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Engineering Notes

Vision-Based Obstacle Avoidance of Wheeled Robots Using Fast Estimation

Amanda Dippold*
Virginia Polytechnic Institute and State University, Blacksburg, Virginia 24060
Lili Ma†
Wentworth Institute of Technology, Boston, Massachusetts 02135
and
Naira Hovakimyan‡
University of Illinois at Urbana-Champaign, Urbana, Illinois 61801

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I. Introduction

THE application of mobile vehicles for military and commercial purposes has increased dramatically in recent years. To minimize human interaction, these vehicles must be able to execute robust and efficient obstacle detection and avoidance using onboard measurements. Inertial measurement units augmented with GPS have traditionally been used for onboard sensing in a wide variety of missions. The reliance of GPS on low-power radio signals from Earth-orbiting satellites makes it vulnerable to intentional (e.g., jamming) or unintentional (e.g., electrical) interference that can degrade system performance [1]. Alternatively, vision-based sensors are being used as they are low cost, light weight, and passive. Vision-based sensors require a robust estimation scheme. The extended Kalman filter (EKF) has been used widely for this purpose [2–7]. Application of the EKF requires linearization about the desired trajectory and is very sensitive to initial errors [8–10]. Improvements of EKF performance with application to obstacle avoidance have been reported in [8,9,11] by using unscented Kalman filters and sigma-point Kalman filters. However, convergence guarantees for the parameter and range estimation cannot be deduced from application of the EKF or its variations.

In this paper, we augment a baseline path-following controller with an online obstacle-avoidance algorithm such that the robot tracks a prespecified path and avoids isolated obstacles using only visual information collected from an onboard camera. The nonholonomic vehicle is a unicycle type that has two identical parallel, nondeformable rear wheels and a steering front wheel. A path-following controller is implemented that allows for global convergence results [12–14]. The obstacle-avoidance algorithm uses a potential function that yields larger values for paths that are close to obstacles and lower values for paths that are far from obstacles. In this sense, obstacles represent local maximums for the potential function and act as a "repellent force" on the prespecified path. The obstacle-avoidance scheme deforms the desired path away from obstacles, thereby decreasing the potential function [15–18].

Conventionally, algorithms for obstacle avoidance have been divided into path-planning algorithms and control algorithms. Path-planning approaches compute a continuous path based on a world model. They are generally computationally expensive, and their ability to handle changing or unknown environments is limited [19]. In contrast, sensor-based control approaches, which detect and avoid unknown obstacles during the execution of the motion, are able to react to sudden changes in the environment. The drawback to these methods is that they may be suboptimal because only local information is used [20]. A complete solution exploits the benefits of both methods by formulating the problem as a local path-planning problem. Local detours around sensed obstacles are generated while the vehicle follows the perturbed planned path. Artificial potential fields are widely used for generating these local detours. Potential field methods (PFM) are an attractive approach due to the methods' simplicity and efficiency in implementation [21]. PFM is introduced in [19] for holonomic vehicles and extended in [15–18] for nonholonomic vehicles.

The visual information collected by the camera is processed by an estimator that provides the inputs to the obstacle-avoidance algorithm. These inputs include estimation of the obstacle's position and size. These in turn command the direction of deformation and duration required for obstacle avoidance. An estimation of the obstacle's unknown position and size is obtained via a fast estimator with quantifiable performance bounds [22,23]. The effect of the estimator's performance on the obstacle-avoidance scheme is presented.

II. Path Following and Obstacle Avoidance

Consider a nonholonomic system of dimension n with kinematics of the form

$$\dot{x}(t) = X_0(x(t)) + X_1(x(t))u_1(t) + X_2(x(t))u_2(t) + \cdots + X_m(x(t))u_m(t) \tag{1}$$

where $x(t) \in \mathbb{R}^n$ is the state vector of the system, and $u_1(t), u_2(t), \ldots, u_m(t)$ are the kinematic control inputs of the system for $m < n$. The vectors $X_1(x(t)), X_2(x(t)), \ldots, X_m(x(t))$ are the *control vector fields*, and the kinematic control inputs $(u_1(t), u_2(t), \ldots, u_m(t))$ are the elements of $\dot{x}(t)$ in the basis $(X_1(x(t)), \ldots, X_m(x(t)))$ [24]. The vector $X_0(x(t))$ is denoted as the *drift* of the system and for kinematic systems is equal to zero. For physical systems, such as the mobile robot example in this paper, $x(t)$ can represent a vector of the position and orientation of the vehicle, and $u_1(t), u_2(t), \ldots, u_m(t)$ can represent the vehicle's speed and rate of rotation.

For the purpose of path following, recall that a path is a curve $p\colon s \to \mathbb{R}^n$, where s is the abscissa along the path. An *admissible path* is a smooth curve in $\mathbb{R}^n$ defined over an interval $[0, S]$ such that there exist m-dimensional smooth mappings $u_1(s), u_2(s), \ldots, u_m(s)$ defined over $[0, S]$, with [24]

$$\frac{\mathrm{d}}{\mathrm{d}s}(p(s)) = \sum_{j=1}^{m} u_j(s) X_j(p(s)), \quad \forall\ s \in [0, S] \tag{2}$$

In this setup, the kinematic inputs $u_1(s), \ldots, u_m(s)$ are the coordinates of $\frac{\mathrm{d}}{\mathrm{d}s}(p(s))$, which can be viewed as the velocity vector at abscissa s along the current path $p(s)$ in the basis $(X_1(p(s)),$

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*Graduate Student, Department of Aerospace and Ocean Engineering. Student Member AIAA.
†Assistant Professor, Department of Electronics and Mechanical. Member AIAA.
‡Professor, Mechanical Science and Engineering. Member AIAA.