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

Christopher Rose
Thomas Denney
David Bevly
Stanley Reeves
Charles Stroud

Electrical and Computer Engineering
Auburn University

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Outline

Introduction

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

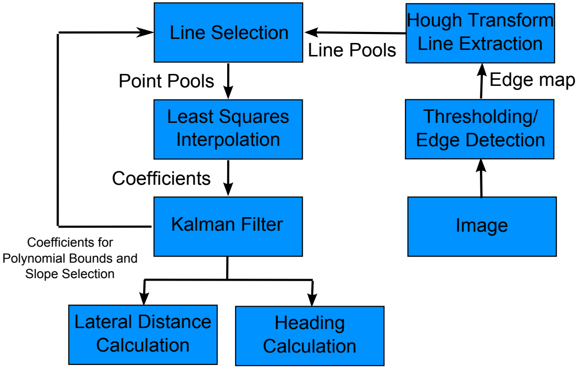
Contributions

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 System

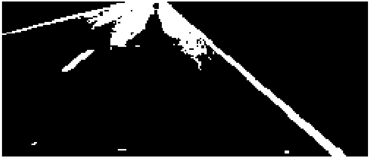
Vision Algorithm



Constant Threshold

Day

Original Image

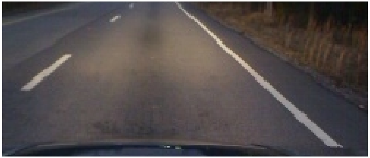


Threshold Image (T=210)

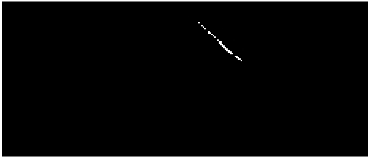
Constant thresholds can provide feature extraction for unchanging or similar environments.

Constant Threshold

Twilight



Original Image



Threshold Image (T=210)

Constant thresholds fail when conditions change, and a new threshold is needed.

Dynamic Threshold

Dynamic thresholds change with respect to the statistics of the image. The threshold chosen for each image is determined by

$$T = \mu + K\sigma$$

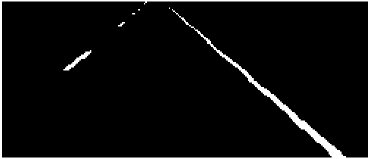
where T is the new threshold, μ is the mean of the grayscale values of the image, σ is the standard deviation of the image, and K is a value chosen based on the expected noise in the image.

Dynamic Threshold

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

Day

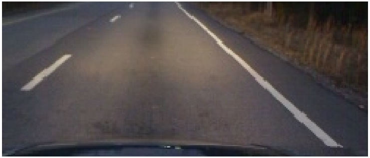
Original Image



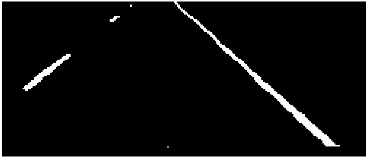
Threshold Image

Dynamic Threshold

Twilight



Original Image



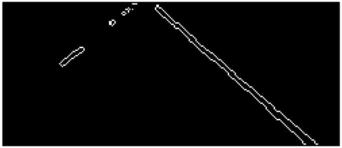
Threshold Image

Edge Detection

Canny Edge Detection

- extracts the edges of the thresholded image

Original Image

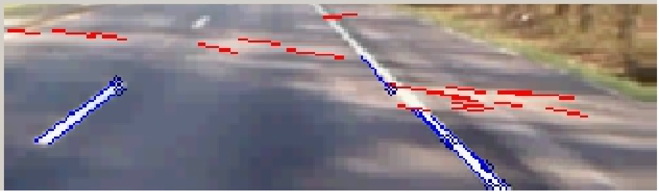


Edge Map

Hough Transform

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

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

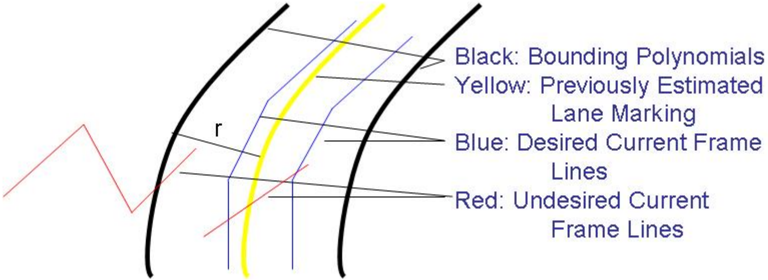
Left Polynomial Bound Calculation

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

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 $x_{1\ldots n}$ and $y_{1\ldots n}$ 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

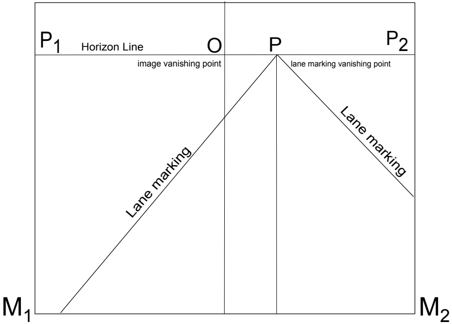
The conversion factor, n, serves as the conversion from image to world space.

$$n = \frac{w_l}{p_c}$$

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

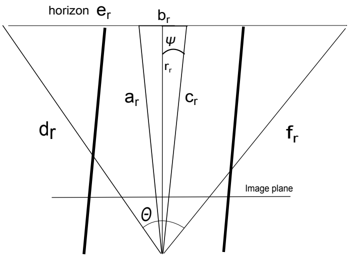
Heading Calculation

The heading, ψ 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

Heading Calculation



Calculation of Heading - Bird's Eye View of Road

The equation for heading is determined by

$$\psi = \arctan\left(\vec{OP}\frac{\tan\frac{\theta}{2}}{\vec{OP_2}}\right)$$

- $\vec{OP}$- distance (pixels) from the center point to the vanishing point
- $\vec{OP_2}$- distance (pixels) from center point to image edge
- θ- visual angle
- ψ- heading angle

Vision System Experimental Results

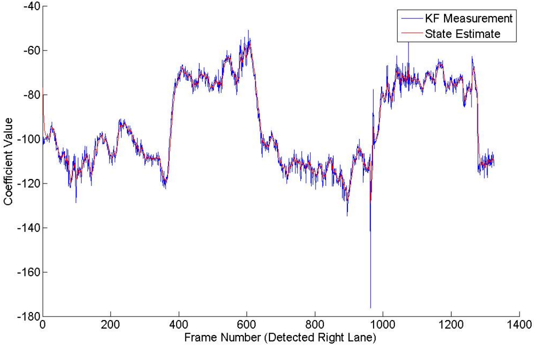
Test Run

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

NCAT Test Track

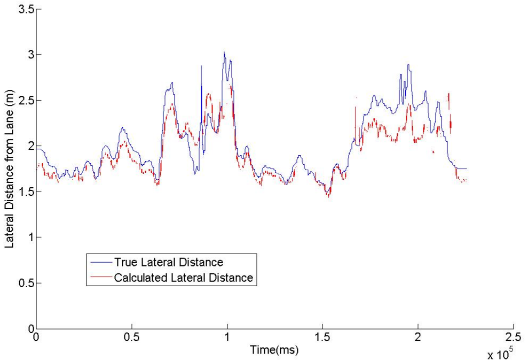
Test Vehicle

Vision System Experimental Results



C Coefficient Measurement Filtering

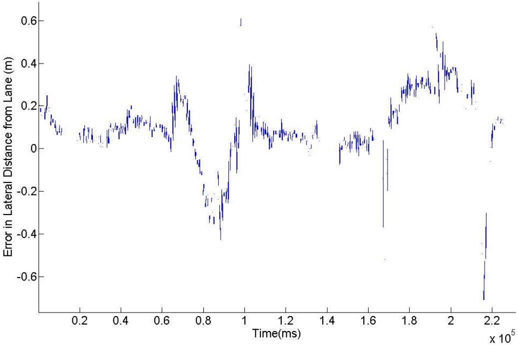
Vision System Experimental Results



True Lateral Distance and Calculated Lateral Distance for Vision System

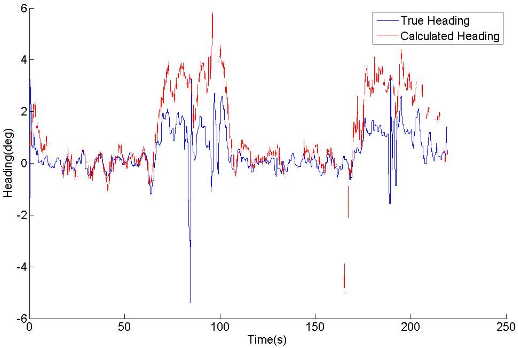
Vision System Experimental Results

- shows detected lane (50% detected)



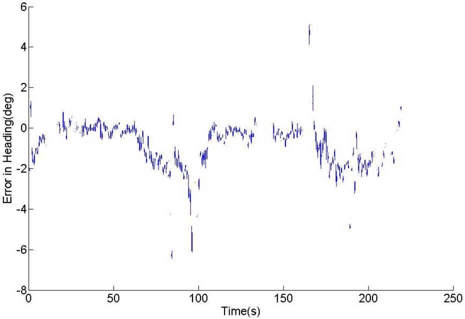
Lateral Distance Error for Vision System On Full Track Test Run

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

(Loading...)

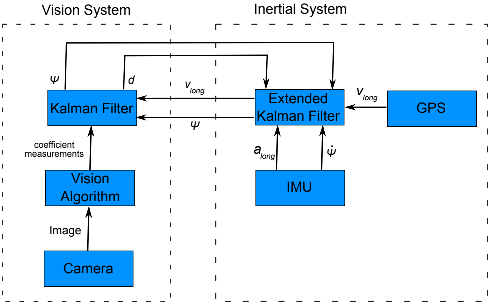
- green: lane estimate (vision measurement)
- red: lane estimate (no vision measurement)
- yellow: lane measurement
- black: polynomial bounds

Vision/INS/Velocity Integration

- 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

Vision/IMU/Velocity

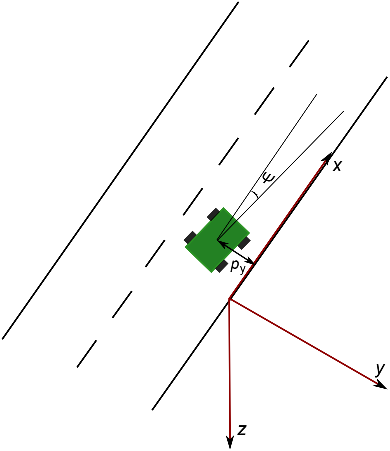


- GPS used for velocity
- wheel odometry, radar, etc. can be used in its place

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



States

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 ψ, and the yaw rate bias b_ψ.

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

Time Update

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_{long}: longitudinal acceleration

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

- b_{ψ}
- b_{long}
- v_x
- ψ

Equations of Motion

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

$$
\begin{aligned}
\dot{p}_x &= v_x \sin(\psi) \\
\dot{v}_y &= a_{long} - b_{long} \\
\dot{b}_{long} &= 0 \\
\dot{\psi} &= \dot{\psi} - b_{\psi} \\
\dot{b_{\psi}} &= 0
\end{aligned}
$$

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.

Time Update - Vision System

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 ψ is determined by

$$m = \frac{v_x \sin(\psi)\Delta t}{n}$$

Time Update - Vision System

The equation for the number of radians per pixel, r is then:

$$r = \frac{2q}{w}$$

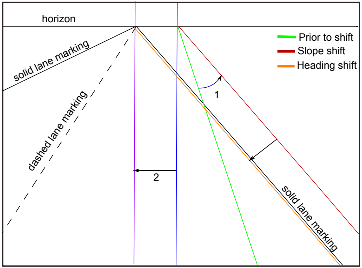
where w is the width of the image and q is the change in the slope in radians of the lane marking model from the vertical lane marking line to the point at which the lane marking line intercepts the edge of the image. This radial conversion factor can be multiplied with the shift of pixels m to obtain the change in slope of the system.

Time Update - Vision 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

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)

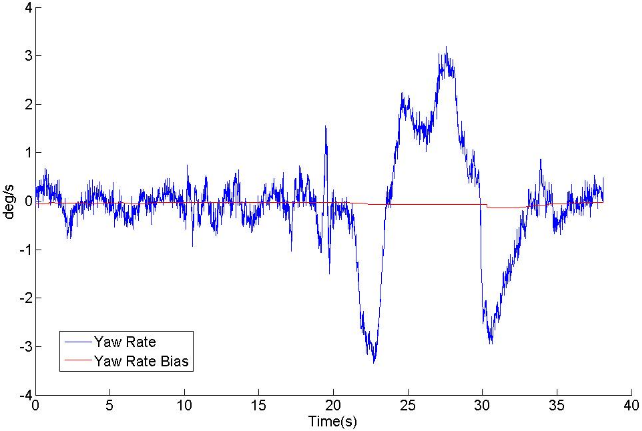
$$K_k = P_k^- H^T (H P_k^- H^T + V_k R_k V_k^T))^{-1}$$
$$\hat{x}_k = \hat{x}_k^- + K_k(z_k - h(\hat{x}_k^-, 0))$$
$$P_k = (I - K_k H_k) P_k^-$$

Vision/IMU/Velocity Experimental Results

Another test run:

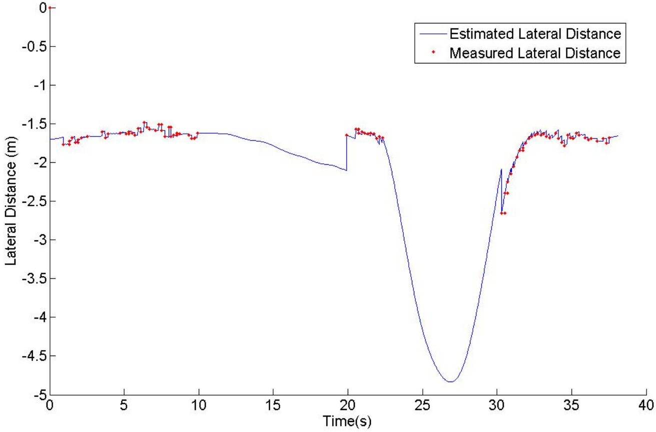
- approximate straight road conditions of a highway
- taken at night under low light conditions
- faded section of lane markings
- double lane change maneuver
- Crossbow 440 IMU
- 30 mph

Vision/IMU/Velocity Experimental Results



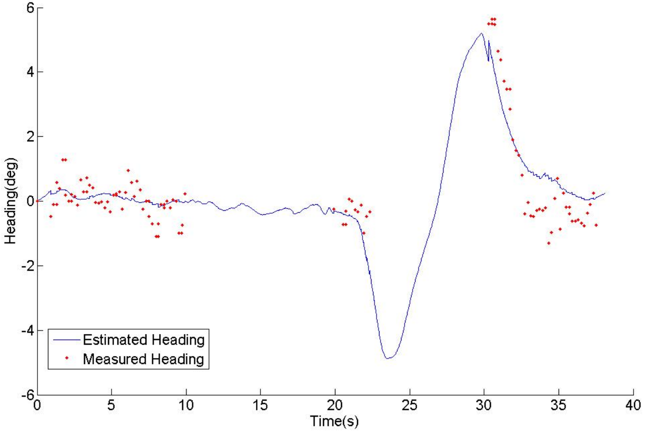
Yaw Rate and Bias

Vision/IMU/Velocity Experimental Results



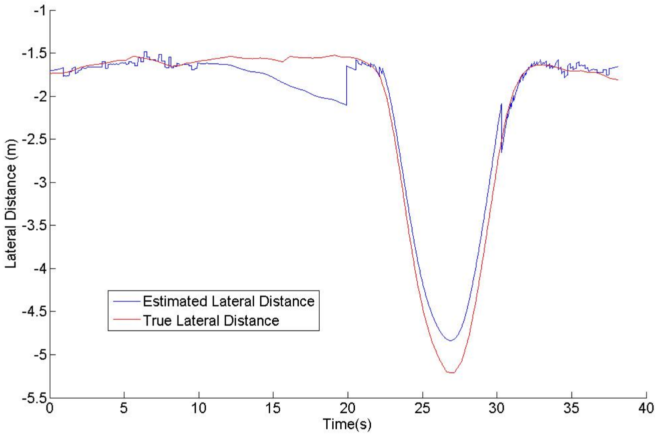
Lateral Distance Estimate and Measurement

Vision/IMU/Velocity Experimental Results



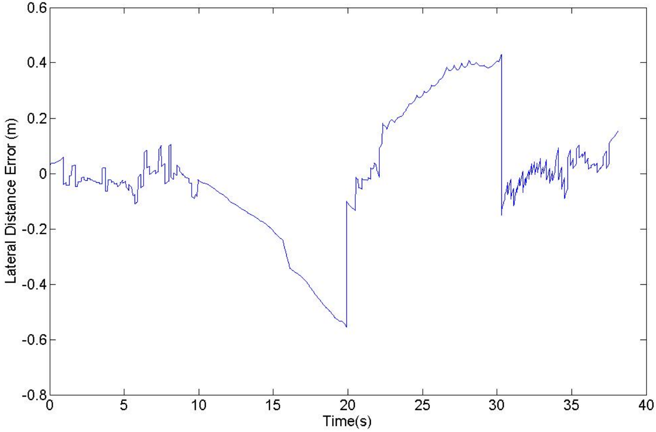
Heading Estimate and Measurement

Vision/IMU/Velocity Results



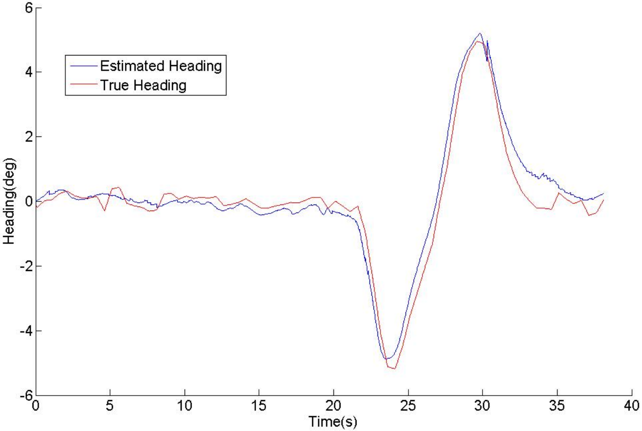
Lateral Distance Truth vs. Estimate

Vision/IMU/Velocity Results



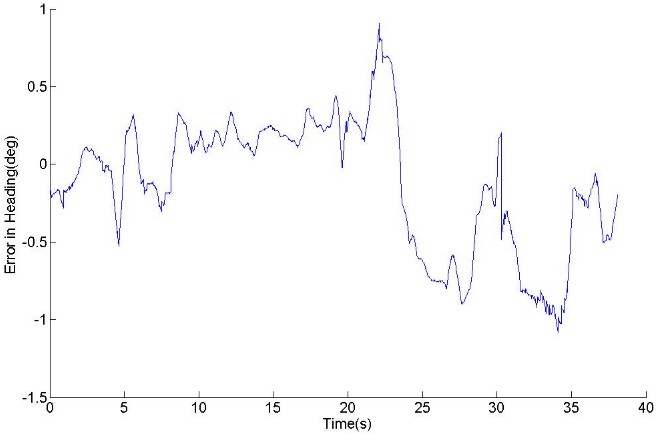
Lateral Distance Error

Vision/IMU/Velocity Results



Heading Truth vs. Estimate

Vision/IMU/Velocity Results



Heading Error

Vision/IMU/Velocity System Video

(Loading...)

- green: lane estimate (vision measurement)
- red: lane estimate (no vision measurement)
- yellow: lane measurement
- black: polynomial bounds

Conclusions

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

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

Acknowledgments

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