LANE FOLLOWING SYSTEM FOR A MOBILE ROBOT USING INFORMATION FROM VISION AND ODOMETRY

Xia Huang, Nasser Houshangi

Electrical and Computer Engineering Department
Purdue University Calumet
Hammond, IN 46323, U.S.A

ABSTRACT

The primary objective of our lane following system is to autonomously drive a mobile robot between two parallel lanes. Usually, the low sampling rate and the visibility of the environment are the main limitations of the vision sensors in a lane following system. In this paper, a higher sampling rate odometry sensor is integrated with a vision-based system using an Unscented Kalman Filter (UKF). The lane following system is implemented on a Pioneer 2 mobile robot and the experimental results indicate the applicability of the approach.

Key Words— Lane following, vision, UKF

1. INTRODUCTION

The sensors for a mobile robot navigation system can roughly be categorized into two groups: relative and absolute sensors [1]. The relative sensors include wheel encoders, accelerometers, gyroscopes, etc. while the absolute sensors include camera, laser, etc. Because of the lack of a single, generally good sensor, the researchers usually combine two or more sensors from each category. A multi-rate fusion method for fusing data from delayed low bandwidth visual observations and high bandwidth rate gyro measurements is presented in [2]. A mobile robot localization system based on the odometry and visual detection of common objects of the environment is presented in [3]. In [4], the fusion of the inertial and GPS data is performed for a vehicle navigation using an Extended Kalman Filter (EKF). For the nonlinear localization system, Unscented Kalman Filter (UKF) is more accurate, stable and far easier to implement compared to EKF [5][6] in most cases. A method for mobile robots position determination by the integration of odometry and a gyroscope based on UKF and a comparison with EKF is presented in [7].

The research presented in this paper is a sequential work of the vision-based lane following system [8]. The visibility of the lane information is checked using the known lane width and its parallel property. If the lane information is visible, then a single camera would be sufficient to perform the lane navigation. However, if the light condition is poor or the image is noisy, the vision sensor may fail to determine the lane position. To overcome this problem and improve the performance, in this paper, the data from a high sampling rate odometery is integrated in the existing lane following system using an Unscented Kalman Filter.

The techniques to obtain position information from a single camera are described in Section II. The algorithm of UKF used to integrate information from vision and odometry is described in Section III. The experimental results of the proposed system implemented on a Pioneer mobile robot is shown and discussed in Section IV, followed by conclusions in Section V.

2. MOBILE ROBOT ORIENTATION AND POSITION DETERMINATION BASED ON A SINGLE CAMERA

The primary objective is to drive the mobile robot autonomously in the middle of the two parallel indoor lanes. The camera is mounted on the upper center of the mobile robot. The camera and mobile robot coordinate frames are assigned as shown in Fig. 1. For simplicity, it is assumed that the two lanes are parallel to each other with the known lane width L. It is also assumed that the mobile robot always starts within the lanes.

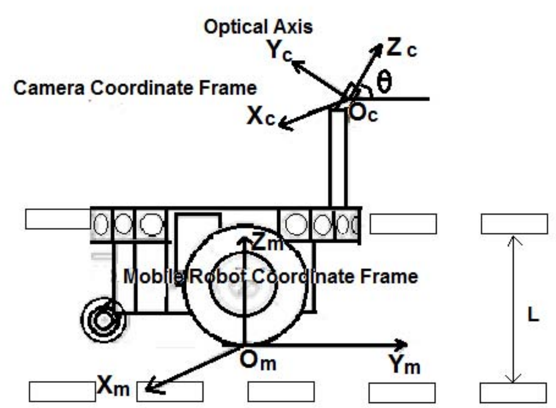

Fig. 1. Coordinate frames for the mobile robot and the camera

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A typical lane image captured by the camera is shown in Fig. 2. As noticed, the main features of the inner lane boundary include: high intensity compared to the background, straight line segmentation and closer to the origin than the outer boundary. The vision performance is influenced by the floor seaming and light spot. Based on those inner lane features, Canny edge detector [10] and Progressive Probabilistic Hough Transform (PPHT) [11] are chosen for the lane detection. The performance of the Canny algorithm depends heavily on the threshold parameters as shown in Fig. 3. As expected, the dominate edges are kept better as the threshold is increased. After applying PPHT to the image, the starting and ending points of each line segment are connected by the black line as shown in Fig. 4. The corresponding line segments in the mobile robot coordinate frame are obtained using the collinearity equations as shown in Fig. 5 [8] [9]. The actual inner lane information is extracted by picking the closest line segments to the origin from the left and right regions and denoted by x_l, x_r and φ_l, φ_r, respectively as shown in Fig. 6.

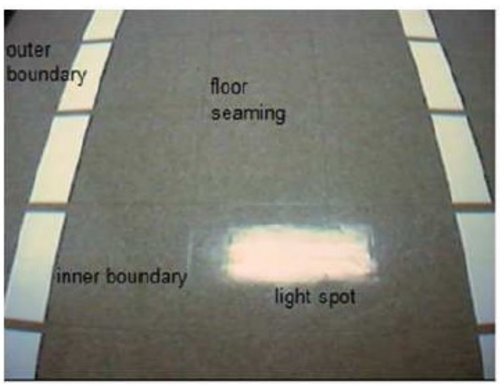

Fig. 2. A typical image of the indoor lane environment

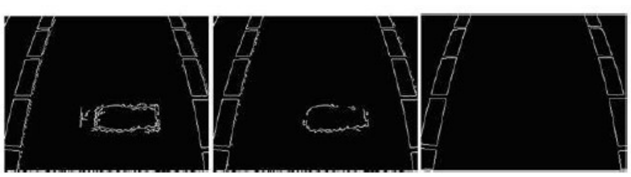

Fig. 3. Detected edge with the increasing threshold

Fig. 4. Line segmentation after applying PPHT

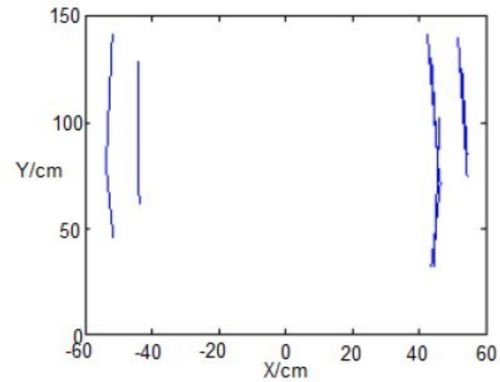

Fig. 5. Line segments in the mobile robot coordinate frame

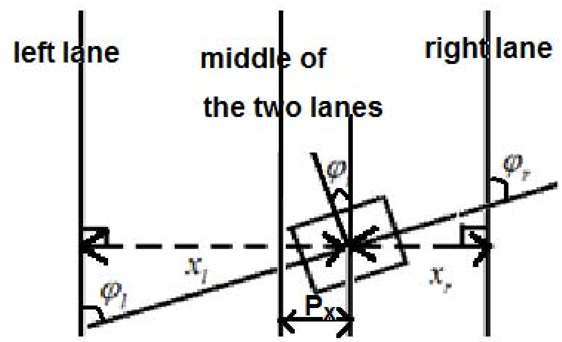

Fig. 6. The orientation and position for the mobile robot with respect to the lanes

Unfortunately, at any given time the lane information may not be always available due to the limitation of camera's field of view. Therefore, three rules are used to determine the reliable lane information. If both left and right lane's information is available, the information of the lane closer to the mobile robot is used. If only one side of lane information is available, then that side of information is used. If neither of the left nor right lane information is available, then a flag is used to indicate the vision information is not available at this moment.

3. VISION AND ODOMETRY DATA INTEGRATION USING UKF

Odometry is one of the most widely used methods for the mobile robot navigation for its short-term accuracy, low cost and high sampling rate. However, the fundamental idea of odometry is the integration of incremental motion over time which leads to unbounded errors. In this paper, odometry information is used in the prediction process between the vision data updates and corrected by the vision information through the correction process when available. This section first introduces the models for the mobile robot orientation and position prediction and observation and then describes the implementation of the Unscented Kalman Filter (UKF) for vision and odometry information integration.

3.1 Odometry Model for Wheeled Mobile Robot

Since the objective is to drive the mobile robot between the two lanes, mobile robot's position along X axis p_x and the orientation φ with respect to the middle of the two lanes are chosen as the state variables as shown in Fig. 6. The odometry prediction model is as follows

$$x(k+1) = \begin{bmatrix} p_x(k+1) \\ \varphi(k+1) \end{bmatrix} = \begin{bmatrix} p_x(k) \\ \varphi(k) \end{bmatrix} + \begin{bmatrix} v(k)\sin(\varphi(k)) \\ \dot{\varsigma} \end{bmatrix} Ts + \omega(k) \tag{1}$$

where k is a positive integer and Ts is the sampling period; v is the body-fixed linear velocity along X axis; and $\dot{\varsigma}$ is the body-fixed angular velocity. ω is the process noise with zero mean and covariance Q.

The output variables are the same as the state variables, and the observation model is

$$z(k+1) = x(k+1) + n(k+1) \tag{2}$$

where n is the measurement noise with zero mean and covariance R. For simplicity the prediction and observation models are written as

$$x(k+1) = f(x(k), v(k), \dot{\varsigma}) \tag{3}$$

$$z(k+1) = h(x(k+1), n(k+1)) \tag{4}$$

3.2 Vision and odometry data integration

For linear systems the Kalman Filter provides the optimal solution for maintaining a consistent estimation of the mean and variance [12]. In order to apply the mechanics of Kalman Filter to nonlinear problems, the extended Kalman Filter (EKF) was developed [13]. However, the EKF is not so much an extension of the Kalman Filter, but simply calls for the replacement of every nonlinear transformation with a linearized approximation. A newer approach called Unscented Transform is proposed in [5]. The UT is founded on the intuition that: With a fixed number of parameters it should be easier to approximate a Gaussian distribution than it is to approximate an arbitrary nonlinear function/transformation [6] [13]. UKF is a straightforward extension of the unscented transform to the recursive estimation [14].

Let $\hat{x}$ be the estimate of x with covariance of P_{xx}

$$\hat{x}(k) = E[x(k)], P_{xx}(k) = E[(x(k) - \hat{x}(k))(x(k) - \hat{x}(k))^T] \tag{5}$$

Since the dimension of the state variable is two, then the five sigma-points χ and weighting factor W for each sigma point are chosen as

$$\begin{aligned} &\chi_0(k) = \hat{x}(k) \\ &\chi_{1,2}(k) = \hat{x}(k) + (\sqrt{(L+\lambda)P_{xx}(k)})_{1,2} \\ &\chi_{3,4}(k) = \hat{x}(k) - (\sqrt{(L+\lambda)P_{xx}(k)})_{3,4} \\ &W_0 = \lambda/(L+\lambda), W_{1,2,3,4} = 1/2(L+\lambda) \end{aligned} \tag{6}$$

where $\lambda = \alpha^2(L+k) - L$ is a scaling parameter. α determines the spread of the sigma points around $\hat{x}$. k is a secondary scaling parameter which is usually set to 0. $\left(\sqrt{(L+\lambda)P_{xx}(k)}\right)_{1,2}$ is the first and second row of the matrix square root of $(L+\lambda)P_{xx}(k)$.

The sigma-points are propagated through the prediction model to calculate the posterior sigma-points $\chi_i(k+1)$ as

$$\chi_i(k+1) = f(\chi_i(k), v(k), \dot{\varsigma}), i = 0,1,2,3,4 \tag{7}$$

The prior state $\hat{x}^-(k+1)$ and its covariance $P_{xx}^-(k+1)$ is predicted by weighting the posterior sigma-points as

$$\begin{aligned} &\hat{x}^-(k+1) = \sum_{i=0}^{2L} W_i \chi_i(k+1) \\ &P_{xx}^-(k+1) = \sum_{i=0}^{2L} W_i \left\{\chi_i(k+1) - \hat{x}^-(k+1)\right\}\left\{\chi_i(k+1) - \hat{x}^-(k+1)\right\}^T \end{aligned} \tag{8}$$

If vision information is not available at time $k+1$, then $\hat{x}^-(k+1)$ will be used as the current mobile robot's position, that is

$$\hat{x}(k+1) = \hat{x}^-(k+1), P_{xx}(k+1) = P_{xx}^-(k+1) \tag{9}$$

If vision information is available at time $k+1$, it is denoted as ${}^v z(k+1)$. The posterior observation points $Z_i(k+1)$ where ($i = 0,1,2,3,4$) can be estimated by propagating the sigma-points through the observation model as

$$z_i(k+1) = h(\chi_i(k+1), n(k+1)) \tag{10}$$

The observation $z^-(k+1)$ and its covariance $P_{zz}^-(k+1)$ are estimated as

$$\begin{aligned} &z^-(t+1) = \sum_{i=0}^{2L} W_i Z_i(k+1) \\ &P_{zz}^-(k+1) = \sum_{i=0}^{2L} W_i \left\{Z_i(k+1) - Z^-(k+1)\right\}\left\{Z_i(k+1) - Z^-(k+1)\right\}^T \end{aligned} \tag{11}$$

The cross-correlation matrix $P_{xz}(k+1)$ is calculated by

$$P_{xz}(k+1) = \sum_{i=0}^{2L} W_i \left\{\chi_i(k+1) - \hat{x}^-(k+1)\right\}\left\{\chi_i(k+1) - \hat{x}^-(k+1)\right\}^T \tag{12}$$

The mean and covariance of the state are corrected using vision information ${}^v z(k+1)$ as follows

$$K(k+1) = P_{xx}(k+1) P_{zz}(k+1)^{-1} \tag{13}$$

$$x(k+1) = \hat{x}^-(k+1) + K({}^v z(k+1) - z^-(k+1)) \tag{14}$$

$$P_{xx}(k+1) = \hat{P}_{xx}^{-}(k+1) - K(k+1)P_{zz}(k+1)K^{T}(k+1) \qquad (15)$$

where K is the Kalman gain.

4. EXPERIMENTAL RESULTS

In order to verify the feasibility and robustness of the proposed lane following system in the indoor environment, several sets of experiments were conducted.

4.1. Experimental setup

The hardware setup includes a Pioneer2-Dxe mobile robot and a CMOSV-X0097-SE Color camera. The camera is fixed on a stand with a tilt angle and the stand is attached to the front of the mobile robot as shown in Fig. 7. The software programs are written using VC++ and Matlab. The image processing part is performed using Open Source Computer Vision (OpenCV) library and the robot control part is performed using Advanced Robotics Interface for Applications (ARIA) library. The Pioneer 2 motor controllers accept several different motion commands. In this implementation, the desired orientation and position commands are sent to the controller directly for mobile robot navigation.

Fig. 7. Hardware setup

4.2 Experimental results

The experiments for camera calibration and vision-based navigation are discussed in [8]. In this paper, the mobile robot is navigated using the information from both vision and odometry under three conditions:

(1) lanes are parallel and straight for 4.5 meters long.

(2) lanes with an angle of 20° to the left.

(3) lanes with an angle of 20° to the right.

The orientation and position of the mobile robot during navigation in each case are shown through Fig. 8 to Fig. 13. The final orientation and position recorded in each case show that the integrated information is closer to the actual value than the only using the vision information. When missing the vision information, the mobile robot is navigated using odometry information with straight lane assumption.

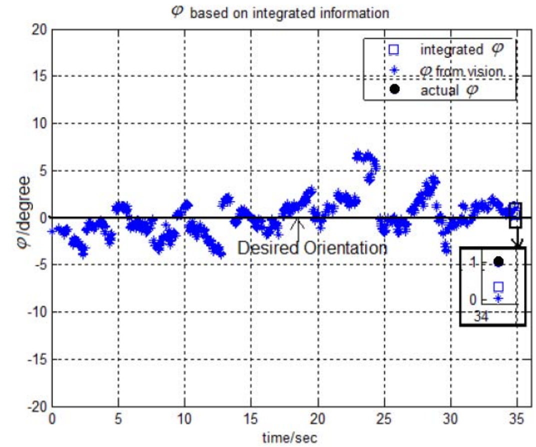

Fig. 8. Orientation based on integrated information for a straight lane

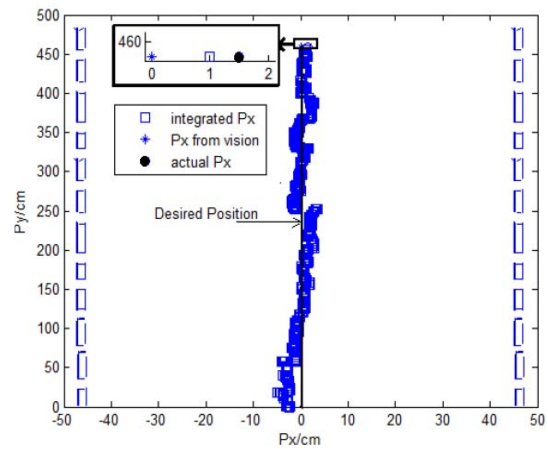

Fig. 9. Position based on integrated information for a straight lane

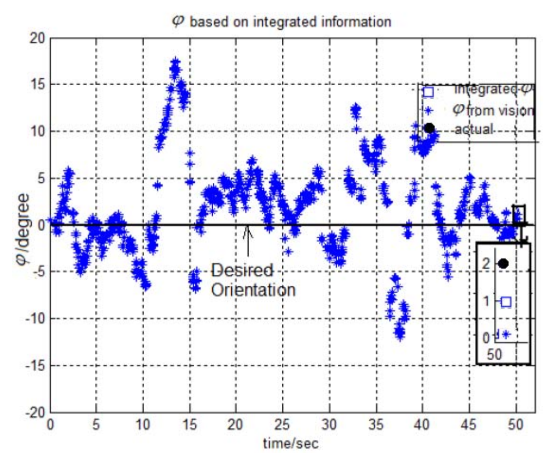

Fig. 10. Orientation based on integrated information for left-curve lane

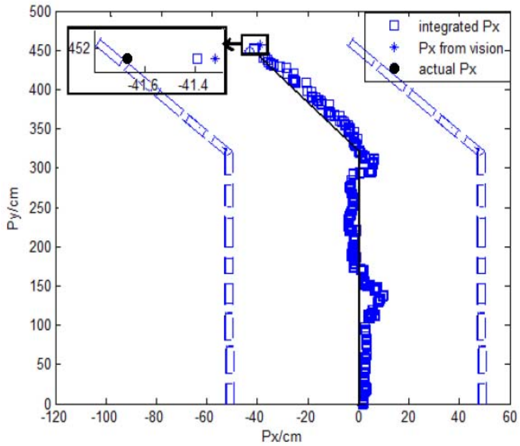

Fig. 11. Position based on integrated information for left-curve lane

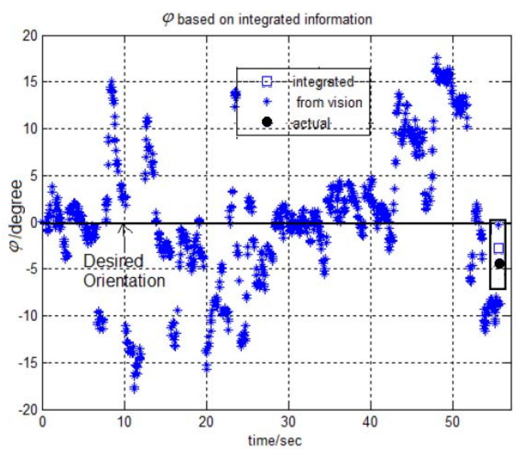

Fig. 12. Orientation based on integrated information for right-curve lane

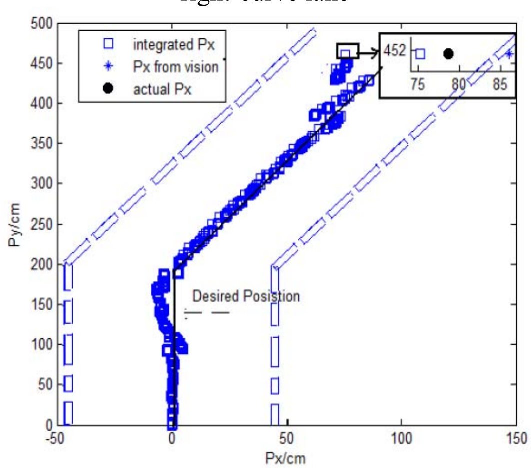

Fig. 13 Position based on integrated information for right-curve lane

5. CONCLUSIONS

In this paper, a low-cost lane following system for a mobile robot is proposed. The information from odometry is integrated with a low sampling rate camera using Unscented Kalman Filter (UKF). UKF is robust and easy to implement for the nonlinear systems. The lane following system based on vision information is compared with the integrated information. The experimental results show that the integrated information improves the performance of the vision-based system.

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