VISION-BASED GRASPING USING MOBILE ROBOTS AND NONLINEAR MODEL PREDICTIVE CONTROL

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Abstract

This paper presents an autonomous grasping system using visual servoing and mobile robots. While this kind of system has many potential significant applications, there have been several key challenges, for example, localization accuracy, visibility and velocity constraints, obstacle avoidance, and so on, to prevent the implementation of such a system. The main contribution of this paper is to develop an adaptive nonlinear model predictive controller to meet all these challenges in one single controller. In particular, the model of the vision-based mobile grasping system is first derived. Then, based on the model, a nonlinear predictive control strategy with vision feedback is proposed to deal with the issues of optimal control and constraints simultaneously. Different from other work in this field, to improve the performance, an adaptive mechanism is proposed in the paper to update the model online so that it can track the nonlinear time-varying plant in a real time manner. To the best of our knowledge, this is the first work to apply model predictive control to mobile visual servoing and consider various constraints at the same time. The approach is validated with two physical experiments. It is shown that the system with the new control strategy is quite successful to carry out an autonomous mobile grasping task in a complex environment.

Key Words

Visual servoing, robot, NMPC, adaptive control

1. Introduction

A vision-based mobile manipulation system is usually made up of an intelligent mobile robot, one or multiple on-board cameras, and an on-board arm with multiple degrees of freedom. Based on the feedback from its various sensors (vision, sonar, laser distance finders, bumpers, and so on), the robot can autonomously navigate in an unstructured and even unknown environment (for example, a planetary surface or a home), identify any objects of interest, grasp or manipulate them visually, and move them to a designated place for further operations.

Since a vision-based mobile manipulation system integrates the advantages of visual servoing control, which is usually applied in industrial robotic arms, and autonomous navigation of mobile robots, it is expected to have significant applications in multiple important fields such as service robots, robotic space exploration, flexible manufacturing systems (FMS), and so on. For example, about the capability of vision-based mobile manipulation, we can imagine that a mobile robot will autonomously pick up some medicines in a specific place at home with its visually grasping capability, move and deliver them to a senior person at another room, and remind him/her to take the medicines in time.

Through combining the capabilities of the mobile base, the cameras and the multi-joint robotic arm in one platform, a vision-based mobile manipulation system is more versatile, powerful, and useful than a traditional mobile robot or an industrial robot. As a result, it can complete more tasks with different requirements. In particular, due to its mobile base and intelligent navigation ability, the robot can move to any place in an unstructured environment easily and search objects it wants. On the other hand, the on-board camera system provides a general and powerful means for the robot to identify and track multiple objects of interest simultaneously. Finally, with the feedback from the vision sub-system, the on-board arm enables the robot to grasp or manipulate objects and deliver them to some places far from it.

Although a vision-based mobile manipulation system is so attractive, there have been some significant challenges to implement such a system. The biggest challenge may rise from visual servoing control of the robotic arm when it is mounted on a mobile base. In the following sections, it will be shown that model for such a system is very nonlinear and highly time-varying. The second challenge is the visibility constraint problem in a mobile visual servoing system. Different from the working environments of industrial robots, the environment of a mobile robot is usually unstructured and even unknown, and the robot

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often moves for a large distance in such an environment. Therefore, the objects of interest are easy to move out of the field of view of the camera so that the visual servoing controller will fail totally. Finally, when the robot is moving in an unstructured environment with obstacles and grasping objects, its physical moving trajectory and velocities are constrained while its optimal control performance still has to be maintained at the same time.

In this paper, a physical vision-based mobile grasping system is developed and validated. In particular, a nonlinear and time-varying model of such a system is derived, and an adaptive nonlinear model predictive control (A-NMPC) scheme is proposed to deal with this model and various constraint issues in the task. To the best of our knowledge, it is the first work to apply nonlinear model predictive control to mobile robot visual servoing and consider multiple constraints at the same time.

2. Related Work

Visual servoing has been a popular research field in the robotics community in the past decade, and much of work has been based on a proportional control law with Lyapunov stability, which is described in [1], [2]. Although the control law in [1], [2] can guarantee the system stability, its controller output is not optimal, and it is unable to consider various constraints (robot location constraints, visibility constraints, velocity constraints, and so on) which are common in a mobile visual servoing system. To get optimal controller outputs, Ginhoux et al. proposed to use generalized predictive controller (GPC) in visual servoing of a robotized surgery task [3]. In particular, a 6 degree of freedom (DOF) robotic arm was developed to track the motion of a pig’s heart based on the visual feedback. Since they employed the GPC scheme, no constraints were considered. In addition, they also used the same idea in teleoperated laparoscopic surgery [4] and 3-D profile following [5]. Since the constraint issue is quite popular in visual servoing tasks, Sauvee et al. [6] implemented a nonlinear model predictive controller for visual servoing of a robotic arm using vision feedback from ultrasound images. In this project, they considered various constraints and linearized the nonlinear model into a constant linear model at the equilibrium point.

Applying model predictive control (MPC) to visual servoing is still in its juvenile stage. Only a little work was reported as above. Although some positive results were obtained in [3]–[8], however, they shared a common shortcoming: to apply the existing MPC technique to visual servoing tasks, a constant linear model was assumed for the nonlinear plant. As a result, the implemented system can only work in a small neighbourhood of the equilibrium point. If the current operation point of the system is far from the equilibrium point (which is common in a mobile manipulation task), the controller performance will deteriorate quickly due to the mismatch between the model and the plant.

In this paper, based on the derived model, an adaptive nonlinear model predictive controller (A-NMPC) is proposed to meet the above challenge and deal with various constraint issues as well, and the developed controller will be applied to a vision-based mobile manipulation task for validation. To the best of our knowledge, this is the first work to apply NMPC to visual servoing for mobile manipulation and consider constraints.

3. Vision-based Mobile Manipulation

3.1 Problem Formulation

In this paper, through closely integrating the visual feedback from the camera with the robot controller, a mobile robot with an on-board 5 DOF arm and a CCD camera, which is shown in Fig. 1, is required to move toward a target object (a paste tube with a red cap) and grasp it robustly.

In this project, in addition to the requirements of accurate localization and grasping, to grasp the object successfully, several constraints have to be considered. The first one is the visibility constraint which requires the target object within the field of view of the camera when the robot is moving. The second one is the location constraint which requires the robot to avoid any obstacles on the ground when it approaches the target object. Finally, the last constraint will limit the translational and rotational velocities of the robot so that it will not run into obstacles or the target object.

3.2 Nonlinear and Time Varying Model

If we assume the initial position and heading of the mobile robot are \((x_0, y_0, \theta_0)\), and its translational and rotational velocities are \(v_t(t)\) and \(\omega(t)\), one can get (1) as follows:

\[
\begin{align*}
    x(t) &= x_0 + \int_0^t v_t(t) \cos(\theta(t)) \, dt \\
    y(t) &= y_0 + \int_0^t v_t(t) \sin(\theta(t)) \, dt \\
    \theta(t) &= \theta_0 + \int_0^t \omega(t) \, dt
\end{align*}
\]

where \(x(t), y(t)\) and \(\theta(t)\) are the position and heading of the robot at time \(t\). If \(\pi(t) = x(t) - x_0, \, \eta(t) = y(t) - y_0, \)
and \( \theta(t) = \theta(t) - \theta_0 \), then one can obtain an approximate linear model as follows:

\[
\begin{bmatrix}
\mathbf{X}(s) \\
\mathbf{Y}(s) \\
\mathbf{Z}(s)
\end{bmatrix} = \begin{bmatrix}
\cos \theta_0/s & 0 \\
\sin \theta_0/s & 0 \\
0 & 1/s
\end{bmatrix} \begin{bmatrix}
V_1(s) \\
\Omega(s)
\end{bmatrix}
\]

(2)

where \( V_1(s) \) and \( \Omega(s) \) are the Laplace transforms of \( v_1(t) \) and \( \omega(t) \), i.e., \( V(s) = L(v(t)) \) and \( \Omega(s) = L(\omega(t)) \).

Since the camera is rigidly attached to the mobile base, when the robot is moving in the ground, the position of the target object in the image will change. The relationship between the target position in the image and the robot translational/rotational velocities, which has been derived in our previous paper [9], is presented here again:

\[
\begin{bmatrix}
\mathbf{U}(s) \\
\mathbf{V}(s) \\
\mathbf{X}(s) \\
\mathbf{Y}(s) \\
\mathbf{Z}(s)
\end{bmatrix} = \begin{bmatrix}
M_{11}(t) & M_{12}(t) & M_{21}(t) & M_{22}(t) & s
\end{bmatrix} \begin{bmatrix}
V_1(s) \\
\Omega(s)
\end{bmatrix}
\]

(3)

where \( \mathbf{U}(s) = L(u(t) - u_0) \) and \( \mathbf{V}(s) = L(v(t) - v_0) \) represent the position of the target object in the image, the 2 \times 2 matrix \( \mathbf{M} \) is constituted by the third and fifth columns of \( \mathbf{L} \mathbf{G}^{-1} \). In particular, \( \mathbf{L} \) is the interaction matrix of the camera projection model and \( \mathbf{G} = \begin{bmatrix} R & s(d)R \\ 0 & R \end{bmatrix} \) represents the velocity transform between the robot frame and the camera frame. The details of the matrix \( \mathbf{L} \) and \( \mathbf{G} \) and (3) can be found in our previous work [9].

It is noted that the matrix \( \mathbf{M} \) is determined by the current values of \( u(t), v(t) \) and the depth \( z(t) \). As a result, \( \mathbf{M} \) is a time-varying matrix [9].

Equations (2) and (3) represent the nonlinear model of the vision-based mobile robotic system shown in Fig. 1. In addition, since the matrix \( \mathbf{L} \) is determined by the current position of the target object in the image, the model is also a time-varying model.

However, if we assume \( M_{11}(t), M_{12}(t), M_{21}(t), \) and \( M_{22}(t) \) are constant, then an approximate linear model of the plant is obtained as follows:

\[
\begin{bmatrix}
\mathbf{U}(s) \\
\mathbf{V}(s) \\
\mathbf{X}(s) \\
\mathbf{Y}(s) \\
\mathbf{Z}(s)
\end{bmatrix} = \begin{bmatrix}
M_{11} & M_{12} & M_{21} & M_{22} & s
\end{bmatrix} \begin{bmatrix}
V_1(s) \\
\Omega(s)
\end{bmatrix}
\]

(4)

4. Adaptive Nonlinear Model Predictive Control

4.1 Nonlinear Model Predictive Control (NMPC)

NMPC has been popular in the areas of control and robotics in these years. The most important advantage of NMPC is that it can consider various input/output constraints in a nonlinear plant while calculating optimal control inputs. The basic idea of NMPC is to calculate an optimal control input sequence for the plant through the model prediction so as to minimize the cost function and meet various constraints on the plant. More details of NMPC can be found in [10].

4.2 Adaptive NMPC Control Scheme

As shown in Section 3, the mobile visual servoing project described in Fig. 1 is related to multiple constraints and has a nonlinear model, so it is natural to apply NMPC to the visual servoing task. However, it is noted that the model described by (2) and (3) is highly nonlinear and time-varying while the classical NMPC algorithm requires a linear model to predict the behaviours of the nonlinear plant [10]. A popular solution, as shown in [3]–[6], is to find a constant linear model at the equilibrium point of the plant and use this constant model in the NMPC controller. While this approach works well in visual servoing of fixed-base robotic arms [3]–[6], it will fail in visual servoing of mobile robots since mobile robots usually move for a large distance which enables its current work point is far away from the equilibrium point. Therefore, a more advanced NMPC scheme is expected for vision-based mobile manipulation tasks.

In this paper, a new NMPC scheme, called A-NMPC, is proposed to meet the above challenge. The A-NMPC control approach is presented in Fig. 2.

In Fig. 2, the A-NMPC controller includes four units: model updating unit, linearized model, constraint unit, and optimizer unit. In particular, the current position of the target object in the image (i.e., \([u, v]^T\)) and the current depth \( z \) are continuously measured with the CCD camera and the laser distance finder and are sent into

Figure 2. The scheme of adaptive nonlinear model predictive control (A-NMPC) for vision-based mobile manipulation.
the model updating unit. Then the linearized model of the plant is updated by the model updating unit with the latest $u, v,$ and $z$ so that the model can always track the nonlinear plant. In addition, three kinds of constraints are considered and set up by the constraint unit which will constraint $[v, \omega]^T$ (the translational and rotational velocities of the robot), $[x, y, \theta]^T$ (the location and heading of the mobile robot in the environment), and $[u, v]^T$ (the position of the target object in the image). Finally, based on the latest linearized model, the constraint requirements and the current outputs of the plant, the optimizer unit will calculate an optimal control input sequence using the quadratic programming algorithm (QP), as described in [10].
4.3 Cost function

The cost function of the A-NMPC controller is presented in (5).

\[
C(k) = H_p \sum_{i=1}^{H_p} \left\| \begin{bmatrix} \hat{u}(k+i|k) - u_d \\ \hat{v}(k+i|k) - v_d \end{bmatrix} \right\|_{Q(i)}^2 \\
+ \sum_{i=0}^{H_u-1} \left\| \begin{bmatrix} \delta \hat{v}(k+i|k) \\ \delta \hat{\omega}(k+i|k) \end{bmatrix} \right\|_{R(i)}^2 
\]

where \( H_p \) is the prediction horizon, \( H_u \) is the control horizon, \((u_d, v_d)\) is the desired position of the target object in the image, \(Q(i)\) and \(R(i)\) are the weight matrices, \(Q(i) \geq 0\) and \(R(i) \geq 0\).

4.4 Constraints

The A-NMPC controller, as shown in Fig. 2, considers three kinds of constraints as follows:

\[
u_{\text{min}} \leq v(t) \leq v_{\text{max}} \quad \text{visibility constraints}
\]
\[
x(t) \leq x_{\text{max}}, y(t) \leq y_{\text{max}}, \quad \theta_{\text{min}} \leq \theta(t) \leq \theta_{\text{max}} \quad \text{robot location constraints}
\]
\[
v_{\text{max}} \leq \nu(t) \leq v_{\text{max}} \quad \text{and} \quad \omega(t) \leq \omega_{\text{max}} \quad \text{robot velocity constraints}
\]

5. Experiments

To validate the proposed A-NMPC controller, a vision-based mobile manipulation system was developed. As shown in Fig. 1, the system includes a PioneerTM DX3 mobile robot, a 5-DOF Pioneer ArmTM, and an on-board Canon CCD camera. The mobile robot has an on-board computer inside its case, which provides sufficient computational resources for running the A-NMPC controller in real time. In addition, the ACTSTM colour blob tracking software was used to track the position of the target object in the image in real time. The NMPC controller was first designed and tested in the MATLAB MPC ToolboxTM. Then it was compiled into a DLL file using the MATLAB CompilerTM, which can be further loaded and called by the C++ main program to control the motion of the robot.
5.1 Un-constrained A-NMPC Controller

In the first experiment, an A-NMPC controller without considering any constraints was tested. The
controller parameters are listed as follows: sampling time
ts = 100 ms, \( H_p = 10 \), \( H_a = 3 \),
\[ Q(i) = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix} \], and
\[ R(i) = \begin{bmatrix} 0.1 & 0 \\ 0 & 0.1 \end{bmatrix} \]. The experimental results are presented in Fig. 3.

5.2 Constrained A-NMPC Controller

In this experiment, the A-NMPC has the following constraints: \( 20 \leq r \leq 450 \), \( 20 \leq c \leq 300 \), \(-20 \text{ cm/s} \leq v_t \leq 20 \text{ m/s}, -6 \text{ deg/s} \leq \omega \leq 6 \text{ deg/s}, y \geq -15 \text{ cm}. \) The experimental results are shown in the attached video and a series of still images grabbed from the video are presented in Fig. 4.

In Fig. 4, a mobile robot with an on-board arm and a CCD camera was required to grasp a target object (a paste tube with a red cap) in an environment with two obstacles. It was shown that the vision-based mobile manipulation system, commanded by the constrained A-NMPC visual servoing controller developed in this paper, avoided the obstacles, moved toward the target object, and grasped it successfully.

In the above visual servoing process, the system outputs and control inputs are presented in Fig. 5.

From Fig. 5(a), (d), and (e), it is clear that the system outputs \((r(t) and c(t))\) and the control inputs \((v_i(t) and \omega(t))\) were constrained within the desired limits while Fig. 5(b) showed that the errors converged to zero quickly. Therefore, from Fig. 5, it can be concluded that the A-NMPC visual servoing controller developed in this paper is quite successful to maintain optimal control performance and respect various constraints (visibility constraints, velocity constraints, and so on) at the same time.

6. Conclusions

In this paper, a vision-based mobile grasping system was developed so that a mobile robot can employ its on-board arm to autonomously grasp objects of interest based on the vision feedback from its camera. First, a nonlinear and time-varying model for the mobile visual servoing system was derived. Then the model was linearized through some assumptions. Second, based on the model, an adaptive nonlinear predictive controller was proposed to enable the mobile robot to grasp objects visually while considering various constraints in the task. This paper is thought to be the first effort to apply MPC to mobile visual servoing so that the optimal control performance and constraint requirements can be met simultaneously. The experimental results validated the effectiveness and robustness of the new controller.

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References


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