 0 \tag{13}$$
$$R(t) = rK^{-1}, \quad r > 0 \tag{14}$$
$$\rho = 2\sqrt{qr}. \tag{15}$$

Then, the receding horizon control for the visual feedback system is asymptotically stabilizing, the receding horizon control law is

$$u^* = -\sqrt{\frac{q}{r}}KNx \tag{16}$$

and the cost-to-go is given by

$$J^* = \rho V(x). \tag{17}$$

If the weights of the terminal cost function are set to (13)-(15), then the controller that satisfies $\inf_u[\dot{M}(x) + l(x,u)] = 0$ is analytically derived.

In the next section, the stabilizing receding horizon control is applied to a planar visual feedback system. It is expected that the control performance is improved using the receding horizon control.

4 Experimental Results

In this section, the proposed stabilizing receding horizon control is tested on an actual planar visual feedback system which is an image based direct visual servo system. The manipulator used in the experiments (see Fig. 1), is controlled by a digital signal processor (DSP) from dSPACE Inc., which utilizes a powerPC 750 running at 480 MHz. Control programs are written in MATLAB and SIMULINK, and implemented on the DSP using the Real-Time Workshop and dSPACE Software which includes ControlDesk and Real-Time Interface. A XC-HR57 camera is attached to the tip of the manipulator. The video signals are acquired by a frame graver board PicPort-Stereo-H4D and the image processing software HALCON. The sampling time of the controller and the frame rate provided by the camera are 16.7 [ms] and 60 [fps], respectively. To solve the real time optimization problem, the software C/GMRES [13] is utilized. The target object is projected on the liquid crystal monitor. The control objective is to bring the image feature parameter vector f to the origin. The experiment is carried out with the initial condition $q_1(0) = \pi/6$ [rad], $q_2(0) = -\pi/6$ [rad], $\dot{q}_1(0) = \dot{q}_2(0) = 0$ [rad/s], $w_f = 0.0001$, $z_{wo} = 0.9$ [m], $s\lambda = 1230$ [pixel], $f(0) = [-120\ \ -160]^T$ [pixel] (1 [pixel] = 0.74 [mm]).

In this experiment, we compare the performance of the receding horizon control law proposed in Theorem 1 and the passivity based control law u_k (4). The weights of the cost function (10) were selected as $Q = \mathrm{diag}\{65, 1.5, 10, 100\} \times 10^{-9}$, $R = \mathrm{diag}\{0.04, 1.7, 0.005, 0.00045\}$ and $\rho = 1$ satisfy $P \geq 0$. The controller parameters for the passivity based control law u_k (4) were empirically selected as $K_\xi = \mathrm{diag}\{6.5, 0.15\}$ and $K_d = \mathrm{diag}\{50, 550\}$. The control input with the receding horizon control is updated within every 16.7 [ms]. It must be calculated by the receding horizon controller within that period. The horizon was selected as $T = 0.02$ [s].

The experimental results are presented in Fig. 3, showing the velocity error ξ_2, the image feature parameter f_y and the control inputs $u_{\xi 2}$ and u_{d2}, respectively. The rise time applying the receding horizon control is shorter than that for the passivity based control. The controller predicts the movement of the target object using the visual information, as a result the manipulator moves more aggressively. This validates one of the expected advantages of the stabilizing receding horizon control for the visual feedback system. From Fig. 3, the asymptotic stability can be also confirmed experimentally. The steady state performance is also better than for the passivity based control. Still, a non-vanishing steady state error is observed most probably due to the influence of the unmodeled manipulator dynamics(e.g. friction). This problem will be investigated in the near future. We assume that an integrator in the control will improve the steady state performance [14].

The performance for other parameter values T and ρ is compared in terms of the integral cost in Table 1. Since the cost of the stabilizing receding horizon method is smaller than the passivity based control method under conditions of the adequate cost function, it can be easily verified that the control performance is improved. With increasing weight of the terminal cost from $\rho = 1$ to $\rho = 1.1$ the cost increases, too. With higher terminal cost the state value is reduced more strictly, using a large control input. In this experiment, since the weights of the control input are larger than those of the state, the cost increased consequently. As the horizon length increases from $T = 0.02$ to $T = 0.1$, the cost is reduced. In the case of $T = 0.5$, the calculation can not be completed within one sampling interval, due to limited computing power.

5 Conclusions

This paper proposes a stabilizing receding horizon control for a planar visual feedback system, which is a highly nonlinear and relatively fast system. It is shown that the stability of the receding horizon control scheme is guaranteed by using the terminal cost derived from an energy function of the visual feedback system. Furthermore, it is verified that the stabilizing receding horizon control nicely works for the planar visual feedback system through experiments with a nonlinear experimental system. In the experimental results, the control performance of the stabilizing receding horizon control is improved compared to that of the simple passivity based control. In this paper, the stabilizing receding controller was implemented for a low level inner loop, in the near future, we would like to tackle the implementation on a high level outer loop.

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Table 1. Values of the Integral Cost

Control Scheme	cost
Passivity based Control	106.1
Receding Horizon Control ($T = 0.02$ [s], $\rho = 1$)	61.8
Receding Horizon Control ($T = 0.02$ [s], $\rho = 1.05$)	108.9
Receding Horizon Control ($T = 0.02$ [s], $\rho = 1.1$)	209.2
Receding Horizon Control ($T = 0.05$ [s], $\rho = 1$)	56.3
Receding Horizon Control ($T = 0.1$ [s], $\rho = 1$)	55.1

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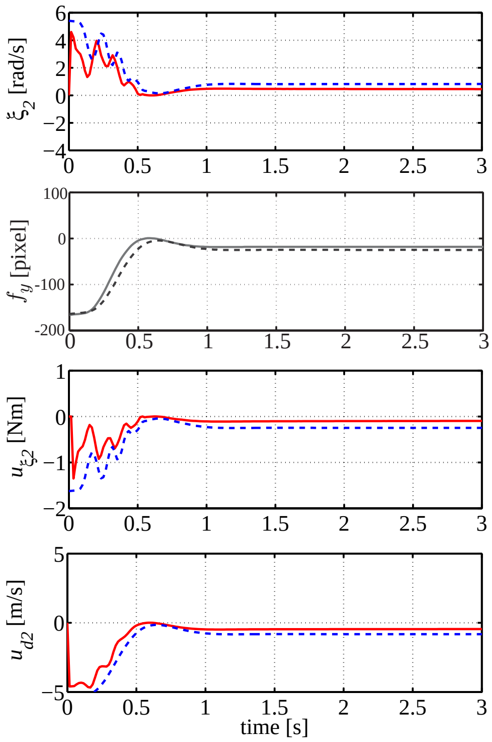

Fig. 3. Experimental comparison with different control schemes
(solid: receding horizon control ($T = 0.02$ [s], $\rho = 1$), dashed: passivity based control)

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