Lane Level Localization with Camera and Inertial Measurement Unit using an Extended Kalman Filter

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Motor vehicle crashes are the leading cause of death among Americans from 1 to 34 years of age. In 2008, 37,261 people died from accidents on the United States’ highways. Of those deaths, 53% were due to road departure. Avoidance of these crashes would save many lives.

Lane departure warning systems are already present in commercial vehicles; however, these systems are limited by the quality of the images obtained from the cameras. Use of other sensors in addition to vision can provide the position within the lane even when lane markings are not visible.
Prior art

C.R. Jung

- linear-parabolic model to create an LDW system using lateral offset based on near field and far field

Y. Feng

- improved Hough transform for detection of road edge and establishment of an area of interest based on the prediction result of a Kalman filter

E.C. Yeh

- obtained heading and lateral distance from single camera images

D.A. Schwartz

- clothoid model for the road is unsuitable for sensor fusion

T.J. Broida

- 3-d motion estimation with a monocular camera
Contributions

Specific contributions include:

- use of vision and inertial data specifically for lateral position estimation in the lane
- lane tracking in the image using inertial data
Vision Algorithm

Line Selection

Point Pools

Least Squares Interpolation

Coefficients

Kalman Filter

Coefficients for Polynomial Bounds and Slope Selection

Lateral Distance Calculation

Heading Calculation

Hough Transform

Line Extraction

Edge map

Thresholding/Edge Detection

Image

Vision System

Introduction
Vision System
Vision/INS/Velocity Integration
Conclusions

Image Processing
Line Processing
Linear Kalman Filter
Calculations
Vision System Experimental Results

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Thresholding/
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Constant Threshold

Day

Original Image

Threshold Image (T=210)

Constant thresholds can provide feature extraction for unchanging or similar environments.
Constant Threshold

Twilight

Original Image  Threshold Image (T=210)

Constant thresholds fail when conditions change, and a new threshold is needed.
Dynamic thresholds change with respect to the statistics of the image. The threshold chosen for each image is determined by

\[ T = \mu + K\sigma \]

where \( T \) is the new threshold, \( \mu \) is the mean of the grayscale values of the image, \( \sigma \) is the standard deviation of the image, and \( K \) is a value chosen based on the expected noise in the image.
Dynamic Threshold

With a dynamic threshold, lane markings are detected in the image even with different lighting conditions.

Day

![Original Image](image1.png) ![Threshold Image](image2.png)

Original Image

Threshold Image
Dynamic Threshold

Twilight

Original Image

Threshold Image
Edge Detection

Canny Edge Detection
- extracts the edges of the thresholded image

Original Image                   Edge Map
Hough Transform

- extracts, merges, and ignores lines from images
- uses the probabilistic Hough transform

Hough Lines
Line Selection

Lines are classified as either left or right lane marking lines using their slope. Two further checks are used to determine the validity of the line as a line of the edge of the lane marking or a false line.

- Polynomial Boundary Checking
- Slope Checking
Polynomial Boundary Checking

Three points on each polynomial bound are calculated:

Right Polynomial Bound Calculation

\[
x_{rb} = x_{est} + r \sin(\tan^{-1}(2ax_{est} + b))
\]
\[
y_{rb} = y_{est} - r \cos(\tan^{-1}(2ax_{est} + b))
\]

Left Polynomial Bound Calculation

\[
x_{lb} = x_{est} + r \sin(\tan^{-1}(2ax_{est} + b))
\]
\[
y_{lb} = y_{est} - r \cos(\tan^{-1}(2ax_{est} + b))
\]

Least squares polynomial interpolation gives the coefficients of each polynomial bound.
Slope Checking

The slope from each line from the Hough transform is compared with the slope from the last estimated lane marking. If within a given tolerance and if the line is within the polynomial bounds, the endpoint and the midpoint of the line is added to the point pool.
Least Squares Polynomial Interpolation

Each lane is modeled with a polynomial equation:

\[ y = ax^2 + bx + c \]

Least squares polynomial interpolation is used to generate the coefficients of the model as follows:

\[ \beta = (f'f)^{-1} f'y \]

where

\[
f = \begin{bmatrix}
1 & x_1 & x_1^2 \\
1 & x_2 & x_2^2 \\
\vdots & \vdots & \vdots \\
1 & x_{n-1} & x_{n-1}^2 \\
1 & x_n & x_n^2 \\
\end{bmatrix}
\]
Least Squares Polynomial Interpolation

and

\[ y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ y_n \end{bmatrix} \]

with

\[ \beta = \begin{bmatrix} c & b & a \end{bmatrix} \]

where \( x_1...n \) and \( y_1...n \) are the image coordinates of each point in the point pool.
Kalman Filter

A linear Kalman filter is used to reduce any erroneous lane marking estimates. The states of the filter are the $a$, $b$, and $c$ coefficients of the left and right lane markings.

$$\hat{x} = \begin{bmatrix} a_L & b_L & c_L & a_R & b_R & c_R \end{bmatrix}$$

The time update has no impact on the states, and the measurement update corrects either the left or right lane marking coefficients using the coefficients from the $2^{nd}$ order polynomial interpolation as the measurements.
Lateral Distance Calculation

Once the lane marking is found, an estimate for the distance of the vehicle to the right lane marking is calculated.

\[ d_r = n \left( \frac{-b + \sqrt{4ay + b^2 - 4ac}}{2a} \right) \]

\[ d_l = n \left( \frac{-b - \sqrt{4ay + b^2 - 4ac}}{2a} \right) \]

where \( a, b, \) and \( c \) are the coefficients of the estimated polynomial model, \( y \) is the row in the image at which the measurement should take place, and \( n \) is the conversion factor.
Lateral Distance Calculation

The conversion factor, \( n \), serves as the conversion from image to world space.

\[
n = \frac{w_l}{p_c}
\]

- \( w_l \)- width of a typical lane (3.6576 m)
- \( p_c \)- pixel count of the lane
Heading Calculation

The heading, $\psi$ is determined from the camera based on the vanishing point of the measured lane markings and the vanishing point of the camera.

Calculation of Heading - Image Space
The equation for heading is determined by

$$\psi = \arctan \left( \frac{\mathbf{OP}_2 \tan \theta}{\mathbf{OP}_2^2 - \mathbf{OP}_2} \right)$$

- $\mathbf{OP}_2$ - distance (pixels) from the center point to the vanishing point
- $\mathbf{OP}_2$ - distance (pixels) from center point to image edge
- $\theta$ - visual angle
- $\psi$ - heading angle
Test Run

- forward-looking camera (QuickCam Pro 9000)
- Hyundai Sonata driven around the right lane
- NCAT test track
- RTK GPS truth data

NCAT Test Track

Test Vehicle
Vision System Experimental Results

C Coefficient Measurement Filtering
True Lateral Distance and Calculated Lateral Distance for Vision System
Vision System Experimental Results

- shows detected lane (50% detected)

Lateral Distance Error for Vision System On Full Track Test Run
Vision System Experimental Results

True Heading and Measured Heading for Vision System On Full Track Test Run
Vision System Experimental Results

Heading Error for Vision System On Full Track Test Run
Vision System Video

- green: lane estimate (vision measurement)
- red: lane estimate (no vision measurement)
- yellow: lane measurement
- black: polynomial bounds
Commercial lane departure warning systems use camera vision to detect lane markings.

Various problems can hinder lane detection

- Environment
- Eroded lane marking lines
- Objects on road

Integration of other sensors can provide lateral distance in the road when camera vision fails

Extended Kalman Filter
Vision/IMU/Velocity Integration

- GPS used for velocity
- wheel odometry, radar, etc. can be used in its place
**Road Frame**

The road frame

- positive x-axis pointing down the road on the right lane marking
- the y-axis pointing perpendicularly to the right
- the z-axis pointing down and perpendicular to the road plane
The states for the extended Kalman filter consist of the lateral distance $p_y$, the longitudinal velocity $v_x$, the longitudinal acceleration bias $b_x$, the yaw $\psi$, and the yaw rate bias $b_\psi$.

$$\hat{x} = \begin{bmatrix} p_y & v_x & b_x & \psi & b_\psi \end{bmatrix}^T$$
Time Update

- propagate the states forward in time
- dead reckoning from IMU

\[
\hat{x}_k^- = f(\hat{x}_{k-1}, u_{k-1}, 0)
\]

\[
P_k^- = A_k P_{k-1} A_k^T + W_k Q_{k-1} W_k^T
\]
Nonlinear Equations \( f(\hat{x}_{k-1}, u_{k-1}, 0) \)

IMU inputs, \( u_{k-1} \), into the time update equations are as follows:

- \( \dot{\psi} \): yaw rate
- \( a_{\text{long}} \): longitudinal acceleration

States, \( \hat{x}_{k-1} \), included in the nonlinear equations are as follows:

- \( b_\psi \)
- \( b_{\text{long}} \)
- \( v_x \)
- \( \psi \)
Equations of Motion

Propagation of the states through time is conducted using the following equations of motion:

\[
\begin{align*}
\dot{p}_x &= v_x \sin(\psi) \\
\dot{v}_y &= a_{\text{long}} - b_{\text{long}} \\
\dot{b}_{\text{long}} &= 0 \\
\dot{\psi} &= \dot{\psi} - b_\psi \\
\dot{b}_\psi &= 0
\end{align*}
\]

Individual noise values are assumed to be zero at each time step. Runge-kutta method (RK4) is used to approximate the solution of the differential equations.
The time update of the Kalman filter for the vision-only system can use the heading and longitudinal velocity to estimate the location of the lane marking in the image.

The number of pixels shifted in image space due to $v_x$ and $\psi$ is determined by

$$m = \frac{v_x \sin(\psi) \Delta t}{n}$$
The equation for the number of radians per pixel, \( r \) is then:

\[
r = \frac{2q}{w}
\]

where \( w \) is the width of the image and \( q \) is the change in the slope in radians of the lane marking model from the vertical lane marking line to the point at which the lane marking line intercepts the edge of the image. This radial conversion factor can be multiplied with the shift of pixels \( m \) to obtain the change in slope of the system.
New coefficients for the lane marking line model in image space after the vehicle has moved laterally within the lane.

\[ b = \frac{b}{1 - brm} \]

\[ c = \frac{c}{1 - brm} \]

Kalman filter time update coefficient change for the linear lane model
Measurement Update

- correction of the states with camera and velocity (from GPS) measurements
- correct for drift from IMU measurements:
  - lateral distance (camera)
  - heading (camera)
  - longitudinal velocity (GPS)

\[
K_k = P_k^- H^T (HP_k^- H^T + V_k R_k V_k^T)^{-1}
\]
\[
\hat{x}_k = \hat{x}_k^- + K_k (z_k - h(\hat{x}_k^-, 0))
\]
\[
P_k = (I - K_k H_k) P_k^-
\]
Another test run:

- approximate straight road conditions of a highway
- taken at night under low light conditions
- faded section of lane markings
- double lane change maneuver
- Crossbow 440 IMU
- 30 mph
Vision/IMU/Velocity Experimental Results

Yaw Rate and Bias

-4 -3 -2 -1 0 1 2 3 4
deg/s
0 5 10 15 20 25 30 35 40
Time(s)

- Yaw Rate
- Yaw Rate Bias
Lateral Distance Estimate and Measurement
Vision/IMU/Velocity Experimental Results

Heading Estimate and Measurement
Vision/IMU/Velocity Results

Lateral Distance Truth vs. Estimate

Lateral Distance (m)

Time (s)
Vision/IMU/Velocity Results

Lateral Distance Error

Lateral Distance Error (m)

Time (s)

0 5 10 15 20 25 30 35 40
Vision/IMU/Velocity Results

Heading Truth vs. Estimate

- Estimated Heading
- True Heading
Vision/IMU/Velocity Results

Heading Error

Error in Heading(deg) vs Time(s)
green: lane estimate (vision measurement)
red: lane estimate (no vision measurement)
yellow: lane measurement
black: polynomial bounds
Two systems are presented for estimating lateral distance in the lane:

- vision only
- vision/IMU/Velocity

Experimental results were compared with truth data to verify the vision/IMU algorithms. Lane model estimation was verified through observation.
Future work entails:

- real time implementation of vision/IMU system
- extension of system to curved roads using a coefficient to compensate for non-inertial frame
- compensation of lateral lane measurement on curved roads due to forward measurement
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