Robotics

Erwin M. Bakker| LIACS Media Lab

21-2 2021

Universiteit Leiden

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Organization and Overview

Period: February 1st – May 10th 2021
Time: Tuesday 16.15 – 18.00
Place: https://smart.newrow.com/#/room/qba-943
Lecturer: Dr Erwin M. Bakker (erwin@liacs.nl)
Assistant: Erqian Tang

NB Register on Brightspace

Schedule:

1-2	Introduction and Overview
8-2	No Class (Dies)
15-2	Locomotion and Inverse Kinematics
22-2	Robotics Sensors and Image Processing
1-3	**Yetiborg Introduction + SLAM Workshop I**
8-3	Project Proposals (presentation by students)
15-3	Robotics Vision
22-3	Robotics Reinforcement Learning
29-3	**Yetiborg Qualification + Robotics Reinforcement Learning Workshop II**
5-4	No Class (Eastern)
12-4	Project Progress (presentations by students)
19-4	**Yetiborg Challenge**
26-4	Project Team Meetings
3-5	Project Team Meetings
10-5	**Online Project Demos**

Website: http://liacs.leidenuniv.nl/~bakkerem2/robotics/

Grading (6 ECTS):

- Presentations and Robotics Project (60% of grade).
- Class discussions, attendance, workshops and assignments (40% of grade).
- It is necessary to be at every class and to complete every workshop.

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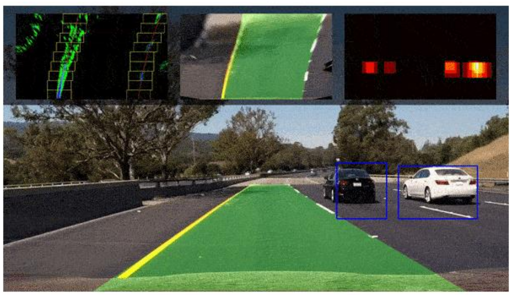
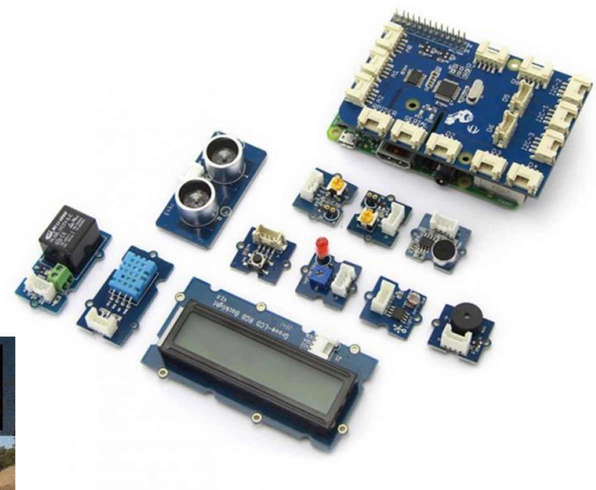
Overview

- Sensors
- Lane Tracking
- OpenCV
- Line Tracking

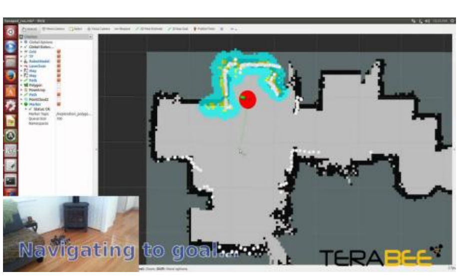


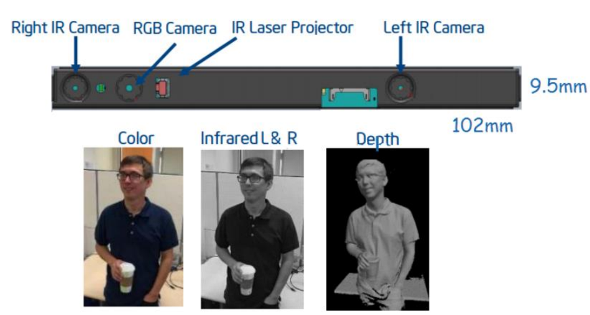


- Project Proposals
- Robotics Discussion Session

ROBOTICS SENSORS

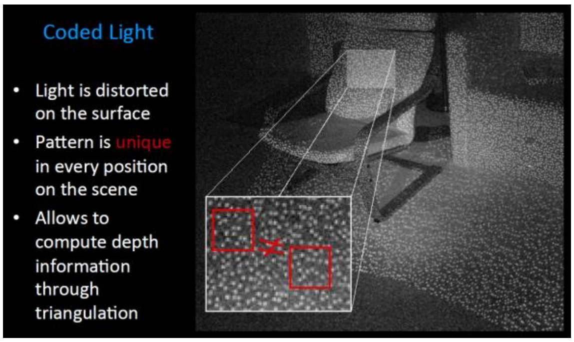
- Bumper switches
- Acceleration, Orientation, Magnetic
- **IR/Visible Light**
- **Pressure**, Force
- **Ultrasonic, Lidar**, Radar
- **Camera's**, stereo camera's
- **Structured Light Camera's**

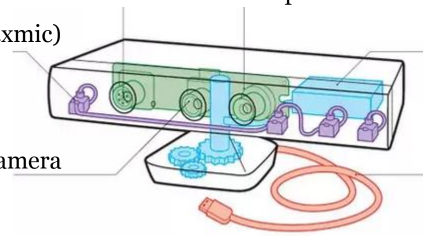




Structured Light

1. Primesense based Occipital
2. Asus X-tion Pro Live
3. Microsoft Kinect v1, v2
4. Intel RealSense F200, R200 (blue)





From: Anyline presentation by Peter Sperl

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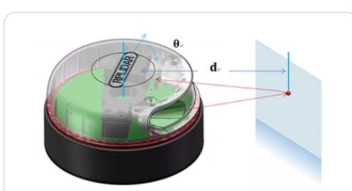
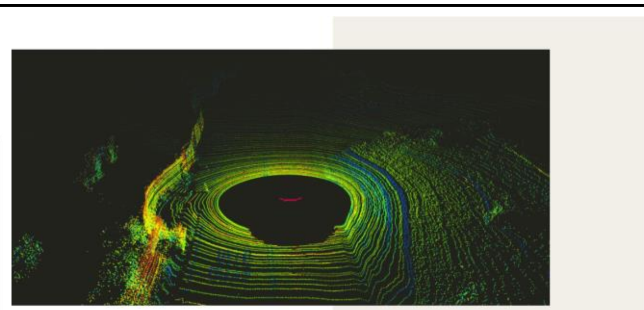
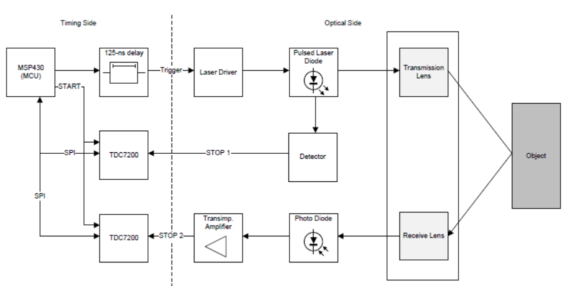
LIDAR Explanation



http://www.slamtec.com/en/lidar/A3

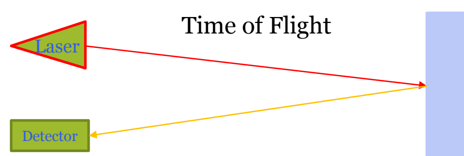


https://news.voyage.auto/an-introduction-to-lidar-the-key-self-driving-car-sensor-a7e405590cff



Texas Instruments LIDAR Pulsed Reference Design

Time of Flight



- Speed of light ~ 3×10^8 m/s
- In 1 picosecond (= 10^{-12} sec) light travels ~ 3×10^{-4} m = 0.3 mm
- During 33 picoseconds light travels ~ 1cm

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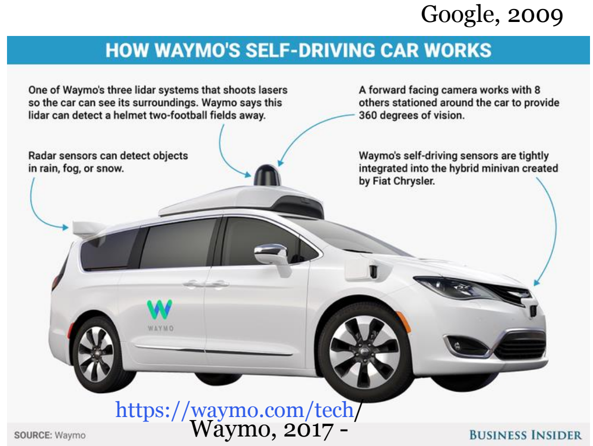
Robotics Self Driving Cars

Google Firefly, 2015

Google, 2009



https://waymo.com/tech/

Waymo, 2017 -

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CES2019

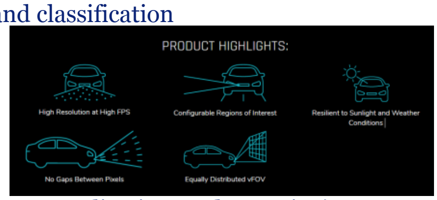
BMW Self Driving Car

InnovizOne Solid-state Lidar (goal: sub $1000 sensor)

- Angular resolution 0.1° x 0.1°
- FOV 120° x 25°
- 25 FPS
- Range 250m

Perception Capabilities

- Object detection and classification
- Lane detection
- Object Tracking
- SLAM



SLAM (Simultaneous Localization And Mapping)

Researcher Hacks Self-driving Car Sensors

$60 lidar spoofing device generates fake cars, pedestrians and walls (2015)

By **Mark Harris**

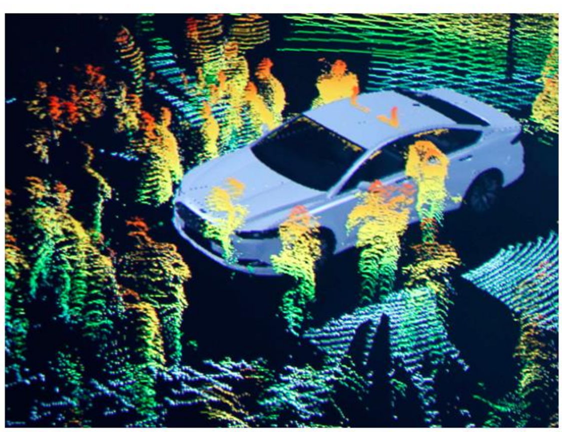
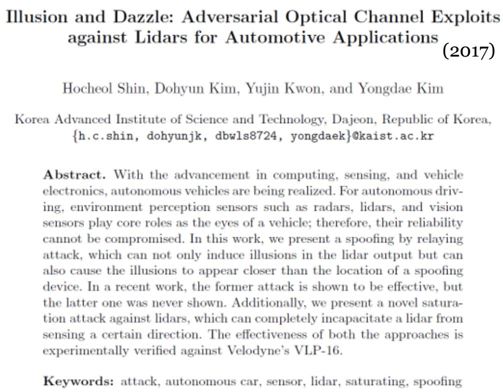


Photo: Jeff Kowalsky/Corbis

https://spectrum.ieee.org/cars-that-think/transportation/self-driving/researcher-hacks-selfdriving-car-sensors

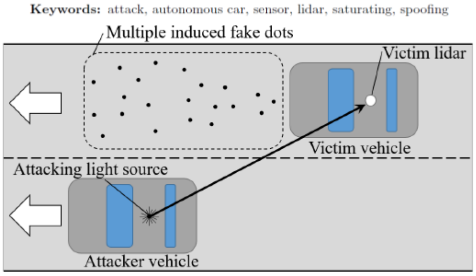

Illusion and Dazzle: Adversarial Optical Channel Exploits against Lidars for Automotive Applications (2017)

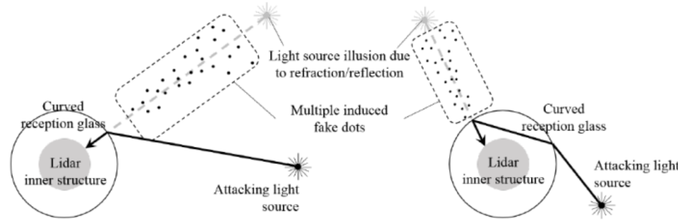
Hocheol Shin, Dohyun Kim, Yujin Kwon, and Yongdae Kim

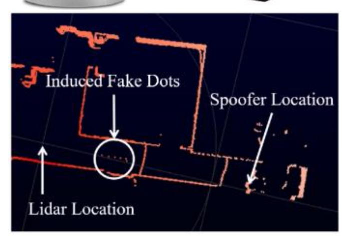
Korea Advanced Institute of Science and Technology, Dajeon, Republic of Korea,
{h.c.shin, dohyunjk, dbwls8724, yongdaek}@kaist.ac.kr

Abstract. With the advancement in computing, sensing, and vehicle electronics, autonomous vehicles are being realized. For autonomous driving, environment perception sensors such as radars, lidars, and vision sensors play core roles as the eyes of a vehicle; therefore, their reliability cannot be compromised. In this work, we present a spoofing by relaying attack, which can not only induce illusions in the lidar output but can also cause the illusions to appear closer than the location of a spoofing device. In a recent work, the former attack is shown to be effective, but the latter one was never shown. Additionally, we present a novel saturation attack against lidars, which can completely incapacitate a lidar from sensing a certain direction. The effectiveness of both the approaches is experimentally verified against Velodyne's VLP-16.

Keywords: attack, autonomous car, sensor, lidar, saturating, spoofing







Adversarial Sensor Attack on LiDAR-based Perception in Autonomous Driving

by Yulong Cao et al.
CCS '19, November 11–15, 2019, London, UK.

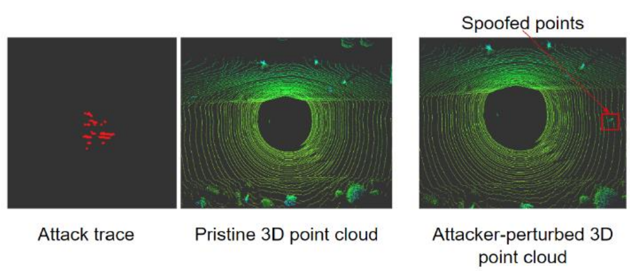
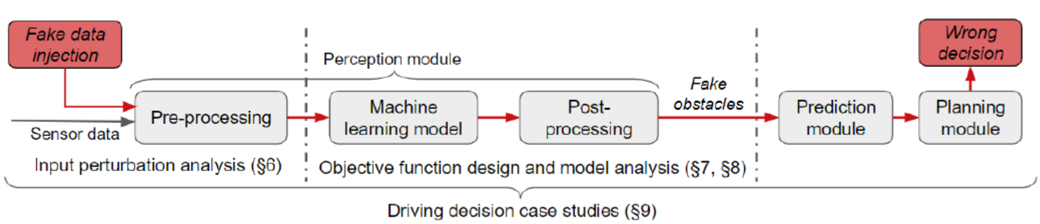


Figure 5: Generating the attacker-perturbed 3D point cloud by synthesizing the pristine 3D point cloud with the attack trace to spoof a front-near obstacle 5 meters away from the victim AV.



RaspberryPi Sensors Kit

GrovePi+ Board for Raspberry Pi

De ATMEGA328 microcontroller communicates with the Raspberry Pi.

- Sound Sensor
- Temperature & Humidity
- Light Sensor
- Button
- Ultrasonic Ranger
- Rotary Angle Sensor
- Gas Sensor

Symbol	MQ-2	MQ-3	MQ-5	MQ-9
Detect Gas	Combustible Gas, Smoke	Alcohol Vapor	LPG, Natural Gas, Town Gas	Carbon Monoxide, Coal Gas, Liquified Gas
Detect Concentration	300-10000ppm	0.04-4mg/L Alcohol	300-10000ppm	10-1000ppm CO;100-10000PPm Gas

Lane Tracking

- Joel C. McCall and Mohan M. Trivedi, **Video Based Lane Estimation and Tracking for Driver Assistance: Survey, System, and Evaluation.** IEEE Transactions on Intelligent Transportation Systems, 2006
- A. Bar Hillel, R. Lerner, D. Levi, G. Raz, **Recent progress in road and lane detection: a survey. Machine Vision and Applications** (2014) 25:727–745
- J. Fritsch, T. Kühnl, F. Kummert, **Monocular Road Terrain Detection by Combining Visual and Spatial Information.** IEEE Transactions on Intelligent Transportation Systems, 2014.
- J. Sattar, J. Mo, SafeDrive: **A Robust Lane Tracking System for Autonomous and Assisted Driving Under Limited Visibility.** January 31, 2017

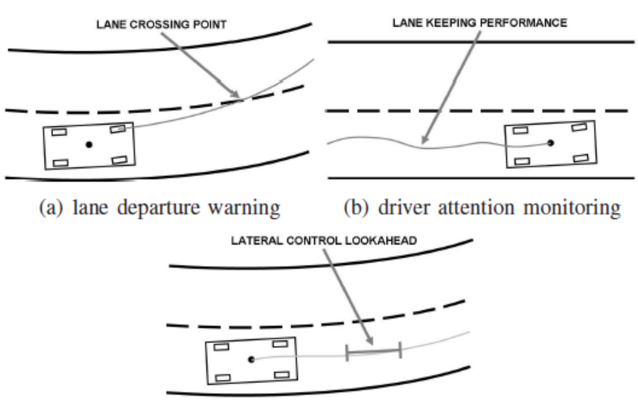
(https://arxiv.org/abs/1701.08449)

Some example project for detecting road features using OpenCV:

https://navoshta.com/detecting-road-features/ by Alex Staravoitau

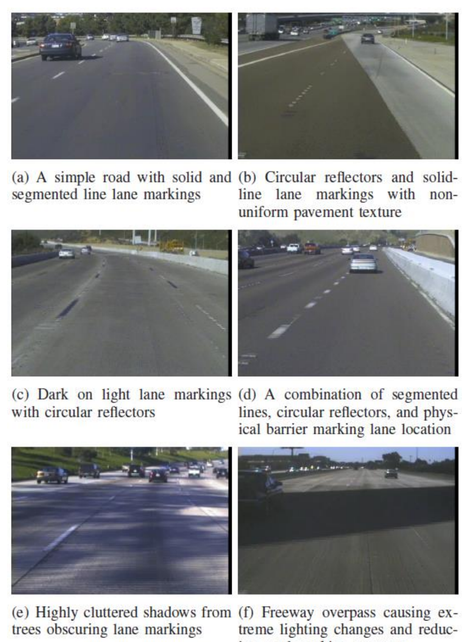
Lane Tracking

Joel C. McCall and Mohan M. Trivedi, **Video Based Lane Estimation and Tracking for Driver Assistance: Survey, System, and Evaluation.** IEEE Transactions on Intelligent Transportation Systems, 2006



(a) lane departure warning (b) driver attention monitoring

(c) vehicle control



(a) A simple road with solid and segmented line lane markings

(b) Circular reflectors and solid-line lane markings with non-uniform pavement texture

(c) Dark on light lane markings with circular reflectors

(d) A combination of segmented lines, circular reflectors, and physical barrier marking lane location

(e) Highly cluttered shadows from trees obscuring lane markings

(f) Freeway overpass causing extreme lighting changes and reducing road marking contrast

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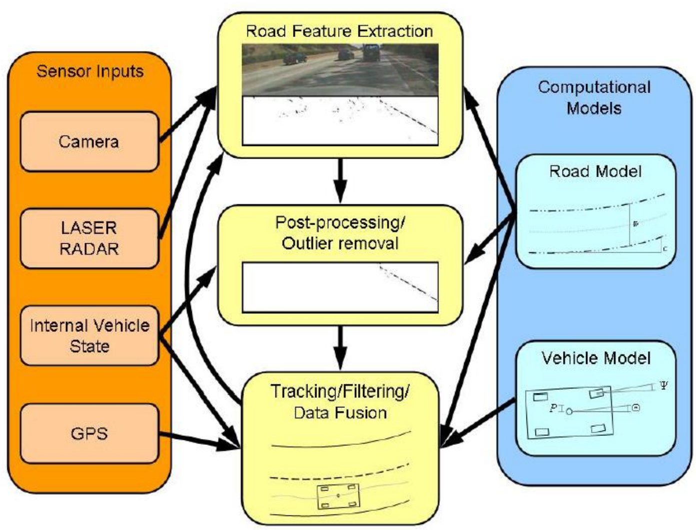
Lane Tracking by Day and Night

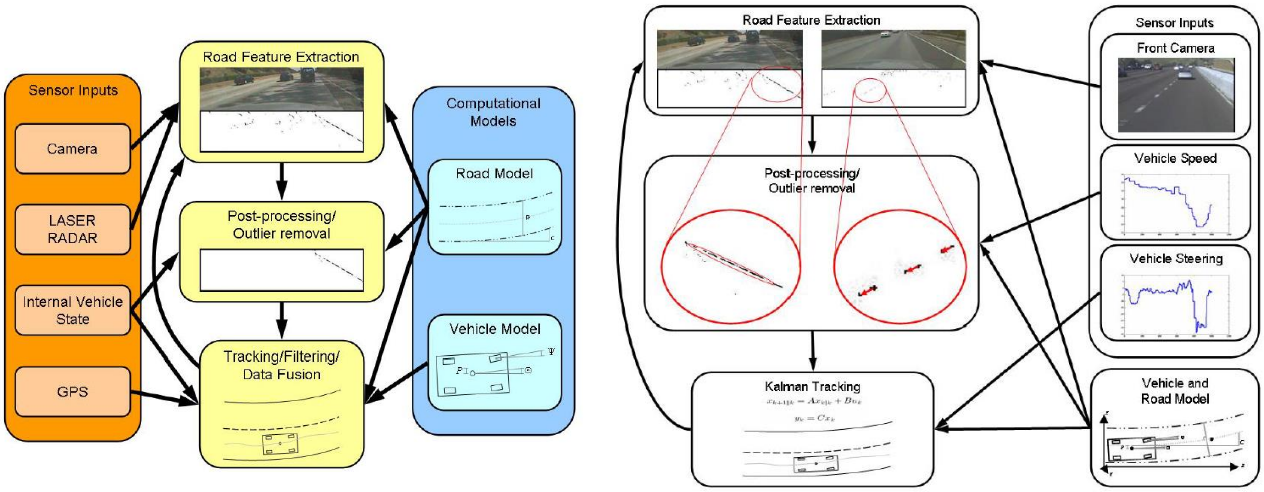
Fig. 3. Images of the same stretch of road shown in the daytime and nighttime

General System

1. camera and vision sensors
2. internal vehicle state sensors
   e.g., speed, steering angle, etc.
3. line detectors, etc.
4. LASER RADAR sensors
5. GPS sensors



A generalized flow chart for lane position detection systems combining multiple modalities an iterative detection/tracking loop and road and vehicle models.



A generalized flow chart for lane position detection systems combining multiple modalities an iterative detection/tracking loop and road and vehicle models.

Vehicle and Road Models

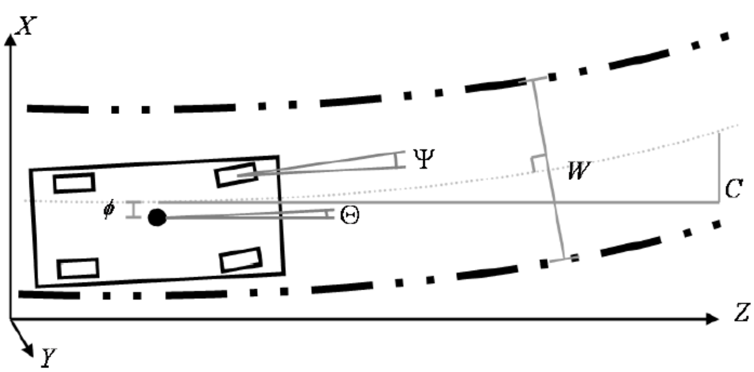


Fig. 6. Vehicle and road models used in the system. We are using a constant curvature road model and linearized vehicle dynamics for use in a Kalman filter.

Kalman Filter: Linear Quadratic Estimation to cope with noisy data.

System	Use[a]	Road Model	Feature Extraction	Postprocessing	Tracking	Evaluation	Comments
VaMoRs (1992) [16]	A	Clothoid Model with vertical curvature	Edge Elements	eliminates points which are not collinear	Linear vehicle dynamics model	Single frame images	Limited processing power. Simple edge detection fails in difficult situations.
YARF (1995) [33]	A	Circular road segments on flat plane	Hue based segmentation and edge detection	Averaging and linear median squares estimation	Operation on single frame	Positive detection rates for feature extraction, single frame images	Multiple detectors. Limited to yellow and white stripes.
ALVINN (1996) [19], [36]	A	Flat road model for generating training data	Image intensity	Neural Network	None	Road tests, various error measure associated with neural networks	Neural network makes it difficult to decouple control from detection, requires lots of training
RALPH (1996) [25]	A B	Constant curvature on flat plane	scan line matched to template	Template matching to slowly evolving near template and fast evolving far template	No inter-frame tracking described	Single frame images	template methods can fail near construction zone or areas where the road has changed. Shows limited quantitative results
GOLD (1998) [20]	C	Constant lane width on flat plane	Adaptive thresholding of pixel differences	Morphological widening	Operation on single frame	Single frame images	Assumes line markings on dark road. some robustness to lighting and occlusion
LOIS (1998) [34]	B A	Parabolic approximation on flat plane	Edge magnitudes and orientations	Maximum a posteriori estimation evaluated by Metropolis algorithm	Kalman filtering	Error histogram from one drive. Standard deviation of error 13cm	Robust to shadowing in presence of strong lane markings. Otherwise untested.
LANA (1999) [24]	B A	Parabolic approximation on flat plane	DCT coefficients for diagonally dominant edges	Maximum a posteriori estimation	Operation on single frame	Single frame images, comparison to LOIS shown	Only using diagonal DCT coefficients limits detection based on orientation of vehicle
Taylor et al. (1999) [12]	A	Constant curvature on flat plane	Template matching	Hough transform	Kalman Filter input into various control schemes	Performance of controllers shown	Focussed on controller performance. Limited real-world testing.
Ma et al. (2000) [13]	A B C	Circular road model on flat plane	Likelihood based on gradient image	Fusion on radar and optical images	Operation on single frame	Single frame images	Designed for elevated or bordered rural roads.

System	Use[a]	Road Model	Feature Extraction	Postprocessing	Tracking	Evaluation	Comments
Southall et al. (2001) [30]	C	Curvature and rate of change of curvature	Threshold both pixel values and cross-correlation to dark-bright-dark function	Factored sampling for particle filter	Particle Filtering via CONDENSATION	Estimates shown for an image sequence, no ground truth or quantitative results	Very limited results and testing. Unclear whether feature extraction will work in difficult situations.
Kwon and Lee (2002) [4], [31]	B	Piecewise linear	multiple "feature transformation modules"	combined with data fusion and constraint satisfaction, heuristic departure warning function	nonlinear filtering	analysis of departure warning system given	Good architecture for sensor fusion. Testing limited to false alarm rate of departure warning.
DARVIN (2002) [5]	A B	DGPS based maps of roads	Image gradient	match to DGPS data	nonlinear filtering	selected frames from experimentation	Directed towards urban driving. Heavy reliance on GPS data.
Lee et al. (2003) [37], [38]	B	Straight road on flat plane	Edge distribution function	Hough transform to extract lanes	Not discussed	Detection rate of lane departure warning	Robust to lighting. Will not work for circular reflectors.
Apostoloff et al. (2003) [29]	C	Not discussed	lane markers, road edge, color, width	Cue scheduling to determine which cues are used	Particle Filtering via Distillation	Success rate, mean absolute error for position, yaw, and road width.	Possibly fail in conditions of strong cues that contradict each other (i.e. fig. 2b)
Kang et al. (2003) [28]	D	Straight road on flat plane	Edge direction and magnitude	Connected-component analysis, Dynamic programming	Single frame operation	Qualitative comparison to hough transform based techniques, Single images shown	Focusses on showing visual comparison to hough transform based technique.
Nedevschi et al. (2004) [22]	D	3D model based on clothoids and roll angle	edge detection	outlier removal based on 3D location found with stereo camera system, roll angle detected	Kalman filtering	single images from road scenes with clearly marked lane boundaries	Simple edge detection not robust to shadows, occlusions
This paper (2004)	C B	Parabolic approximation on flat plane	Steerable filters, adaptive road template	Statistical and motion based outlier removal	Kalman Filtering	Extensive error evaluation described in section V-B	

Steerable Filters

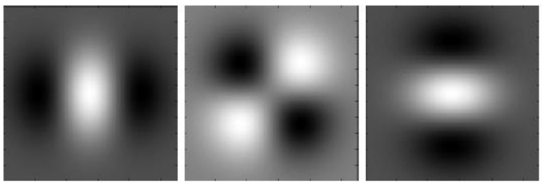


Fig. 7. A basis set for steerable filters based on the second derivatives of a two-dimensional Gaussian.

(a) A highway scene with complex shadowing from trees.

(b) Detection results for lines tuned to the lane angle.

Fig. 9. Filter results when lane markings are shadowed with complex shadows and non-uniform road materials.

(a) A typical highway scene encountered during evaluation.

(b) Results of filtering for circular reflectors.

(c) Results from filter for a line tuned to the lane angle.

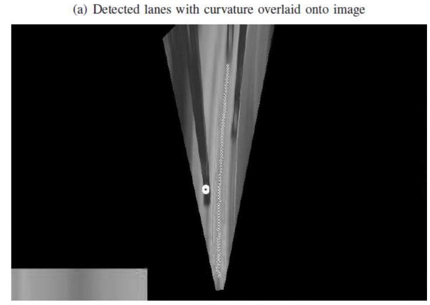
Fig. 8. Application of Steerable filter road marking recognition for circular reflectors and solid lines on a highway

Inverse Perspective Warping and Template Matching

A perspective transformation, can be used to obtain an overview of the road ahead of the vehicle. This can make the problem of lane boundaries extraction easier.

- Curvature detection done by using an intensity template of past images in order to detect the curvature of the road ahead.

(a) Detected lanes with curvature overlaid onto image



(b) Inverse perspective warping showing curvature detection (small white dots) and template (lower left corner)

Fig. 10. Curvature detection in the VioLET lane tracking Document1 - Word

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A. System Test-bed Configuration and Test Conditions

Fig. 11. The LISA-Q intelligent vehicle test bed. Inset are close up views of the front camera (left inset) used for detection and tracking and side camera (right inset) used for generating ground truth.

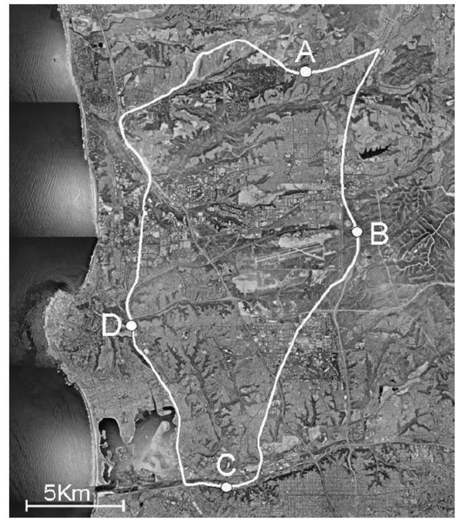
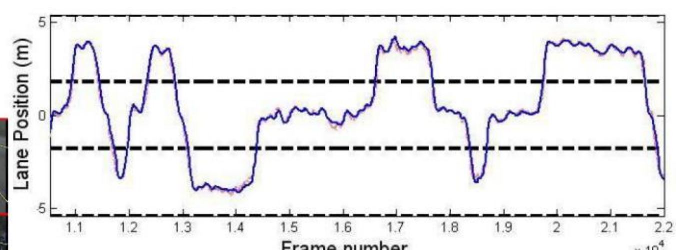


Fig. 14. The 65Km route in San Diego used in the evaluation. The route is overlayed on aerial photography. Points A, B, C, and D are sections of road used in the evaluation (photography courtesy USGS)

Results

Fig. 15. Scenes from dawn (row 1), daytime (row 2), dusk (row 3), and nighttime (row 4) data runs for each of the four sections of road (A, B, C, and D in figure 14). These scenes show the environmental variability caused by road markings and surfaces, weather, and lighting.



ig. 12. Detected lateral position in meters (solid blue) superimposed on ground truth (dashed pink) plotted vs. frame number with dashed lines marking ie position of lane boundaries for an 11,000 frame (slightly over 6 minute) sequence.

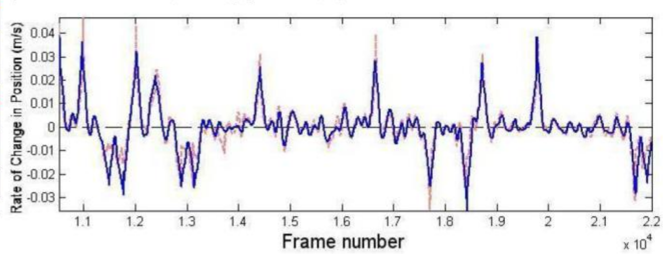


Fig. 13. Detected departure rate in m/s^2 (solid blue) superimposed on ground truth (dashed pink) plotted vs. frame number with dashed line marking the abscissa for the same sequence shown in figure 12.

Ground truth = pink dashed line

Challenges: Occlusions and Highlights

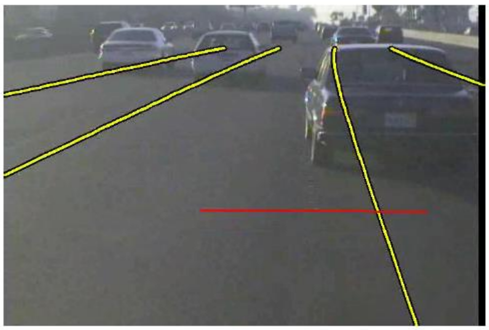


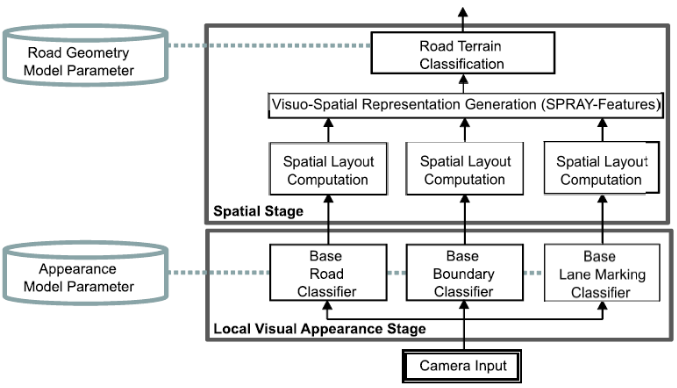
Fig. 16. Error due to occlusion of the road by a vehicle on the dusk dataset on road segment C. The red horizontal line shows the proximity of the occluding vehicle detected by the in-vehicle LASER RADAR sensors.

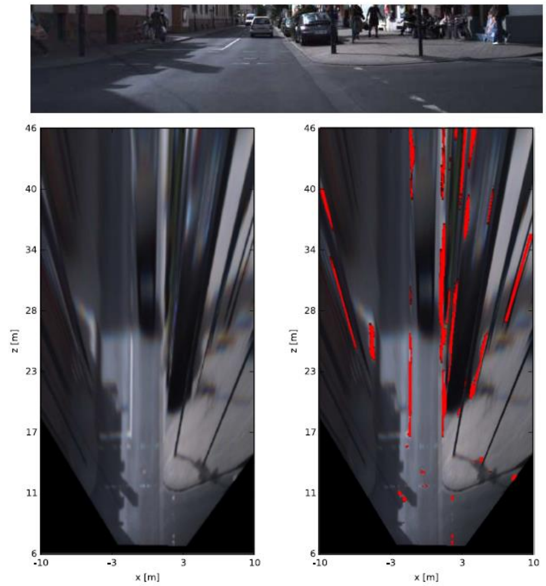
Fig. 17. Scenes from the special case scenarios of complex shadowing (top row) and tunnels (bottom row). These scenes highlight the extreme variability that can occur within short sections of road.

Lane Tracking

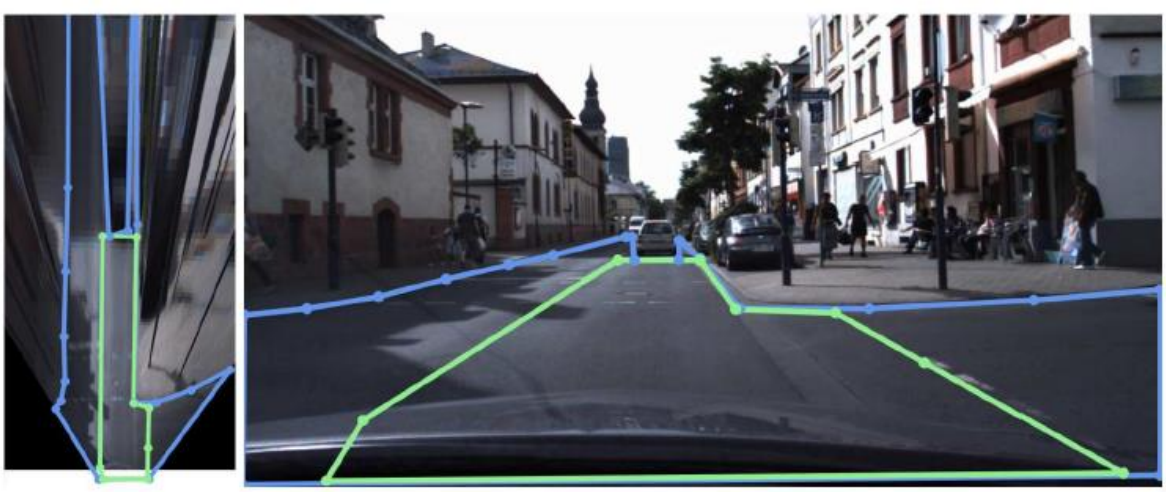
J. Fritsch, T. Kühnl, F. Kummert, **Monocular Road Terrain Detection by Combining Visual and Spatial Information.** IEEE Transactions on Intelligent Transportation Systems, 2014.

Overview System





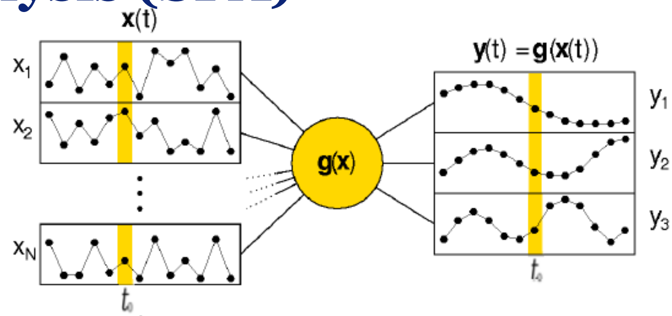
Ground Truth

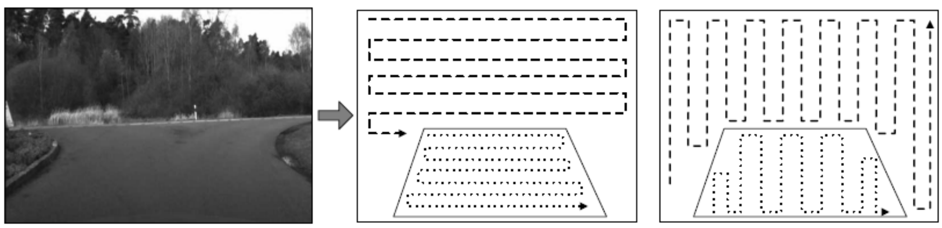


Slow Feature Analysis (SFA)

Slow Feature Analysis (SFA)

Generating the slowest varying output functions $y_j(t)$ from a multidimensional input signal $x(t)$



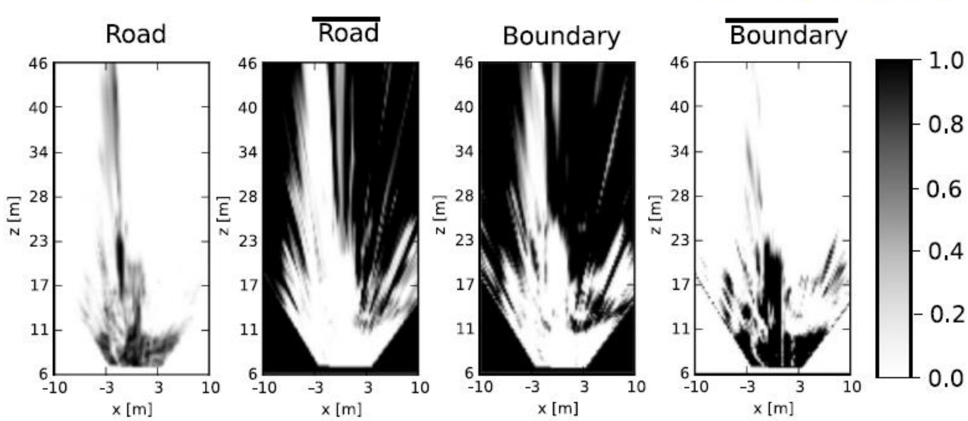


Spatial patch sequence extraction for SFA training: on the left the horizontal path and on the right the vertical path is illustrated. The paths are partitioned into road (dotted) and non-road (dashed) sections.

Result of the base road and base boundary classification for the given ground truth scene.

From left to right the positive and negative part of the confidence values is depicted for each base classifier.

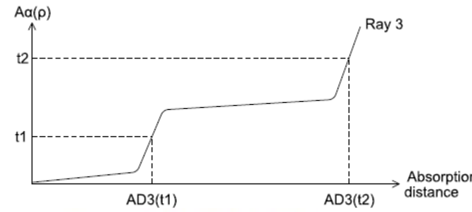
Dark points denote high confidence of the classification.

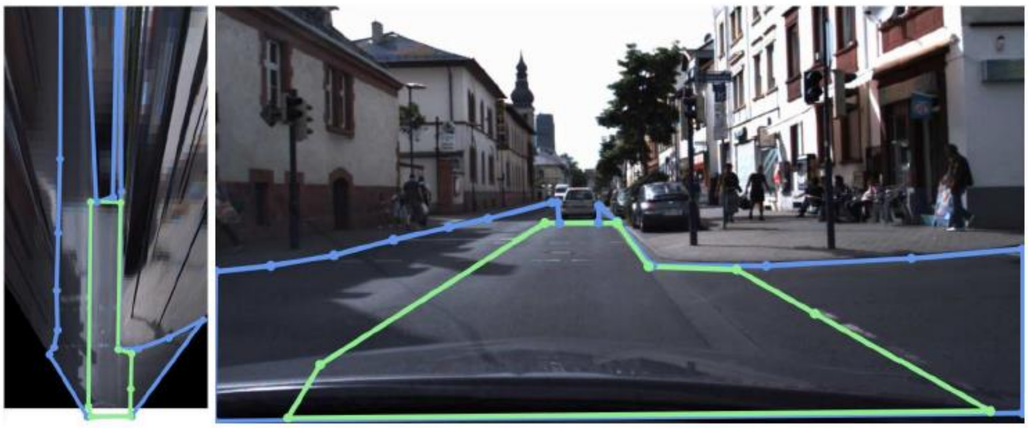


Feature vectors:

- SFA features
- Color features (RGB)
- Walsh Hadamard texture features

Ground Truth

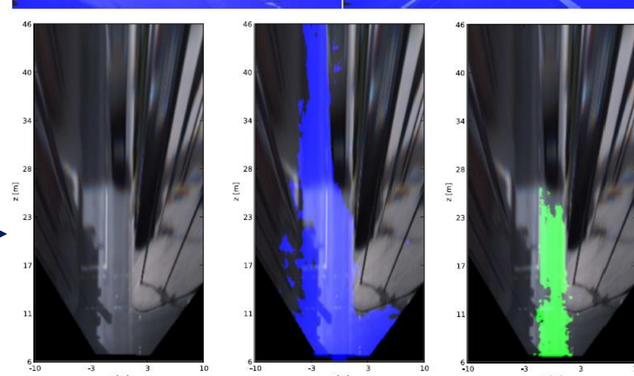




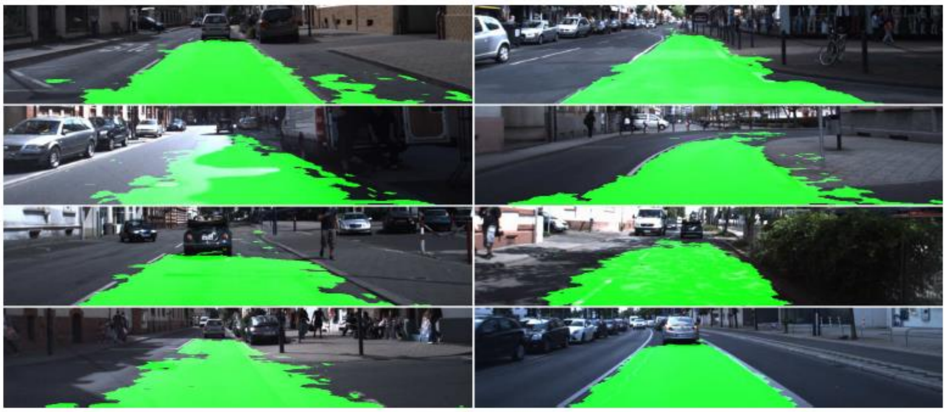
Results

Result of the road terrain classification for the ground truth (above):

- The classification result for road area (middle blue).
- The classification result for the ego-lane (right green)



Results



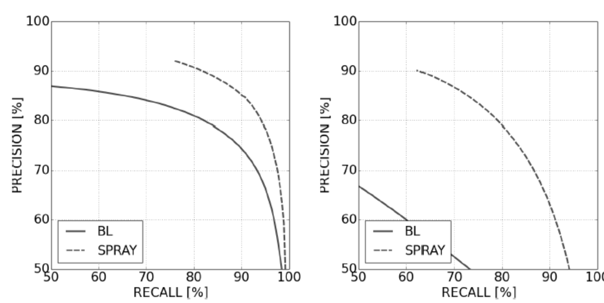
- Ego Lanes

Results

RESULTS OF PIXEL-BASED EVALUATION.

	AP	F_{max}	Prec.	Recall	Acc	FPR	Q_{test}
perspective road area							
BL	89.1	85.6	79.4	92.8	78.9	50.4	74.8
SPRAY	95.6	94.5	94.0	95.0	92.5	12.8	89.5
metric road area							
BL	70.0	66.3	56.4	80.5	68.1	39.7	49.6
SPRAY	89.8	87.0	87.1	86.9	89.9	8.2	77.0
perspective ego-lane							
BL	80.1	81.7	76.4	87.7	90.2	9.0	69.1
SPRAY	85.2	87.6	84.7	90.6	93.6	5.4	77.9
metric ego-lane							
BL	61.7	60.3	56.6	64.6	92.5	4.8	43.2
SPRAY	78.9	79.5	79.6	79.4	96.4	2.0	66.0

(BL = Baseline)



(a) Perspective evaluation (b) Metric evaluation

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Harmonic mean of precision and recall.

Image Processing using OpenCV

Core module: the basic building blocks of this library for manipulating the images on a pixel level.

Imgproc module: the image processing (manipulation) functions inside OpenCV.

High Level GUI and Media (highgui module)

Image Input and Output (imgcodecs module)

Video Input and Output (videoio module)

Camera calibration and 3D reconstruction (calib3d module)

2D Features framework (feature2d module): feature points detectors, descriptors and matching framework found inside OpenCV.

Video analysis (video module) algorithms usable on your video streams like motion extraction, feature tracking and foreground extractions.

Object Detection (objdetect module) face detectors, etc.

Deep Neural Networks (dnn module)

Machine Learning (ml module) machine learning classes for statistical classification, regression and clustering of data.

Graph API (gapi module)

Computational photography (photo module) for advanced photo processing.

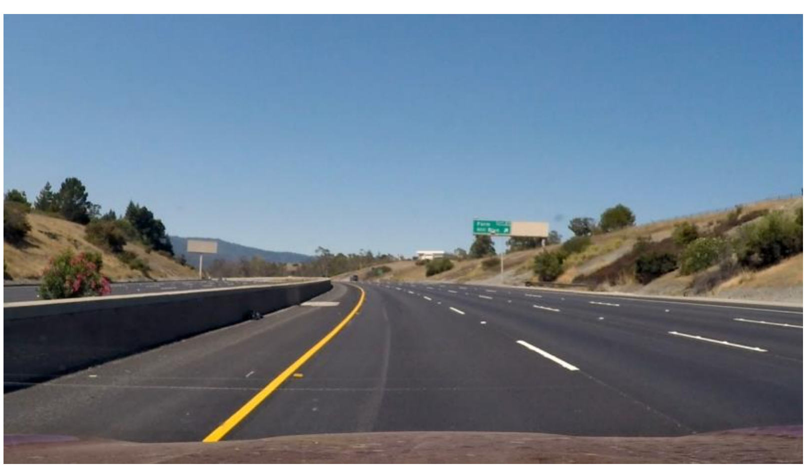
Images stitching (stitching module) create photo panoramas and more with OpenCV stitching pipeline.

GPU-Accelerated Computer Vision (cuda module); OpenCV iOS:

Lane Tracking

Some example project for detecting road features using OpenCV:

https://navoshta.com/detecting-road-features/ by Alex Staravoitau



Overview Processing Pipeline

Camera calibration

- Each camera gives image distortions, these can be rectified using information from a camera calibration. OpenCV has functionality to calibrate and correct camera images. Calibration is done using chessboard images.

Edge detection

- OpenCV has many different edge detectors using gradient and color information. These edges can be used for the detection of structures such as lines etc.

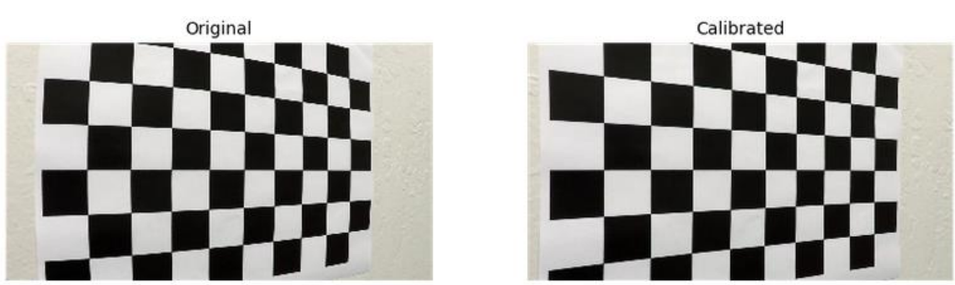
Perspective transformation

- A perspective transformation, can be used to obtain an overview of the road ahead of the vehicle. This can make the problem of lane boundaries extraction easier.

Fitting boundary lines

- The resulting frame pixels are determined that may belong to lane boundaries.
- These are then used to approximate lines, road properties and vehicle position.
- Furthermore a rough estimate on road curvature and vehicle position within the lane is determined using known road dimensions.

Processing Pipeline: Camera Calibration



Original vs. calibrated images

… cv2.findChessboardCorners(image, (9, 6), None) // Inner corners 9x6

… cv2.calibrateCamera(pattern_points, image_points, (image.shape[1], image.shape[0]), None, None)

corrected_image = cv2.undistort(image, self.camera_matrix, self.dist_coefficients, None, self.camera_matrix)

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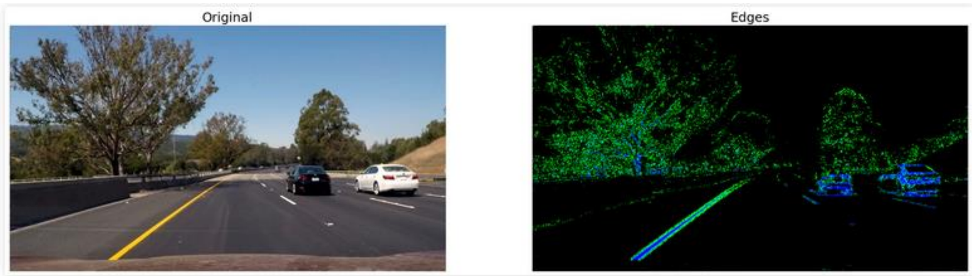
Processing Pipeline: Edge Detection



Original vs. highlighted edges

Gradient Absolute Values, Ranges within certain magnitudes, Gradient Directions

- Sobel Operator (using a convolutional Kernel)

Color Ranges

- HLS Color Space: Hue, Lightness, and Saturation (for road detection, etc.)

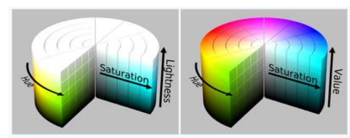


Fig. 2a. HSL cylinder. Fig. 2b. HSV cylinder.

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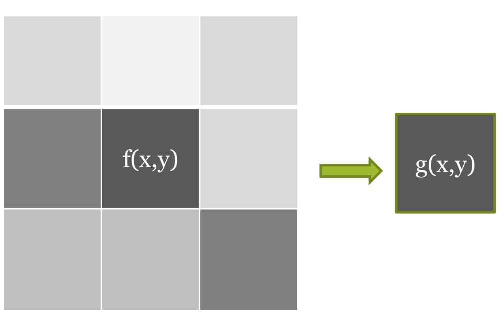
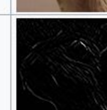
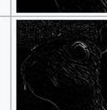
Image Processing using Convolutional Kernel

$$g(x,y) = \omega * f(x,y) = \sum_{dx=-a}^{a} \sum_{dy=-b}^{b} \omega(dx,dy) f(x+dx, y+dy)$$



Operation	Kernel ω	Image result g(x,y)
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	

https://en.wikipedia.org/wiki/Kernel_(image_processing)

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Processing Pipeline: Perspective Transformation

Original vs. bird's eye view

…. transform_matrix = cv2.getPerspectiveTransform(source, destination)

…. image = cv2.warpPerspective(image, transform_matrix, (w, h))

Processing Pipeline: Perspective Transformation

Boundary detection pipeline

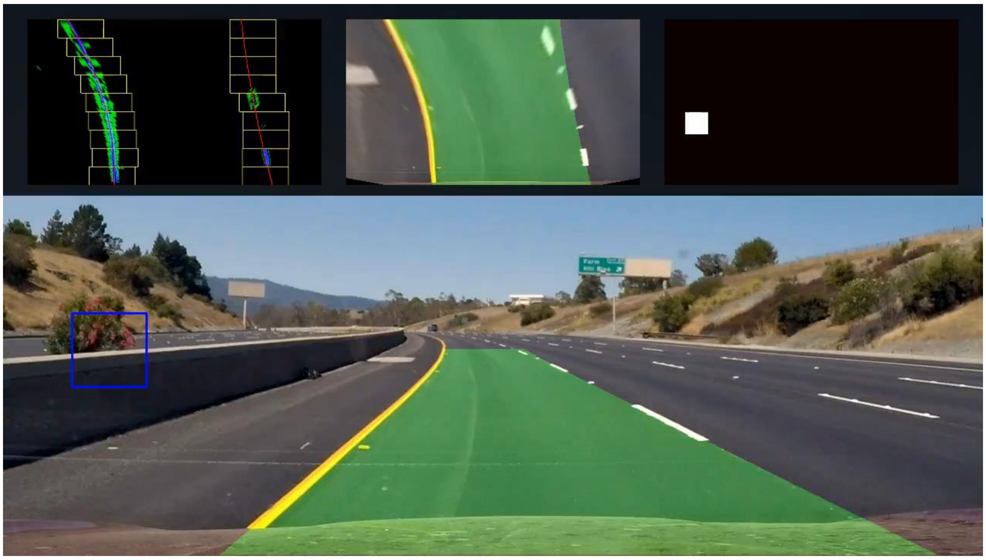
Left: The *original* image after the camera calibration and perspective transform.

Right: After edge detection with edges highlighted in **green** and **blue**.

Scanning windows boundaries for areas with pixel that may belong to lines are highlighted in **yellow**,

A second order polynomial approximation of the collected points in **red**.

Lane and Vehicle Tracking



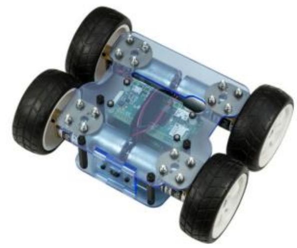
Some remarks

Alex Staravoitau:

“This clearly is a very naive way of detecting and tracking road features, and wouldn’t be used in real world application as-is, since it is likely to fail in too many scenarios: “

- Going up or down the hill.
- Changing weather conditions.
- Worn out lane markings.
- Obstruction by other vehicles or vehicles obstructing each other.
- Vehicles and vehicle positions different from those classifier was trained on.
- …

Organization and Overview



Period: February 1st – May 10th 2021
Time: Tuesday 16.15 – 18.00
Place: https://smart.newrow.com/#/room/qba-943
Lecturer: Dr Erwin M. Bakker (erwin@liacs.nl)
Assistant: Erqian Tang

NB Register on Brightspace

Schedule:

1-2	Introduction and Overview
8-2	No Class (Dies)
15-2	Locomotion and Inverse Kinematics
22-2	Robotics Sensors and Image Processing
1-3	**Yetiborg Introduction + SLAM Workshop I**
8-3	**Project Proposals (presentation by students)**
15-3	Robotics Vision
22-3	Robotics Reinforcement Learning
29-3	**Yetiborg Qualification +** **Robotics Reinforcement Learning Workshop II**
5-4	No Class (Eastern)
12-4	Project Progress (presentations by students)
19-4	**Yetiborg Challenge**
26-4	Project Team Meetings
3-5	Project Team Meetings
10-5	**Online Project Demos**

Website: http://liacs.leidenuniv.nl/~bakkerem2/robotics/

Grading (6 ECTS):
- Presentations and Robotics Project (60% of grade).
- Class discussions, attendance, workshops and assignments (40% of grade).
- It is necessary to be at every class and to complete every workshop.

Robotics Project Proposals Presentations

Monday 8-3 2021

Present your Robotics Project Proposal during a **5 minute (max)** talk. Clearly state the title of your project, the team members, your goals, how you will pursue them, what are the challenges and what at least can and should be delivered on the demo day on May 10th 2021.

Note: Groups of 4-5 members are allowed.

The presentation should contain slides for:
1. Title and group members.
2. Goal of the project.
3. How will you pursue these goals.
4. What are the challenges.
5. What at least can and should be delivered on the demo day on May 10th 2021.

The LIACS Media Lab can support your project with some materials for your project. Please clearly state any materials that you would need for your proposal. Note that these materials are limited so project goals may need to be adjusted accordingly.

Each presentation will be followed by a short class discussion.

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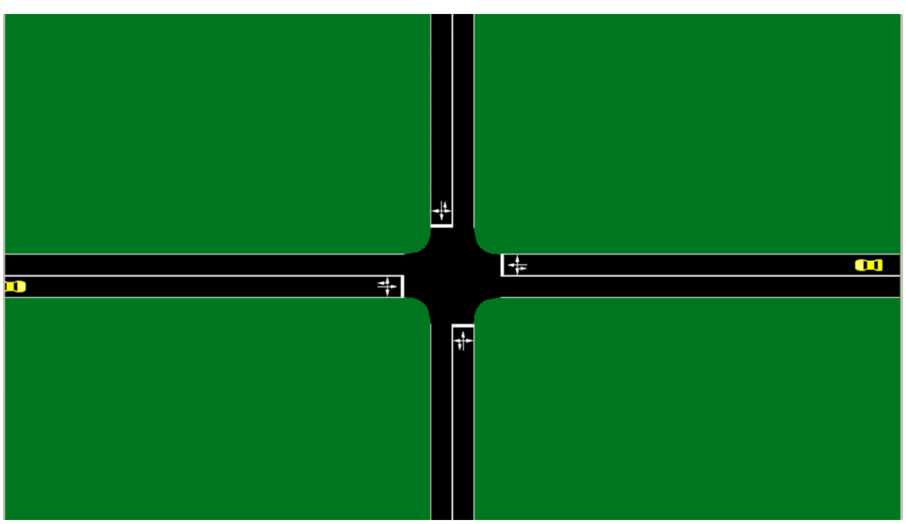
Previous Projects

1. Evolutionary Locomotion
2. Nao plays Tic-Tac-Toe
3. Slam Robot Project.
4. Dolphin Drone: Drone Recognition and Maneuvering with Hoops.
5. Delivery Drone.
6. Programming a NAO to play a tune using a xylophone.
7. Floor mapping with Swarm Robotics
8. Tootballing Yetiborg
9. Cat Flap Opening Based on Audio/Video/RFID
10. DrawBot
11. Traffic coordination (simulation).
12. Plane filling curves (simulation).

1. AimBot
2. Artificial Muscles
3. Ball Tracking Car
4. BorrelBot
5. Fetch Bot
6. Floor Mapping Robot
7. Gesture Control Pachenko
8. Hexapod
9. Nao Pose
10. Position Estimation
11. Race Car Training
12. Face Touch

Traffic coordination (simulation).



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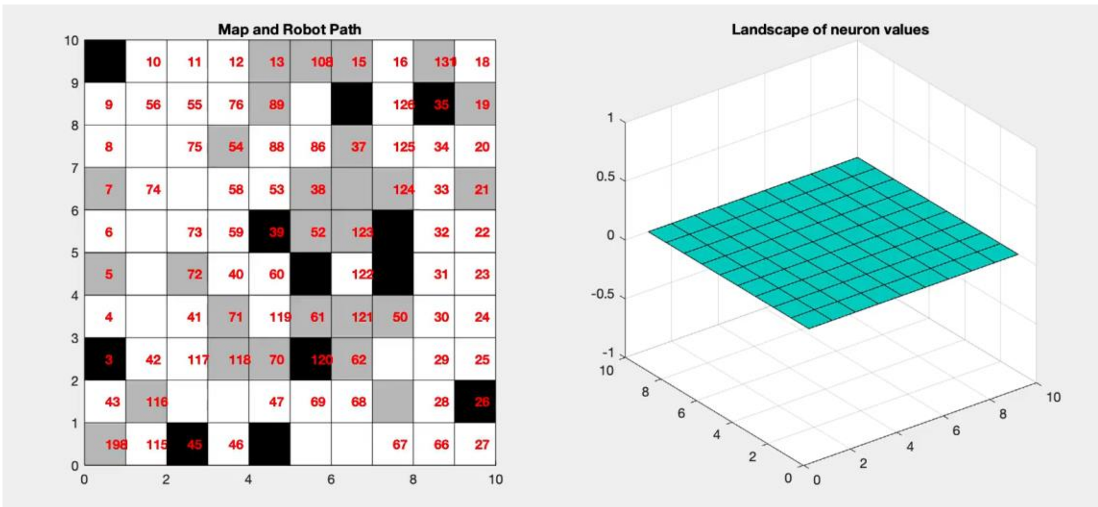
Roombas with Brains: Neural Networks for Coverage Path Planning



Gesture Controlled Pachenko

Gesture Controlled Pachinko Game

Aaron Dunlea, Nathan van der Putten, Malte Wilhelm

liacs Leiden Institute of Advanced Computer Science

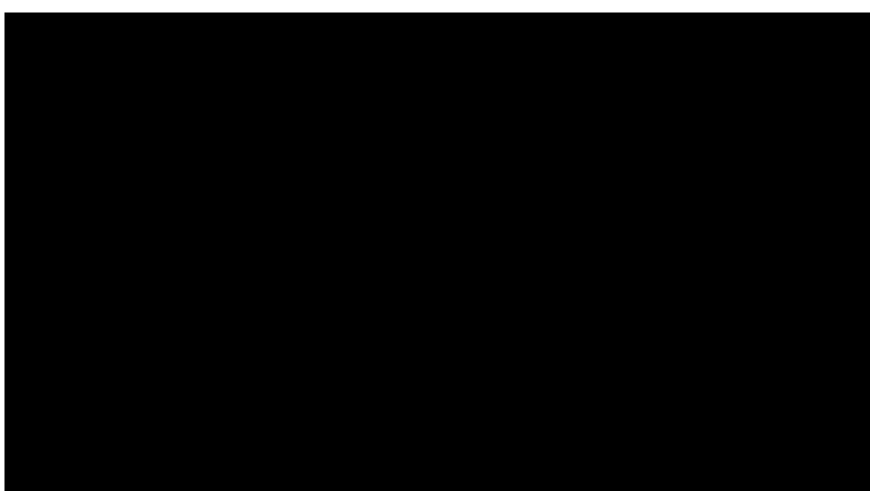
Universiteit Leiden The Netherlands

Traffic coordination (simulation).

DrawBot
AimBot
FetchBot

Cellular Automaton: https://youtu.be/maC1eo8_-lI
Dragon Curve: https://youtu.be/9ilDP_pvDEk

https://vimeo.com/425043774



S.P.I.N. - Spider Python INator

Marcel Huijben (s1780107)
Martijn Swenne (s1923889)
Sebastiaan Alvarez Rodriguez (s1810979)
Robin Voetter (s1835130)

References

1. Joel C. McCall and Mohan M. Trivedi, Video Based Lane Estimation and Tracking for Driver Assistance: Survey, System, and Evaluation. IEEE Transactions on Intelligent Transportation Systems, 2006
2. A. Bar Hillel, R. Lerner, D. Levi, G. Raz, Recent progress in road and lane detection: a survey. Machine Vision and Applications (2014) 25:727–745
3. J. Fritsch, T. Kühnl, F. Kummert, Monocular Road Terrain Detection by Combining Visual and Spatial Information. IEEE Transactions on Intelligent Transportation Systems, 2014.
4. J. Sattar, J. Mo, SafeDrive: A Robust Lane Tracking System for Autonomous and Assisted Driving Under Limited Visibility. January 31, 2017 (https://arxiv.org/abs/1701.08449)
5. https://navoshta.com/detecting-road-features/ by Alex Staravoitau
6. OpenCV.org

Robotics Discussion Session
Wednesday 24-2 at 15.15
Robotics Kaltura Room

During this session we discuss some practical aspects of robotics in an informal and interactive setting.

Especially for people who did not work with microcontrollers, servo’s, sensors etc. before.