ADAPTIVE NONLINEAR MODEL PREDICTIVE CONTROLLER FOR VISUAL SERVOING OF MOBILE MANIPULATION

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ABSTRACT  
This paper presents an autonomous mobile manipulation system which has the ability to identify an object of interest, approach the object, and grasp it using visual servoing. A kinematic model of the robot system and a camera model are utilized to represent the physical system where velocities of the joint of the robot are the inputs and the position of the feature point in the image is the output. An Adaptive Nonlinear Model Predictive Controller (ANMPC) is developed for visual servoing which incorporates a multi-input multi-output (MIMO) control system and accepts constraints, including environmental constraints (e.g., obstacles, boundaries, visibility) as well as physical constraints of the robots (e.g., limits on joint movement, velocity, torque, and so on). Moreover, it linearizes the nonlinear and time-invariant model with respect to the current positions of the feature points and robot joints, on line, using an adaptive approach. The developed control architecture predicts the system outputs and generates optimized controller outputs according a cost function. The performance of the developed system is evaluated using computer simulations.

Keywords: Visual servoing, mobile robotics, model predictive control.

INTRODUCTION  
Mobile manipulation through visual servoing, which utilizes vision information to control the motion and manipulation of a mobile robot and its on-board arm has drawn increased research attention in recent years due to the diversity of the associated scientific and engineering issues and the significance of potential applications. Many practical applications can benefit from this work. An example is a group of autonomous mobile robots exploring an unknown and unstructured environment such as Mars in search of interesting material and carrying the collected samples to a base station. Another example is a warehouse or an industrial assembly line where mobile robots identify correct parts using vision information and transport them to a goal location for assembly. Other potential applications include deep-sea salvage, medical surgery, and robotic warfare. Yet there exist some challenges and open-questions in this field; for example:

1) Visibility constraint.
2) Time variation of the system.
3) System nonlinearity.
4) Physical constraints, including robot’s physical constraints and environmental constraints.

In the present context, any visual servo control system requires an efficient and reliable vision tracking system in order to keep the object of interest inside the camera view. This is important because visual servoing relies on the information from vision information and the controller will fail if there is no feedback from the vision system. Secondly, mobile manipulation system is usually a high degrees of freedom (DOF) nonlinear and time-varying system, as discussed later. Moreover, automaton robots work in real world environments that are highly uncertain and dynamic. Therefore, physical constraints (e.g., robot velocity and joint limit.) and environmental constraints (e.g., obstacles and other mobile robots) must be taken into account.

This paper aims to complement the existing research activities in this area, with the end objective of developing an autonomous mobile robotic grasping systems using visual servoing. The paper specifically addresses some challenges in vision-based autonomous mobile robot manipulation through:

1) Mathematic modeling of the mobile manipulation system.
2) Development of effective control strategies for robust control of motion and manipulation of mobile robots.
3) Consideration of physical constraints and visibility constraints.

RELATED WORK

The earliest research of visual servoing was reported in 1979 [1], and the term visual servoing has become rather common since the 1990s [2]. The subject has been under study in various forms for more than thirty years, in contexts ranging from simple pick-and-place tasks to today’s real-time, complex tasks involving multiple robots and objects, autonomous cooperation, and dynamic, unstructured and unknown environments. Visual servo control can be classified into position-based visual servo (PBVS) control and image-based visual servo (IBVS) control [3]. In the former, features are extracted from images and used in conjunction with camera models and a geometric model of the target object to estimate the pose of the target with respect to the cameras. The controller seeks to reduce the error between the current pose and the desired pose in a 3D workspace. In contrast, image-based visual servo control uses the 2D image features directly. Consequently, image-based visual servo control reduces the computational burden, omits unnecessary image interpretation, and eliminates the calibration errors in sensors and cameras. In this paper, the image-based vision servo control strategy is utilized in a mobile manipulation application.

Most visual servoing projects today mainly concern object modeling and the quality of the vision feature feedback while paying less attention to controller design. Notably, a simple P (Proportional) control law or a PID (Proportional, Integral, Derivative) control law is commonly used in the literature. However, a PID controller may not be adequate to handle the robustness and stability issues of real-life applications. Spong and Hutchinson [3, 4] reviewed proportional control with Lyapunov stability, which is the controller that is most commonly used by researchers. This method can guarantee the stability of the system. However, the controller is linear, and controller outputs are not optimal. Moreover, it cannot consider robot constraints and environment constraints. Although such simple controllers may provide stability, they will not handle system constraints, which commonly exist in real robotic applications.

Wang, Lang and de Silva [5] proposed a hybrid controller which is a combination of a traditional IBVS controller and Q-learning controller. It divides the camera view into two regions: safe region and dangerous. If the feature point is inside the safe region, the traditional IBVS will work. If the feature point moves to the dangerous region, the Q-learning controller will be effective, pushing the feature point into the safe region. This hybrid controller can guarantee visibility. However, robot physical constraints and environment constraints are not accounted for. Moreover, the controller output is not optimized. In this context, Model Predictive Control (MPC) is considered suitable in visual servo control because it naturally takes into account constraints. The few reported studies in this area [6, 7] have the common drawback in that they utilize simplified constant models for robots, which in fact are nonlinear and time-varying. Therefore, these approaches are effective only in a small neighborhood of operation.

In this paper, an adaptive nonlinear model predictive controller (ANMPC) for image-based visual servoing is proposed to address the challenges such as optimized controller outputs, considering robot constraints, environmental constraints, and visibility. The developed controller is applied and validated in a mobile manipulation system for a robotic search and rescue mission.

PROBLEM FORMULATION

A. Task description

Figure 1 gives a graphical representation of the overall system. A mobile robot manipulation system, which contains a Pioneer PowerBot mobile robot with a RobuArm manipulator mounted on it, is designed to grasp the objects of interest in the workspace. The manipulation system has 2 cameras—one web camera which is installed on the robotic hand acting as camera in hand configuration and one wide angle Bumblebee stereo camera which can estimate the depth information between robot and the object of interest.

![Figure 1: Overall system.](image)

The robot will search for objects of interest in a work environment, aided by the local sensing capability (e.g., camera, laser sensor, sonar sensor, and gyroscope) of the robot. When the robot detects the object of interest in the work space, the visual servoing system is activated to guide the robot to the object and grasp it. Physical constraints of the robot are taken into account as well as the visibility constraint in the controller.

B. Modeling

Figure 2 shows the kinematic chain of the mobile robot with arm and hand. It is an 8 DOF system with one prismatic joint (translation of the mobile base) and seven revolution joints (rotation of the mobile base; and 6 revolute joints of the robotic arm).
Finally, the position of the feature point \((u, v)\) is acquired through integration.

C. Adaptive Nonlinear Model Predictive Control (ANMPC)

The principle of classical Model Predictive Control (MPC) is summarized in Figure 3. In each iteration \(k\), an estimated model is used to predict the future states. Then, an optimal control law is computed based on the principle of forcing the predicted states to converge to a desired set-point while minimizing a cost function [8].

The classical predictive control law may present problems when applied in a visual servo system for mobile robots. In particular, because in image-based visual servoing, the current velocity of the visual feature points and depth information are involved in the interaction matrix [4] of the camera model, the mathematical model of the plant (mobile base, camera and manipulator) is nonlinear and time-varying. The issues of nonlinearity and time variance will become more serious when visual servoing is applied to a mobile robot, in view of long and arbitrary movements of its base. Due to possible large motions and nonholonomic constraints in a mobile robotic system, the traditional visual servo-based velocity controller will usually show poor performance. A customized nonlinear model predictive controller is proposed here to meet these challenges and to improve the performance of the visual servo system. The proposed architecture for nonlinear time-varying model predictive control is shown in Figure 4.

In Figure 3, since MPC assumes a linear model, the nonlinear plant is approximated to an adaptive linear model and updated in each iteration of the control loop using the current velocity and depth information. This nonlinear model predictive controller for visual servoing explicitly optimizes the positioning performance of the robot and simultaneously considers various constraints such as joint limits, singularities, nonholonomic constraints, and so on. The cost function [8] is given by:

\[
\mathcal{C}(k) = \sum_{i=0}^{N} \left[ \frac{1}{2} \left( \sum_{i=1}^{N} \left[ \begin{array}{c} z \end{array} \right] \right) \right] + \sum_{i=0}^{N} \left[ \begin{array}{c} h \end{array} \right] \right]^{2} + \sum_{i=0}^{N} \left[ \begin{array}{c} h \end{array} \right] \right]^{2} (6)
\]

where \(H_p\) and \(H_u\) are the prediction horizon and the control horizon, respectively. \((u, v)\) is the desired system output which is the position of the feature points in the image plane. \(Q(i)\) and \(R(i)\) are the weighting matrices [9]. Moreover, visibility and joints constraints are taken into account in the ANMPC controller.
CONCLUSIONS

In this paper, an adaptive nonlinear model predictive (ANMPC) controller was proposed and developed for a mobile manipulation system. It is a new architecture for visual servo control of a mobile robot system, where adaptive model linearization, nonlinear model predictive control, and visual servoing are integrated to improve the performance of traditional image-based visual servo control. First, a mathematical model of an 8DOF mobile robot manipulation was generated. Then the nonlinear and time-varying model was linearized by the current states of the system at each iteration of the control loop. Second, the model predictive controller was utilized to provide optimized control outputs considering robot’s physical constraints, environmental constraints, and visibility constraints. The simulation results using the Matlab MPC Toolbox™ showed the effectiveness of the proposed approach.

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