Challenges and opportunities in ADAS: A talk on my thesis

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Overview

- Compilation of recent scientific publications
 - Key resources
 - Compilation of ITSC 2015 and ITS Trans. 2015 papers
 - Summary of topics
- My research interests
 - Basic considerations
 - Problem formulation
 - Proposed approach
- State-of-the-art technologies
 - Object detection

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ITS research

ITS Conferences

- 2015 IEEE 18th International Conference on Intelligent Transportation Systems (ITSC 15).
- 2015 IEEE Intelligent Vehicles Symposium (IV 2015).

ITS Journals

• IEEE Transactions on Intelligent Transportation Systems (IF: 2.377)

Related Conferences & Journals

- IEEE Transactions on Pattern Analysis and Machine Intelligence (IF: 5.781)
- 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- 2015 IEEE International Conference on Robotics and Automation (ICRA).
- 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS).

ICRA 2015

Ref.	Sensor(s)	Task	Key concepts
Paz	Color Monoc.	Road segmentation	3D geomet. data, appearance-b'd color segmentation (MAP1)
Wei	2D LIDAR	Road context inference	Random obs'd vehicle states, probabilistic ap. (GNG ² , GP ³)
Ali	-	Platooning control	CTH ⁴
Driggs-C.	Monitoring	Driver behaviour	Realistic data, flexible algorithm
Amanatiadis	Laser+Color	Vehicle 'extraction'	"A-robot-for-a-wheel"
Cunningham.	LIDAR	Decision making	POMDP ⁵ , forward simulation (MPDM ⁶)
Zhang	Color Monoc.	Traversable reg. detec.	Multi-scale super-pixels, ELM ⁷ , online learning
Maddern	2D LIDAR	Localization	Prior maps, localization cost function, probab. framework

Table: ICRA papers on ITS

¹ Maximum A Posteriori estimation.

²Growing Neural Gas.

 $^{^3{\}sf Gaussian\ Process.}$

⁴Constant Time Headway policy.

 $^{^{5}\}mathsf{Partially}$ Observable Markov Decision Process.

⁶ Multipolicy decision-making.

⁷Extreme Learning Machine.

IROS 2015

Ref.	Sensor(s)	Task	Key concepts
Vatavu Galceran Verginis Heinrich Sezer	Omnid. stereo - Camera -	Obstacle det. & track. Veh. track. (oclusions) Platooning Trajectory optimization Vehicle interaction	Industrial AGVs ⁸ , DEM ⁹ , classification, ICP ¹⁰ , Kalman filter Ocluded state estimation, dynamics model, hGMM ¹¹ , KLD ¹² Unicycle vehicles, decentralized kinematic control Rules and heuristics, LQG ¹³ , GPU T-junction intersections, intention-aware decision, MOMDP ¹⁴

Table: IROS 2015: WeDT15 Regular session (ITS)



⁸ Automated Guided Vehicles.

⁹ Digital Elevation Map.

¹⁰ Iterative Closest Point.

 $^{^{11}}_{\rm hybrid~Gaussian~Mixture~Model.}$

¹² Kullback-Leibler Divergence.

 $^{^{13}{\}rm _{Linear-Quadratic~Gaussian.}}$

¹⁴ Mixed Observability Markov Decision Process.

Ref.	Sensor(s)	Task	Key concepts
Quintero(UAH)	Infrared cams	Pedestrian intention	Intentions 1 s ahead, B-GPDM ¹⁵ , Naïve Bayes classifiers IMM ¹⁶ Filter, head pose estimation, real-time Pressure sensors attached to sole of a pedestrian Pose estim., likelihood field model, importance sampling
Schulz(Bosch)	Stereo cam	Pedestrian intention	
Wada(JP)	Pressure (sole)	Pedestrian avoid.	
Chen(CN)	LIDAR	Vehicle tracking	

Table: ITSC 2015: Interaction of Automated Vehicles with other Traffic Participants



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 $^{{15\}atop {\sf Balanced\ Gaussian\ Process\ Dynamical\ Models}}$

¹⁶ Interacting Multiple Model
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Ref.	Sensor(s)	Task	Key concepts
Borrmann(DE) Nilsson(Volvo) Keller(DE) Jahangiri(US) Damerow(DE) Levi(GM) Stolte(DE) Ward(SE) Scanlon(Toyota) Westerhoff(DE) Nilsson(SE) Söntges(DE) Guo(Toyota) Tian(KIT) Romera(UAH)	- Cameras - Rear-view cam Cam, radar, Infrast. cam EDRs ²² Camera - Stereo cam Grey cam.	Resource management Automated driving Emergency maneouvers Red-light runn. pred. Behavior planning Pedestrian detection Automated driving Driver intention Driver behavior Camera control Maneuver intention Evasive trajectories Id. leader vehicle Cyclist detection Vehicle det. & track.	Heterogeneus embedded platf., fail-operational scheme Long vehicles, driver model, prediction models Traject. planning, predictory ctrl., real-time SVM & RE ¹⁷ classif., mRMR ¹⁸ feat. selection FDM ¹⁹ interaction-aware prediction, prob. models AFS ²⁰ , NMS ²¹ tracking, local-motion features Protective vehicle for highway road works Intersections, k-NN, RF, SVM Pre-crash acceleration profile model at intersections Parameter selection, image quality Simple logic rules, lane change maneuvers Upper bound of solution, reports if no solution exists Vehicles detect., lane assignm., ctrl. based on leader Cascaded classifiers, shared features, geometric constr.
Romera(OATT)	Filone Cam	venicie det. & track.	Multi-scale, simple geometric constr., vanishing point

Table: ITSC 2015: Advanced Vehicle Safety Systems (I-IV)

¹⁷ Random Forests

¹⁸ minimum Redundacy Maximum Relevance

¹⁹ Foresighted Driver Model

Accelerated Feature Synthesis

 $²¹_{\hbox{Non-maximal suppression}}$

²² Event Data Recorders

Ref.	Sensor(s)	Task	Key concepts
Stellet(Bosch)	CAN, laser	Vehicle motion pred.	EM ²³ Gaussian process noise at longitudinal predict.
Hashimoto(JP)	Grey cams	Pedestrian behavior	Turning vehicle, DBN ²⁴ context integrat., particle filter
Janardh.(Volvo)	Radar, cam	Collision avoidance	Rigid trucks, steering within lane, PD controller
Durai.(Daimler)	Rad+las+stereo	Data association	T2TA ²⁵ , likelihood-ratio tests, non-kinematic inform.
Koesdw.(CA)	Press., Kinect	Driver inattention	(S-)PCA ²⁶ dimen. red., RF class., PSO ²⁷ multi-view cl.
Kang(KR)	GPS	Vehicle localiz.	GPS under failure of vision, clothoidal constraints
Jiang(FR)	Posit., inertial	Vehicle dynamics	Low-cost, roll-pitch dynamics, RLS ²⁸ , Kalman filters
Eggert(Honda)	-	Lane-change behav.	Trajectory alternatives, "Foresighted Driver Model"
Nishino(JP)	Camera, CAN	Markings deteriorat.	Projection transform, GIS, stripping ratio distribution
Li(CH)	Cameras, CAN	Maneuvers transition	Highways, driving data, transition probabilistic model
Herrmann(TUM)	Braking+steer.	Criticality classificat.	Evasion, MinMax optimal ctrl., RF class. with feat. sel.
Horgan(Valeo)	<u>-</u> .	ADAS survey	Vision-based ADAS, taxonomy
Sieber(DE)	= .	Emergency steering	Distracted driver, human-machine interaction
Monteil(IE)	Trajectory data	Driver behaviour	IDM ²⁹ car-following model, EKF, real-time

Table: ITSC 2015: Advanced Vehicle Safety Systems (V-VIII)

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^{23}{}_{\mathsf{Expectation}}\,\,\mathsf{Maximization}
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²⁴ Dynamic Bayesian Network

 $²⁵_{\begin{subarray}{c}{\mathsf{Track-to-track}}\end{subarray}}$

^{26 (}Supervised) PCA

 $^{{}^{27}}_{\mathsf{Particle Swarm Optimization}}$

²⁸ Recursive Least Squares

Ref.	Sensor(s)	Task	Key concepts
Chen(TW)	Color cam	Rear light status	Symmetrical SURF, rear lamp response func., no thresh.
Takeuchi(JP)	3D LIDAR+maps	Blind area predict.	Residential areas, lane network info., particle filter
Köhler(DE)	Stereo cam	Pedestrian intention	Motion contour HoG descr., silhouettes, L-SVM
Fang(FR)	Color+LIDAR	Object tracking	Small region from pix., bidirectional region growth in las.
Gonçalves(TUM)	Eye+Kinect	Driver state	Emergency take over request, collision probability
Rajaram(ÙS)	Color cam	Pedestrian detect.	Analysis of state-of-the-art, strengths and limitations
Philipsen(DK)	Color cam	Traffic light rec.	Database, learning-based detect., integral channel feat.

Table: ITSC 2015: Advanced Vehicle Safety Systems (VIII-IX)

Ref.	Sensor(s)	Task	Key concepts
Rapp(DE) Raaijma.(Audi) Fernánd.(UAH) Rieken(DE) Driggs(US) Gan(CN)	Short rg. radars Camera Stereo cam LIDAR - Color cam	Localization Roundabouts Road detection Environ. model Driver intent Pre. vehicle det.	Urban, Monte-Carlo, grid-based Markov chain, Lvy process Roundab. geometry model, a priori map Decision trees class., 2D(texture,)+3D(normals,) featur. Perception-driven, lane detect., grid-based repres., tracking High level goals, labelled dataset of lane changes, classif. 4-dim mapping of colors, corners/edges feat., SVM, PSO
Noh(KR) Savastürk Bender(AU) Seeger(BMW)	LIDAR+pose IR+stereo GPS+IMU+CAN Stereo+LIDAR	Situation assesm. Vehicle detect. Driver intent Grid mapping	High-level fusion, prob. situation ass., local dynamic map Comparison study, stereo + mono IR sensor combination Intersections, predicting manoeuvres, QDA ³⁰ , driving data Multiple hypoth., evidential grid map., neighboring cells
Kumar(US) Bisoffi(IT) Rus(RO) Nguyen(VAG) Liu(GE)	Grayscale cam CAN Stereo Cam+LIDAR Driver cam	Speed lim. sign Driver intention Pedestrian rec. Markers detec. Face detection	Real-time, shape & intensity,task MSERs ³¹ , Kalman f., NN ³² Desired long. <i>jerk</i> (deriv. of accel.), Kalman f., scaling tec. Intensity, depth and flow feat., modality pertinence, L-SVM Detection, Kalman f., GMM, RANSAC road boundary est., Eyes occluded by shadow, driver intention, robust algorit.
Kopinski(GE) Costea(RO) Ramyar(US)	ToF Phone cam GPS+CAN	Hand gesture rec. Pedestrian detec. Driver behaviour	Depth data, MLPs ³³ , PCA, dynamic hand gestures Real-time, channel feat. based multiscale detect. scheme Intersect., Takagi-Sugeno fuzzy models, Gath-Geva cluster.

Table : ITSC 2015: Driver Assistance Systems

 $^{{\}bf 30}_{\textstyle {\bf Quadratic\ Discriminant\ Analysis}}$

 $[\]mathbf{31}_{\mathsf{Maximally Stable Extremal Regions}}$

³² Neural Network

³³ MultiLayer Perceptrons

Ref.	Sensor(s)	Task	Key concepts
Vasic(FR) Zhang(CN) Kehl(Daimler) Rapp(DE) Nilsson(DA) Belaroussi(FR) Asvadi(PT) Wenzel(Bosch) Karaimer(TR) Xie(BMW) Drage(AU) Vitor(BR) Schmidt(Audi)	LIDAR, GPS 3D LIDAR Stereo cam Short rg. radars LIDAR+cam Cam, map Laser, pose Phone cam Omnid. cam Multi-laser LIDAR Stereo cam Two cams	Multi-obj. track. Road bound. det. Road sign detect. Grid map Track fusion Fog model Object det&track. Addit. traffic sign Vehicle classif. Calibration Road edge detec. Semantic info. Lane bound. det.	GM-PHD ³⁴ filt., detect-beftrack, rect. shape, GCl ³⁵ fusion Double layer beam model, intersection shape recog., UGV HSL color segment., 3D sign geometry, temp. integration Group-wise grid map registration, graph-based approach Correlated inputs, comparison, state estimation accuracy Estimating visibility cond. from traffic sign information 2.5D grid/map, object-level represent., data ass. & Kalman f. Comparison, MSER-based approach ³⁶ , database Shape/gradient-based class., kNN, HOG, SVM, vehicle types Online extrinsic cal., planar checkerboard, noise, real-time Multi-layer LIDAR, orientation and position measurem. Semantic ctxt., evidential grids, Texton/Dipston maps, boost 3D model as consecutive linear segments, error model
Rummel.(FR) Smart(CA) Dierkes(DE)	LIDAR, CAN Stereo cam -	Occupancy grid Marking detect. Road representat.	Conditional Monte Carlo dense occupancy tracker Bird's Eye view, filtering bef. IPM ³⁷ , semi-supervised learning Uncertainty repres., multiple hypothesis, repres. language

Table: ITSC 2015: Sensing, Vision and Perception

³⁴ Gaussian Mixture Probability Hypothesis Density

 $^{{\}footnotesize \begin{array}{c} {\bf 35} \\ {\sf Generalized \ Covariance \ Intersection} \end{array}}$

 $^{{^{36}}}_{\text{Maximally Stable Extremal Regions}}$

 $^{{\}bf 37}_{\sf Inverse\ Perspective\ Mapping}$

Ref.	Sensor(s)	Task	Key concepts
Kataoka(JP)	Camera	Pedestrian intent.	Pedestrian activities class., DT ³⁸ recog., detection-based ROI
Shreve(Xerox)	Color cam	Static occlusion	Location of static occlusions to help well-known tracking alg.
Yalla(Toyota)	Color cam.	Ease of driving	Classification by Holistic Anal. of Scene Envir., machine learning
Sanberg(NL)	Stereo cam	Free-space segm.	Color-only stixel segment., real-time, based on slower disparity seg
Xu(Xerox)	Infras. cams	HOV ³⁹ lane	Overhead gantries or roadsile poles, front & rear seats, fusion
Van Gastel(NL)	Infras. cam	Pedestrian track.	Crowded scenes, occlusion handling, changes in motion pattern
Woudsma(NL)	Pano cam	Road mark, map	Learning, IPM, segmentation, MRF ⁴⁰ probab., traffic situations
Cui(CN)	Color cam	Taillights detect.	Daytime, veh. detec., candidates clustering, rear-light state

Table: ITSC 2015 Special Sessions: Computer V. and Imaging Sys. in Transportation



³⁸ Dense Trajectories

³⁹ High Occupancy Vehicle

⁴⁰ Markov Random Field

Ref.	Sensor(s)	Task	Key concepts
Di(CN)	Color cam	Road scene parsing	Nonparametric, spatial prior, previously observed histograms
Kawan.(JP)	Color cam	Pedestrian re-detec.	Distant pedestr., detec. from other vehicles, prior knowledge
Kellner(Audi)	Stereo cam.	Curb detec.	Position & orientation invariant, grid map, 3D polygonal chain
Fern.(UEM)	Color+laser	Urban hotspots	On-board perception, pre-collision system, event data recorder
Premebi.(PT)	LIDAR	Env. modelling	Pc. 41 sampling, spatial interp., polar-grid repres., Kriging pred
Delp(Toyota)	LIDAR	Object clas.&track.	Path planning, bicycles, real-time, anytime algorithm

Table: ITSC 2015 Special Sessions: Envir. Perception for Automated On-road Veh.



⁴¹ Point Cloud

Ref.	Sensor(s)	Task	Key concepts
Aeber.(BMW) Fu(CN)	Various LIDAR+Cam	Object class. Path planning	Type of an object, high-level fusion, Dempster-Shafer evidence th. Decision making for autonom. veh., GIS, structured road models
Jian(CN)	LIDAR, pose	SLAM	FastSLAM, STSRCDKF ⁴² , prop. distribution of the particle filter
Klingel.(DE) Ulbrich(DE)	GPS, CAN Various	Traject. predic. Behavior plan.	Intersect., context info., 5 s into future, probab. multiclass class. Assesment for lane changes, dyn. Bayesian net., unscented var. tf.
Kohl.(DE) Wang(CN)	- LIDAR	Maneuver plan. Semantic label.	Undest. of complex sit., behaviour gener., semantic scene model. Using pc. to label obi., Voxel-Neighbor Struc., RF clas., CRF ⁴³

Table: ITSC 2015: Automated Vehicle Operation, Motion Plan. and Navigation

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 $^{^{\}rm 42}{\rm Strong\ Tracking\ Square\ Root\ Central\ Difference\ Kalman\ filter}$

 $^{^{\}rm 43}_{\rm Conditional\ Random\ Fields}$

Ref.	Sensor(s)	Task	Key concepts
landola(US) Neum.(BMW) Kim(KR)	Color cam Stereo cam	HOG Computat. Free space detec. Bicv. collision av.	Energy/time-efficient HOG, reduced precision, SIMD parallelism Confidence estimation, semi-automatic ground truth Intersection/longitudinal collision, wireless access, simulation
Nguyen(Valeo)	Fisheye cam	Moving-static sep.	Optical-flow based 3D reconstr., moving object detect., efficient Uneven road surface detec., motion patterns, HMM class. model
Barn.(Hitachi)	Camera	Vehicle behavior	
Poggenh.(DE)	Stereo cam	Road markings	Charact., arrows, lines, crossings, histogram of width, OCR, ANN Safety-critical car-cyclist scenarios class., machine learning Beh. of pedestrians at crosswalks, model, features, relevance det.
Cara(NL)	Laser	Car-cyclist scen.	
Völz(Bosch)	LIDAR	Pedestr. behav.	

Table: ITSC 2015: Various sessions

Ref.	Sensor(s)	Task	Key concepts
Satzoda(US) Nanxi.(US) Higgs(US) Gahroo.(US) Wang(US) Hong(US) Guan(CA) Laftc.(US) Qiao(CN) Gallen(FR) Qu(CN) Töpfer(VAG) Attal(FR) Vatavu(RO)	Multiple Cam+CAN CAN+rad+ Trajectories EEG ⁴⁵ Accel., gyro. Laser IMU GPS Grey cam CAN, gyro. Camera Acc., gyro. Stereo cam	Drive analysis Driver distract. Driver behavior Inters. phases Driver distraction Inertial par. est. Road features Localization Trajectory pred. Night fog Driver model Scene underst. Riding pattern Object track.	NDSs ⁴⁴ , data reduction, extracting semantic info., lane semantics Drivers' behav. with visual/cognit. distractions, feat., binary clas. Link driv. states to driv. actions, seg.&clus. of driving beh. Baum-Welch/Bayesian learning, Dirichlet prior, Viterbi inference Predict distraction (map viewing) using brain activity Four-wheel nonlinear vehicle, roll dynam., dual unscented Kalman f. Road curbs from a set of profiles, road markings, cracks Loc. using terrain data, lineal dyn. model encoding, bank of models Hidden Markov model-based Trajectory Prediction, parameter selec. Night visibility index, presence of night fog, correlation idx., halos SMPC ⁴⁶ , driver steering skills, mimic driver's perception Estimation of topolog., hierarchical model, nonparam. belief prop. Machine-learning, database, GMM, HMM Crowded env., occ. grid, free-from object delimiters, particle f.



⁴⁴ Naturalistic Driving Studies

⁴⁵ Electroencephalographic signals

 $^{{\}rm 46}_{\rm Stochastic\ Model\ Predictive\ Control}$

Ref.	Sensor(s)	Task	Key concepts
Salmane(FR) Kim(SG)	Infras. cam LIDAR, cam	Level crossings Cooperat. perc.	Smart video surveillance, tracking, HMM, Dempster-Shafer Multimodal coop., see-through, lifted-seat/satellite/all-around views
Peng(CN)	Grey cam	Logo recogn.	Poor quality, SRSD ⁴⁷ feat., multiscale scanning locat&class.
Seo(CMÚ)	Color cam	Workzone recog.	ld. of workzone signs, boundaries of workz., driving cond. changes
Zhang(DE)	Color cam	Pedestrian detec.	Statistic. model upright human body, head/upper/lower, Haar-like
Yu(CN)	Camera	Pedestr. detec.	Variab. handling, heterogeneous feat., HOG LBP ⁴⁸ , MVPPE ⁴⁹ det.
Guo(CN)	MMW ⁵⁰ rad.	Road edge rec.	Stripe Hough Transform, extraction of the geometry of road path
Wu(SG)	Stereo cam	Road surface	Nonparametric, depth cue, road scene attrib., planar/nonplanar
Gaikwad(IN)	Grey cam	Lane departure	PLSF ⁵¹ contrast impr., Hough t., params. based on Euclidean dist.
Shiau(TW)	Color cam	Illumin. adjust.	Low-cost, efficient algorithm & HW architecture
Iryo(JP)	Infras. cam	Pedestr. behav.	Prob. beh. of pedestrians on flashing green, Monte Carlo simulation
Miseik.(NO)	Cameras	Pedestr. detec.	Joint mobile and static cameras, automated industrial vehicles
Jiang(CN)	-	Pedestr. beh.	TTC ⁵² , differences between driving cultures, midblock crosswalks

 $^{{\}bf 47}_{\sf Statistical\ Random\ Sparse\ Distribution}$

⁴⁸ Local Binary Pattern

⁴⁹ Multi-view-pose part ensemble

⁵⁰ Milimiter-wave

 $^{^{51}}_{\rm Piecewise\ Linear\ Stretching\ Function}$

 $^{^{52}}_{\rm Time\ To\ Collision}$

Ref.	Sensor(s)	Task	Key concepts
Mouats(GB) Desira.(US)	Stereo vis&therm	Visual odometry Lane change	Log-Gabor feat., cosine similarity, Pyramidal Lucas-Kanada track. Minimizing the disruption of traf. flow, V2V, V2I
Almag.(US) Zhang(CN) Zou(JP)	Color cam Stereo cam Cameras	Traffic lights Speed control Calibration	CVD ⁵³ , traffic light standards, fail-safe mechanisms, 400ft Obstacle det. & track., particle filter, sparse repres., control alg. Nonoverlapping cams., laser pointer, coplanar/colinear meth.
Green.(GB)	Color cam	Traffic signs	Text-based signs, MSERs ⁵⁴ , HSV thresh., OCR, temporal info.
Mora(UJI) Yu(TW) Suhr(KR) Kim(KR) Brown(US)	- Infras. cam Stereo cam Rad.+cam Cam+gyro+map	Path planning Scene detect. Road profile Situation ass. Vehicle state	PFP ⁵⁵ , Lagrange-Euler formulation, control inputs, real time Det. rain+night, traffic flow, salient region det., block seg., SVM Cubic B-spline, piecewise linear function, Hough t., dynamic prog. Track-to-track fusion, curvilinear coord. conv., lane assesment Theoretical estimator performance, steady-state Kalman f.



⁵³ Color Vision Deficiency

 $^{{\}small 54}_{\small Maximally\ Stable\ Extremal\ Regions}$

 $^{{\}bf 55}_{\sf Potential\ Field\ Projection}$

Ref.	Sensor(s)	Task	Key concepts
Guo(Toyota)	Stereo cam	Situat. awar.	Unmarked roads, road bound., vehicles, contextual infor., precrash
Malik(AU)	Various	Driving maneuv.	Fuzzy logic, intelligent driver training system, safety rules
Tanig.(JP)	CAN	Driver behav.	Unsuperv. learning, DAA ⁵⁶ with temporal predic., driving context
Nilsson(SW)	CAN	Driver capabilit.	Assesing when the control can be safe. transferred to the driver
Bresson(FR)	Cam+odom.	SLAM	Monocular SLAM, EKF, minimal Cartesian repr., avoid. lineariz. fail.
Flohr(DE)	Stereo cam	Pedestr. orient.	Joint estimat. of head and body orient., prob. density funct., part. f.
Fortin(FR)	Laser	Veh. det&track.	No detection step, Monte Carlo, geometr. invariant, multitarget
Lee(TW)	NIR cam	Pedestrian det.	Nighttime, IR projector, part-based, block-based segmentation
Huang(CN)	Camera	Logo recog.	CNN, no precise detection or segment. required, pre-training strategy
Ma(CN)	-	Motion plann.	RRT ⁵⁷ , rule-template set, extension of search tree, model-based pred.
Guo(TW)	Camera	Vehicle verif.	Feat. descr., conf. hypothesis, CT ⁵⁸ subbands, GGD ⁵⁹ , MLE ⁶⁰
Shim(KR)	L.+cam	Auton. driving	Unified Map built with onboard sensors, path planner, commercial
Vicen.(CMU)	Camera	Gaze/distract.	EOR ⁶¹ , facial track., head pose, gaze est., 3D geom. reasoning
Math.(GB)	Camera	Road marking	Reading rules encoded in road mark., RUSBoost, CRF ⁶² , semantics
Bosetti(IT)	IMU+GPS	Curve behavior	Longitud. speed that ought be used to drive on curvy roads, model
Agostin.(FR)	CAN, GPS	Driv. events	Learning-based, database, discrim. feat., decis. trees, logistic regres.

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Double Articulation Analyzer

⁵⁷ Rapidly Exploring Random Tree

 $^{{}^{58}}_{\text{Curvelet-Transformed}}$

 $^{{\}footnotesize \begin{array}{c} {\rm 59} \\ {\rm Generalized \ Gaussian \ Distribution} \end{array}}$

⁶⁰ Maximum Likelihood Estimation

Ref.	Sensor(s)	Task	Key concepts
Yu(CN)	Laser	Urban facil.	Street light poles, traffic signposts, voxel-based growing, 3D matching
Wang(CN)	V&I info.	Danger eval.	Driver-vehicle-road interact., driving safety field, risk eval., traffic factors
Dong(CN) Negru(RO)	Infr. cam	Vehicle type	Semi-supervised CNN, frontal-view, Laplacian filter, softmax, feat. learning Contrast restoration in fog conditions, math. model, diff. geometry field
Li(CN)	Camera Infr. cam	Image enh. Vehicle detec.	Multiscale AND-OR graph, inference process, global/local feat., appear.
Wulf(Bosch)	inir. cam	HMI	Driver's situation awareness, driving safety, simulator, head-up display
Mercado(NL)	_	Obstac. int.	Velocity obstacle (VO) representation, trai, prediction err.

Table: ITS Trans. vol. 16, num. 4 (II)

Ref.	Sensor(s)	Task	Key concepts
Mukhtar(MY)	Review	Vehicle det.	Vision-based vehicle detection for collision avoidance systems
Askel.(NO)	Radar	Veh. track.	Waveform solving, 2D APES estimator, track a laterally moving veh.
Tak(KR)	In-veh+V2V	Safety meas.	Rear-end collision risk, deceleration-based surrogate safety measure
Guan(CN)	LIDAR	Road markings	Automated road marking inventory, 2D GRF ⁶³ images from 3D
Luzheng(CN)	-	Control model	Driver's neuromuscular dyn., QN ⁶⁴ -based driver lateral ctrl. model
Ohn-Bar(US)	Camera	Veh. detect.	Intracategory diversity, visual/geom. clusters, AdaBoost, orientation
Xu(CN)	CAN	Driver models	Style-oriented driver model for speed control, vehicle test data (VTD)
Kosaka(JP)	Color cam.	Veh. detect.	Nigth, headlights/taillights, LoG, Center Surround Extremas, SVM
Rezaei(IR)	Camera	Veh. detect.	Global Haar-line feat., tail-light, visual symmetry, intervehicle distance
Yoon(KR)	-	Path planning	Reduced states of search space, kinematics-aware node expansion
Gao(CN)	Cam+depth	Pedestr. track.	Multipedestrian, detection in RGB, 3D motion/app./depth feat.
Zou(CN)	Infr. cam	Veh. detect.	Nighttime, headlights, AdaBoost, grouping/track., maximal indp. set
Chen(CN)	-	Veh. control	Tracking a ref. path, hierarchical, three layers, Lyapunov function
Hu(CN)	Infr. cam	Veh. color	Vehicle color recognition, spatial pyramid deep learning, CNN
Cao(CŃ)	Stereo cam	Path plann.	Local disp. map, V-intercept slope, obst. detect., path planning, A*



⁶³ Georeferenced Feature

⁶⁴ Queuing Network

Topics: putting things in perspective

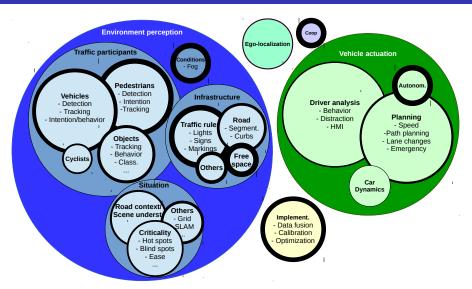


Figure: Topics at ITSC 2015 and ITS Transactions vol. 16. Source: own work

4 0 1 4 4 4 5 1 4 5 1

Plan

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Let's start with basics



Figure : Intelligent Vehicle based on Visual Information 2.0⁶⁵

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⁶⁵ David Martín et al. "IVVI 2.0: An intelligent vehicle based on computational perception". In: Expert Systems with Applications 41.17 (Dec. 2014), pp. 7927-7944. ISSN: 09574174. DOI: 10.1016/j.eswa.2014.07.002. URL: http://www.sciencedirect.com/science/article/pii/S0957417444003947%20http:

Environment perception: sensors (I)



Figure: Stereo-vision system

- Depth estimation is straightforward
- Lots of labelled data available in the KITTI dataset
- Rigorous groundtruth based on their Velodyne LIDAR

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Environment perception: sensors (II)



Figure: Expected scenes from stereo and lateral cameras

- **Prolongation** of the field of view (HFOV $\sim 152^{\circ}$)
- Depth estimation is not straightforward
- No labelled data or groundtruth available

Environment perception: sensors (and III)

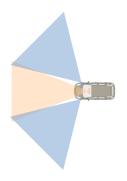


Figure: Joint horizontal field of view with the new cameras

- **Prolongation** of the field of view (HFOV $\sim 152^{\circ}$)
- **Depth** estimation is not straightforward
- No labelled data or groundtruth available

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Vehicles today: ability to make autonomous decisions

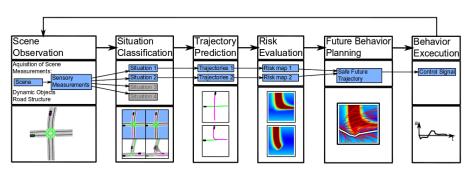


Figure: General approach for situation based risk evaluation and behavior planning⁶⁶

⁶⁶ Florian Damerow and Julian Eggert. "Risk-Aversive Behavior Planning under Multiple Situations with Uncertainty". In: Proc. IEEE International Conference on Intelligent Transportation Systems. 2015, pp. 656–663. ISBN: 9781467365963. DOI: 10.1109/ITSC.2015.113.

Traffic scene understanding (I)

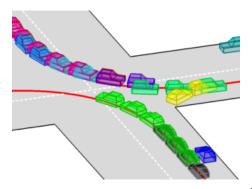


Figure : Inference: Scene Layout and Objects (Result)⁶⁷

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⁶⁷Andreas Geiger. "Probabilistic Models for 3D Urban Scene Understanding from Movable Platforms". Ph.D. dissertation. Karlsruher Institut für Technlogie. 2013

Traffic scene understanding (II)



Figure: Intersection scenario⁶⁸

⁶⁸ Andreas Geiger and Bernd Kitt. "Object flow: A descriptor for classifying traffic motion". In: *Proc. IEEE Intelligent Vehicles Symposium*. 2010, pp. 287–293. ISBN: 9781424478668. DOI: 10.1109/IVS.2010.5548122.

Traffic scene understanding (III)



Figure: Intersection from a Lane Detector's Point of View⁶⁹

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⁶⁹ Andreas Geiger. "Probabilistic Models for 3D Urban Scene Understanding from Movable Platforms". Ph.D. dissertation. Karlsruher Institut für ∃echnlogie, ≥2013 ≥

Traffic scene understanding (III)



Figure : Intersection from a Lane Detector's Point of View⁶⁹



Figure: Intersection from a Human's Point of View

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⁶⁹ Andreas Geiger. "Probabilistic Models for 3D Urban Scene Understanding from Movable Platforms". Ph.D. dissertation. Karlsruher Institut für Jechnogie, 2013

Traffic scene understanding (and IV)

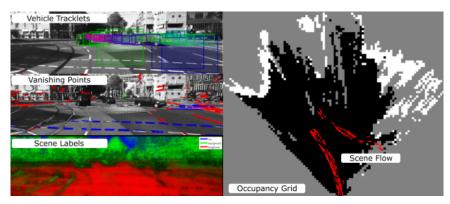


Figure: Video-based Image Cues (Inputs)⁷⁰

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⁷⁰Andreas Geiger. "Probabilistic Models for 3D Urban Scene Understanding from Movable Platforms". Ph.D. dissertation. Karlsruher Institut für ∃echnlogie, ≥2013 ≥

Situation assessment (I)

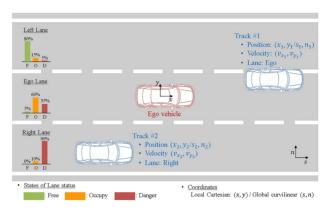


Figure: Example of object and situation assessment⁷¹

⁷¹ Junsoo Kim et al. "Curvilinear-Coordinate-Based Object and Situation Assessment for Highly Automated Vehicles". In: IEEE Transactions on Intelligent Transportation Systems 16.3 (2015), pp. 1559–1575.

Situation assessment (and II)

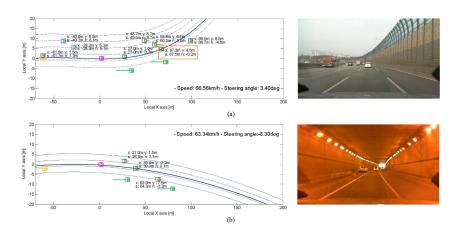


Figure : Object assessment result in curved road cases⁷²

⁷²Junsoo Kim et al. "Curvilinear-Coordinate-Based Object and Situation Assessment for Highly Automated Vehicles". In: *IEEE Transactions on Intelligent Transportation Systems* 16.3 (2015), pp. 1559–1575.

Situation awareness pipeline

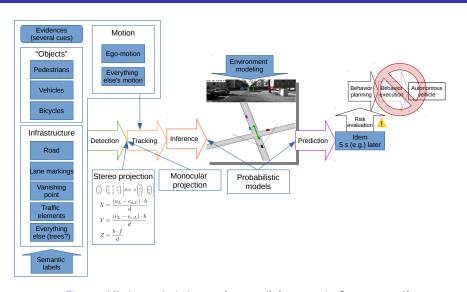


Figure: Mind map depicting my (expected) future work. Source: myself

But... is behavior planning so far away? $(I)^{73}$



Red Physical road boundary

Yellow/Cyan Virtual lane markings

Blue Suggested path

Green Virtual emergency lane

Figure: Example results

⁷³Chunzhao Guo et al. "A Multimodal ADAS System for Unmarked Urban Scenarios Based on Road Context Understanding". In: *IEEE Transactions on Intelligent Transportation Systems* 16.4 (2015), pp. 1690–1704.

But... is behavior planning so far away? (and II)⁷⁴

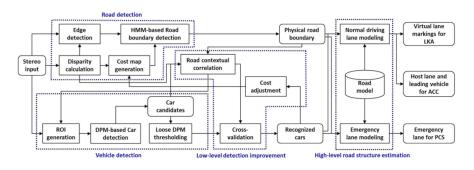


Figure: Flow diagram of the system

⁷⁴Chunzhao Guo et al. "A Multimodal ADAS System for Unmarked Urban Scenarios Based on Road Context Understanding". In: IEEE Transactions on Intelligent
Transportation Systems 16.4 (2015), pp. 1690–1704.

Objects & Context: a chicken-and-egg problem (I)

"We recognize a car because it's on the road. But how do we recognize a road? — because there are cars!" ⁷⁵

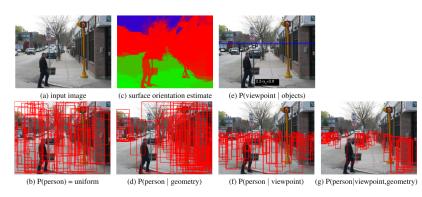


Figure : Pedestrian detection with/without evidences

⁷⁵ Derek Hoiem, Alexei A. Efros, and Martial Hebert. "Putting objects in perspective". In: International Journal of Computer Vision 80.1 (2008), pp. 3–15. ISSN: 09205691. DOI: 10.1007/s11263-008-0137-5.

Objects - Context: a chicken-and-egg problem (and II)

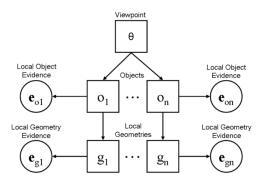
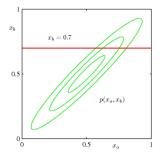
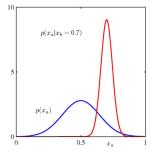


Figure : Graphical model of conditional independency for viewpoint, object identities and the 3D geometry of surfaces surrounding the objects 76

⁷⁶Derek Hoiem, Alexei A. Efros, and Martial Hebert. "Putting objects in perspective". In: *International Journal of Computer Vision* 80.1 (2008), pp. 3–15. ISSN: 09205691. DOI: 10.1007/s11263-008-0137-5.

Managing uncertainty: probabilistic theory (I)

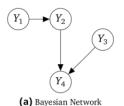


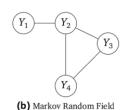


joint, marginal, conditional probability

Figure: Illustration of joint, marginal and conditional probabilities

Managing uncertainty: probabilistic theory (and II)





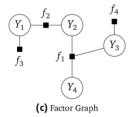


Figure: Graphical models

Managing uncertainty: a toy example

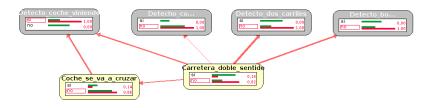


Figure: Toy Bayes Network with UNED's ELVIRA software

Managing uncertainty: a real example⁷⁷

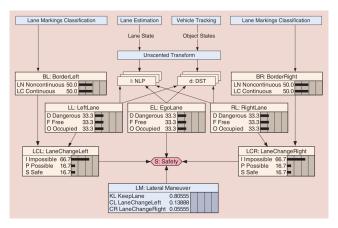


Figure: Bayesian network with chance nodes (ocher), a utility node (red), and a decision node (blue) for deriving lane change maneuver decisions.

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Plan

- Compilation of recent scientific publications
 - Key resources
 - Compilation of ITSC 2015 and ITS Trans. 2015 papers
 - Summary of topics
- 2 My research interests
 - Basic considerations
 - Problem formulation
 - Proposed approach
- State-of-the-art technologies
 - Object detection

Situation awareness pipeline (again)

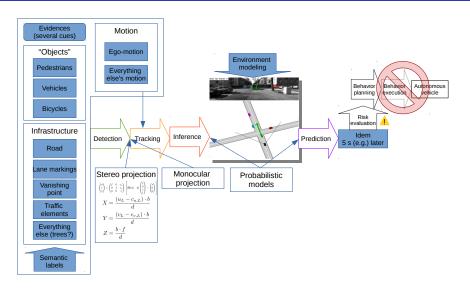


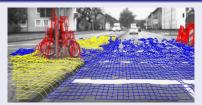
Figure: Mind map depicting my (expected) future work. Source: myself

Obstacle detection using stereo vision (I)

Probabilistic occupancy maps: Stixel world



Digital elevation maps: distance from the road surface

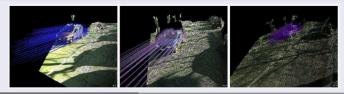


Obstacle detection using stereo vision $(and II)^{78}$

Scene flow segmentation: 6D vision - each 3D point is tracked



Geometry-based cluster



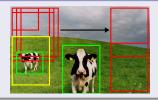
⁷⁸Nicola Bernini et al. "Real-time obstacle detection using stereo vision for autonomous ground vehicles: A survey". In: *Proc. IEEE International Conference on Intelligent Transportation Systems*. 2014, pp. 873–878. ISBN: 978-1-4799-6078-1. DOI: 10.1109/ITSC.2014.6957799.

Object detection methods (I)

Feature-based methods: Implicit shape model



Sliding-window-based methods: Viola-Jones, Dalal-Triggs, DPM



Object detection methods (II)

Proposal Regions + complex predictor (CNN)

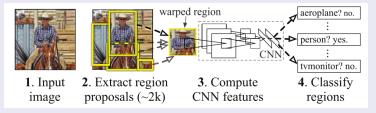


Figure: R-CNN: object detection system overview^a

^aRoss Girshick et al. "Region-based Convolutional Networks for Accurate Object Detection and Segmentation". In: *Proc. IEEE Conference on Computer Vision and Pattern Recognition*. 2014, pp. 580–587. ISBN: 978-1-4799-5118-5. DOI: 10.1109/TPAMI.2015.2437384.

What is happening in object detection? (I)

Deep Learning is leading to large improvements

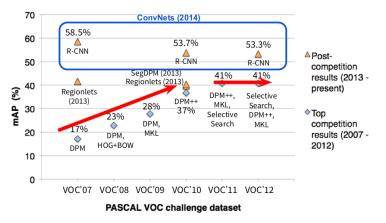


Figure: PASCAL Visual Object Classes Challenge - Results

What is happening in object detection? (II)

But recently, the Convolutional Neural Networks (CNNs) [50] have achieved better accuracy results than BoW. These networks have a more sophisticated structure than standard representations, comprising several layers of non-linear feature extractors. That is the reason they are called deep, in contrast with classical representation that are called shallow. Their structure is handcrafted and they contain a very large number of parameters learnt from data. CNN have demonstrated their performance [22][31][65][71][76], which is significantly better than standard image encodings [9], when they have been applied to standard image classification and object detection benchmark datasets such as ImageNet ILSVRC [20] and PASCAL VOC [25].

Figure : Fidalgo Fernández, Eduardo. Ph. D. dissertation. Universidad de León.

But... what is a CNN? What is Deep Learning?

A CNN is a **special case** of a Multi-Layer-Perceptron.

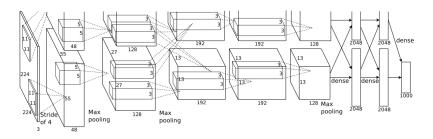


Figure: "Alexnet" Convolutional Neural Network⁷⁹

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⁷⁹Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: *Advances In Neural Information*Processing Systems. 2012, pp. 1097–1105. ISBN: 978162748003 arXiv: 1102.0183.00

So... why is everybody so excited?



Figure: Convolutional Neural Network

- All the way from pixels to classifier is learned
- One layer extracts features from output of previous layer
- Features are no longer hand-crafted!
- Not everything is happy: CNN are slow unless they use GPU and...
 we really don't know what they do.

An approach for object classification (I)

R-CNN: Regions with CNN features

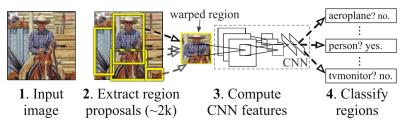


Figure: R-CNN: object detection system overview⁸⁰

December 16, 2015

⁸⁰Ross Girshick et al. "Region-based Convolutional Networks for Accurate Object Detection and Segmentation". In: Proc. IEEE Conference on Computer Vision and Pattern Recognition. 2014, pp. 580-587. ISBN: 978-1-4799-5118-5. DOI: 10.1109/TPAMI.2015.2437384.

An approach for object classification (II)

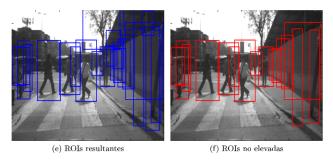


Figure: Dr. Musleh's approach for obstacle detection⁸¹

- Objects are supposed to be homogeneous in its disparity value.
- Sub-pixel accuracy obtained by SGBM is completely wasted.

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An approach for object classification (III)

Another approach: selective search⁸² segmentation - Very Slow!



Figure : Object proposal from edges

⁸² J. R R Uijlings et al. "Selective search for object recognition". In: International Journal of Computer Vision 104.2 (2013), pp. 154–171. ISSN: 09205691. DOI: 10.1007/s11263-013-0620-5.

An approach for object classification (IV)

One more approach:

- Object proposals from edges
- Fast edge detection with structured forests⁸³. Color or color+depth information can be used!



Figure : Object proposal from edges

http://www.mendeley.com/catalog/structured-forests-fast-edge-detection/10 Carlos Guindel (UC3M)

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⁸³Piotr Dollar and C. Lawrence Zitnick. "Structured Forests for Fast Edge Detection". In: *Proc. IEEE International Conference on Computer Vision*. 2013, pp. 1841–1848. ISBN: 978-1-4799-2840-8. DOI: 10.1109/ICCV.2013.231. arXiv: arXiv:1406.5549v1. URL:

An approach for object classification (and V)

Results (check videos):

- Default training for VOC Pascal classes! (own training has not been performed yet)
- No depth information
- Using the smallest net (because of Tesla restrictions)
- Classification (CNN) running on GPU with a MATLAB wrapper.
 Disparity running on OpenCV with a MATLAB wrapper. Everything else running on MATLAB.
- Times:
 - Edges: 180 ms (MATLAB)
 - Boxes: 230 ms (MATLAB)
 - Classification: 140 ms (with thousands of region proposals)
- OpenCV 3.0 has a new function for structured-forest edges.

Situation awareness pipeline (again)

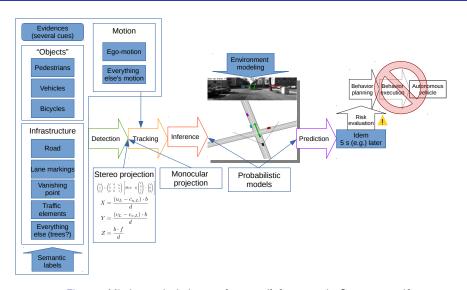


Figure: Mind map depicting my (expected) future work. Source: myself

Motion: "scene flow"

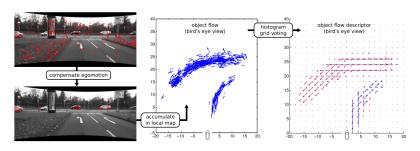


Figure: Scene flow overview84

⁸⁴ Andreas Geiger and Bernd Kitt. "Object flow: A descriptor for classifying traffic motion". In: *Proc. IEEE Intelligent Vehicles Symposium*. 2010, pp. 287–293. ISBN: 9781424478668. DOI: 10.1109/IVS.2010.5548122.

Road detection⁸⁵

- Image preprocessing. Obstacles can be removed, shadows weakened, image area truncated, etc.
- Feature extraction. Color and texture statistics for road segmentation, road patch classification or curb detection. Evidence for lane marks for lane detection.
- Road/lane model fitting. A road and lane hypothesis is formed by fitting a road/lane model to the evidence gathered.
- **Temporal integration**. The road and lane hypothesis is reconciled with road/lane hypotheses from the previous frame.

^{**}SAharon Bar Hillel et al. "Recent progress in road and lane detection: a survey". In: Machine Vision and Applications 25.3 (2014), pp. 727–745. ISSN: 09328092. DOI: 10.1007/s00138-011-0404-2.

The End