



CDS 270-2: Lecture 4-3 Road Detection and Tracking

(Application example for Extended Kalman Filtering and Moving Horizon Estimation)



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Overview

Goals

- Motivate use of the extended Kalman filter and moving horizon estimation with a practical example (road tracking).
- Derive implementations of EKF and MHE for road tracking
- Present live and simulated results from application of both approaches

Outline

- 1. Motivation for road tracking
- 2. Road tracking problem statement / define approach
- 3. Derive dynamic equations and connect EKF concepts
- 4. Results: EKF road tracking and following on Alice
- 5. Present moving horizon estimation alternative
- 6. MHE implementation and simulation results (preliminary)

Context: nested feedback control

- "Two degree of freedom" controller design (cf. Mark Milam thesis)
- A.k.a. inner-outer loop

• Early application of receding horizon control techniques to fast-dynamics processes (orig. developed in context of chemical processes)



Caltech ducted fan



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Context: autonomous navigation

Traditional deliberative approach to robotic navigation • Follows two-degree-of-freedom design • Map represents spatially-encoded constraint set for optimization Environment sensor Path Path Actuation Vehicle Follower Planner Vehicle state sensors State estimator Mapper

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Sensor suite

- Combination of LADAR and stereovision range sensors used
- All sensors fixed (not gimbaled)



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Environment sensors

- 5 fixed single-axis LADAR units, oriented horizontally
 - → 4 pitched downward at different amounts for sweeping ground elevation
 - → 1 horizontal for aiding road boundary detection
- 5 fixed Firewire cameras
 - \rightarrow 2 B/W stereovision pairs
 - \rightarrow 1 color camera for road detection

Perception and mapping

- Mapping accomplished with layered approach:
- 1. RDDF (a priori data) layer
- 2. Elevation-based speed layer
- 3. Road finding layer (speed bonus)

Layers combined in speed map





Goal: Model-based road estimation

- Produce best estimate of parameterized road centerline
- Does not depend on grid-based mapping framework

• Can be converted to map if road boundaries are tracked

Alice: Road finding implementation

- Road following using integrated camera and LADAR data implemented for race
- Tracked vanishing point by grouping of dominant orientations (Rasmussen 2004)
- Boundaries of road estimated from horizontal LADAR and integrated with vanishing point data (Rasmussen 2006)
- Vanishing point updated by particle filter
- Assumes straight line parameterization for road



Image from (Rasmussen 2004)





Figure 11: Sample road follower output on test run: (a) Computed road direction & Alice direction (blue, cyan lines respectively–same in (d)); (b) Dominant orientations ($[0, \pi]$ angle proportional to intensity); (c) Vanishing point votes \mathbf{I}_{VP} ; (d) Overhead view of estimated road region (green area): Alice is purple rectangle, bumper ladar returns are red points, ladar-derived obstacle function h(x) is shown in yellow at bottom.



Road detection, tracking and following

Motivation

• Unimproved roads are a common presence in desert driving (95% of 2005 Grand Challenge race, e.g.)

• Lots of research in **image processing** for detecting roads

- Typically frame-by-frame (no dynamics)
- Sensitive to lighting conditions
- No direct range information
- Improved on this state-of-the-art with processing of LADAR range images



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Problem statement:

Provide and update a model-based estimate of the road, given LADAR range image sequences and sensor pose information

Parameterization:

• Road heading, curvature, curvature rate (clothoid model), width



Road modeling



• Sensor used: single axis laser detection and ranging (LADAR)

• Features are extracted from sequences of range images that correspond to estimated road centerline location







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Road parameterization by curvature

• Parameterization: Used clothoid model (piecewise constant rate of change of curvature)

 Including heading and excluding curvature rate improved results significantly

$$\begin{aligned} \kappa(s) &= \kappa_0 + \kappa_1 s \\ \theta(s) &= \theta_0(s) + \int_0^s \theta(\tau) \ d\tau \\ x(s) &= x_0(s) + \int_0^s \cos \theta(\tau) \ d\tau \\ y(s) &= y_0(s) + \int_0^s \sin \theta(\tau) \ d\tau \end{aligned}$$

Road parameter estimation

• Extended Kalman filter implemented to track road heading and curvature parameters

• Location of road centerline used as input in Kalman filter update model



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Kalman Filter C++ implementation

/* cvCreateKalman args: dimension of state, meas, control vectors */
CvKalman* kalman = cvCreateKalman(2, 1, 0);

/* set measurement matrix to [1 0] */

cvSetIdentity(kalman->measurement_matrix, cvRealScalar(1));

/* set process covariance matrix */

cvSetIdentity(kalman->process_noise_cov, cvRealScalar(0.0)); cvSetReal2D(kalman->process_noise_cov, 0, 0, PROC_CURVATURE_COV); cvSetReal2D(kalman->process_noise_cov, 1, 1, PROC_CURVRATE_COV);

/* set measurement noise variance to something (scalar) */
cvSetIdentity(kalman->measurement_noise_cov,
cvRealScalar(MEAS_NOISE_COV));

```
/* initialize posteriori error estimate covariance matrix */
cvSetIdentity( kalman->error_cov_post, cvRealScalar(1.0e-2));
```

```
/* predict point position (2nd arg is control vector) */
const CvMat* predicted = cvKalmanPredict( kalman, NULL );
```

/* adjust Kalman filter state estimate. */
const CvMat* corrected = cvKalmanCorrect(kalman, measurement);

Road following EKF results (sim + live)





- Video: fully autonomous demonstration of road following using data only from one roof-mounted LADAR unit (Cremean, Murray 2006)
- 10 minute run at ~10 mph average speed
- Video sped up ~5X
- Model-based estimation method successfully tracks road heading and curvature

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Mappe

Moving Horizon Estimation (in progress)



$$\min_{x_0,\{w_0,\dots,w_{T-1}\}} \sum_{k=0}^{T-1} \|y_k - h_k(x_k)\|_{R_k^{-1}}^2 + \|w_k\|_{Q_k^{-1}}^2 + \|x_0 - \bar{x}_0\|_{P_0^{-1}}^2$$

Find initial state and process noise sequence such that

- 1. measurement data is matched (first term small);
- process noise not larger than expected (second term small);
- initial state not too far away from initial guess (third term small).
 (from Wednesday lecture)

Recursive batch state estimation (no arrival cost yet)

1. Solve

$$\{z^*, \{\hat{w}_k\}_{T-N}^{T-1}\} = \arg\min_{z \in \mathcal{R}_{T-N}, w_k} \left(\sum_{k=T-N}^{T-1} L_k(w_k, v_k) + \mathcal{Z}_{T-N}(z)\right)$$

subject to dynamics and $x_k \in \mathbb{X}_k$, $w_k \in \mathbb{W}_k$, $v_k \in \mathbb{V}_k$. (Use (S)QP, NPSOL, NTG,...)



References

(See lecture page for references:

http://www.cds.caltech.edu/~murray/wiki/index.php?title=Alice:_Road_Following)

Reading

- Cf. (extended) Kalman filter reading materials from Monday 4/17/06 lecture.
- Cf. Moving Horizon Estimation reading materials from Wednesday 4/19/06 lecture.
- Model-Based Estimation of Off-Highway Road Geometry using Single-Axis LADAR and Inertial Sensing
 [®], Lars B. Cremean and Richard M. Murray, To appear, Proc. of 2006 International Conference on Robotics and Automation

Additional Resources

- The Open Source Computer Vision (OpenCV) Library has a well-documented C++ class that implements the Kalman filter, and a host of image processing tools. See <u>http://www.intel.com/technology/computing/opencv/</u> and <u>http://opencvlibrary.sourceforge.net/</u>
- An Octave (MATLAB clone) toolbox for implementing nonlinear receding horizon control and moving horizon estimation is available at <u>http://jbrwww.che.wisc.edu/home/tenny/nmpc/</u> ^[2]. The release is somewhat old (2003); be sure to get the CVS version to avoid some known bugs.
- For numerical solving, SNOPT is commercial software, but CDS cluster has a license for it. NPSOL is another option. SNOPT
 5.3 user manual available at http://citeseer.ist.psu.edu/gill99users.html