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M.Sc. Matthias Schreier,
Darmstadt

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Bayesian Environment Representation, Prediction, and Criticality Assessment for Driver Assistance Systems

Berichte aus dem

Institut für
Automatisierungstechnik
und Mechatronik
der TU Darmstadt

Bayesian Environment Representation, Prediction, and Criticality Assessment for Driver Assistance Systems

Vom Fachbereich
Elektrotechnik und Informationstechnik
der Technischen Universität Darmstadt
zur Erlangung des akademischen Grades
eines Doktor-Ingenieurs (Dr.-Ing.)
genehmigte Dissertation

von

Matthias Schreier, M.Sc.

geboren am 30. Dezember 1985 in Schweinfurt

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This work deals with the questions i) how to represent the driving environment in an environment model, ii) how to obtain such a representation, and iii) how to predict the traffic scene for criticality assessment. Bayesian inference provides the common framework of all designed methods. First, Parametric Free Space (PFS) maps are introduced, which compactly represent the vehicle environment in form of relevant, drivable free space while suppressing irrelevant details of common occupancy grids. They are obtained by a novel method for grid mapping and tracking in dynamic environments. In addition, a maneuver-based, long-term trajectory prediction and criticality assessment system is introduced together with the Time-To-Critical-Collision-Probability (TTCCP) metric for uncertain, multi-object driving situations. Finally, the Advanced Driver Assistance System (ADAS) PRORETA 3 is described, which constitutes an integrated approach to collision avoidance and vehicle automation.

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Preface

This dissertation is the result of my work at the Control Methods and Robotics Lab of the Institute of Automatic Control and Mechatronics, TU Darmstadt. It was embedded in the PRORETA 3 project – a research cooperation with Continental.

At first, I want to thank my supervisor Prof. Jürgen Adamy for his support in all matters. He provided a very pleasant working climate in his lab with great freedom to develop and realize own ideas. I am also grateful to Prof. Hermann Winner for his acceptance to act as a second referee and his motivating and constructive feedback in the PRORETA meetings.

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Last but not least, there are my parents to be grateful to. They always supported me in all my decisions and showed exceptional interest in everything I did. The same holds for Marina, whom I deeply thank for her extensive support and understanding in all matters.

Darmstadt, in September 2015 Matthias Schreier

On voit par cet Essai, que la théorie des probabilités n'est au fond, que le bon sens réduit au calcul.

Pierre-Simon Laplace

Contents

Abbreviations and Symbols

Abbreviations

ADAS	Advanced Driver Assistance System
AFFP	Accelerator Force Feedback Pedal
BBF	Binary Bayes Filter
BN	Bayesian Network
BOF	Bayesian Occupancy Filter
CA	Constant Acceleration; Cooperative Automation
CAS	Collision Avoidance System
CCP	Critical Collision Probability
CPHD	Cardinalized Probability Hypothesis Density
CPT	Conditional Probability Table
CTRA	Constant Turn Rate and Acceleration
CTRV	Constant Turn Rate and Velocity
CV	Constant Velocity
DATMO	Detection and Tracking of Moving Objects
DBF	Discrete Bayes Filter
DBN	Dynamic Bayesian Network
DBSCAN	Density Based Spatial Clustering for Applications with Noise
EKF	Extended Kalman Filter
FN	False Negative
FP	False Positive
FR	Follow Road
FV	Follow Vehicle
GNNF	Global Nearest Neighbor Filter
GPB	Generalized Pseudo-Bayesian
HF	Histogram Filter
HMI	Human Machine Interface
HMM	Hidden Markov Model
IF	Information Filter
IMM	Interacting Multiple Model

IMM-PDAF	Interacting Multiple Model Probabilistic Data Association Filter
IMM-UK-PDAF	Interacting Multiple Model Unscented Kalman Probabilistic Data Association Filter
JPDAF	Joint Probabilistic Data Association Filter
KF	Kalman Filter
LAT	Lateral Motion
LC	Lane Change
LE	Lane Existence
LGS	Linear Gaussian System
LON	Longitudinal Motion
MAP	Maximum A Posteriori
MHT	Multi Hypothesis Tracking
MMSE	Minimum Mean Square Error
NNSF	Nearest Neighbor Standard Filter
$\mathrm{OE}_{\mathrm{fro}}$	Object Existence in front
OpenGL	Open Graphics Library
PDA	Probabilistic Data Association
PDAF	Probabilistic Data Association Filter
PDF	Probability Density Function
PF	Particle Filter
PFS	Parametric Free Space
PMD	Predicted-Minimum-Distance
PMF	Probability Mass Function
PSD	Power Spectral Density
RBPF	Rao-Blackwellized Particle Filter
SA	Situation Awareness
SC	Safety Corridor
SLAM	Simultaneous Localization and Mapping
SLAMMOT	Simultaneous Localization, Mapping, and Moving Object Tracking
TB	Target Brake
TE	Turn Existence
TLC	Time-To-Line-Crossing
TN	True Negative
TP	True Positive
TPMD	Time-To-Predicted-Minimum-Distance
TR	Trash maneuver class
TTB	Time-To-Brake
TTC	Time-To-Collision

TTCCP	Time-To-Critical-Collision-Probability
TTK	Time-To-Kickdown
TTO_{fro}	Time-To-Object in front
TTR	Time-To-React
TTS	Time-To-Steer
TTU	Time-To-Turning
TTX	Time-To-X
TU	Turn
UKF	Unscented Kalman Filter
VSMM	Variable Structure Multiple Model

Notation

x	Scalar
$\hat{x}$	Estimated quantity
$\hat{x}^{\text{B}}$	Bayesian point estimate
$\hat{x}^{\text{M}}$	MMSE estimate
$\hat{x}^{\text{MAP}}$	MAP estimate
$\hat{x}_k^-$	Quantity predicted to time step k
$\tilde{x}$	Sample drawn from a distribution with pdf $p(x)$
$\dot{x}$	Time derivative of x
$\boldsymbol{x}$	Column vector
$\boldsymbol{x}^T$	Row vector
$\boldsymbol{x}_{0:k}$	Sequence of vectors $\boldsymbol{x}_{0:k} = \{\boldsymbol{x}_0, \boldsymbol{x}_1, \ldots, \boldsymbol{x}_{k-1}, \boldsymbol{x}_k\}$
$\{\boldsymbol{x}_i\}_{i=1}^N$	Set of N vectors
$\boldsymbol{\mathcal{X}}$	Set of vectors ordered column-wise in matrix form
$\boldsymbol{X}$	Matrix
$\boldsymbol{X}^T$	Transpose of matrix $\boldsymbol{X}$
$\boldsymbol{X}^{-1}$	Inverse of matrix $\boldsymbol{X}$
$\lvert\boldsymbol{X}\rvert$	Determinant of matrix $\boldsymbol{X}$
$\sqrt{\boldsymbol{X}}$	Matrix square root of $\boldsymbol{X}$ of the form $\boldsymbol{X} = \sqrt{\boldsymbol{X}}\sqrt{\boldsymbol{X}}^T$
$\boldsymbol{X} \succ \mathbf{0}$	Matrix $\boldsymbol{X}$ is symmetric and positive definite
$\boldsymbol{X} \prec \mathbf{0}$	Matrix $\boldsymbol{X}$ is symmetric and negative definite
$\boldsymbol{X} \oplus \boldsymbol{x}$	Addition of the vector $\boldsymbol{x}$ to each column of matrix $\boldsymbol{X}$
$\mathbf{0}$	Zero vector or matrix
$\emptyset$	Empty set
$\mathbb{1}$	Identity vector or matrix

$\mathrm{diag}(\cdot)$	Diagonal matrix with $\mathrm{diag}(x_1, \ldots, x_n) = \begin{pmatrix} x_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & x_n \end{pmatrix}$
$\mathbb{E}(\cdot)$	Expectation operator
$\int_{\boldsymbol{x}}(\cdot)\mathrm{d}\boldsymbol{x}$	Integration over the whole range of $\boldsymbol{x}$, e.g. if $\boldsymbol{x} \in \mathbb{R}^n$, then $\int_{\boldsymbol{x}}(\cdot)\mathrm{d}\boldsymbol{x} = \int_{\mathbb{R}^n}(\cdot)\mathrm{d}\boldsymbol{x}$
$f(\cdot)$	Scalar function
$\boldsymbol{f}(\cdot)$	Vector function
$\frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}}$	Derivative of a scalar function $f(\boldsymbol{x})$ with respect to $\boldsymbol{x} \in \mathbb{R}^n$ in denominator layout with $\frac{\partial f(\boldsymbol{x})}{\partial \boldsymbol{x}} = (\frac{\partial f(\boldsymbol{x})}{\partial x_1} \ldots \frac{\partial f(\boldsymbol{x})}{\partial x_n})^T$
$\frac{\partial \boldsymbol{f}(\boldsymbol{x})}{\partial \boldsymbol{x}}$	Jacobian matrix of a vector function $\boldsymbol{f}(\boldsymbol{x})$
$p(x)$	Pdf of a continuous random variable x
$p(\boldsymbol{x})$	Pdf of a continuous random vector $\boldsymbol{x}$
$p(X)$	Pmf of a discrete random variable X; For binary X: Probability that X is true
$p(\neg X)$	For binary X: Probability that X is false
$p(X_j)$	Probability that a discrete random variable X is in state j: $p(X_j) = p(X = j)$
$p(\boldsymbol{x}, \boldsymbol{y})$	Joint pdf of $\boldsymbol{x}$ and $\boldsymbol{y}$
$p(\boldsymbol{x}\|\boldsymbol{y})$	Conditional pdf of $\boldsymbol{x}$ given $\boldsymbol{y}$
$p(X\|Y)$	Conditional pmf of X given Y written as a CPT

Important Functions and Transformations

$\Gamma(\cdot)$	Gamma function
$\delta(\cdot)$	Dirac delta distribution
$\boldsymbol{f}(\cdot)$	System function
$\boldsymbol{h}(\cdot)$	Measurement function
$I_{\mathrm{C}}(\cdot)$	Collision indicator function
$l(\cdot)$	Log odds ratio
$L(\cdot)$	Loss function
$\mathcal{L}^{-1}(\cdot)$	Inverse Laplace transformation
$\mathcal{N}(\boldsymbol{x}; \boldsymbol{\mu}, \boldsymbol{P})$	Multivariate Gaussian pdf of a random vector $\boldsymbol{x}$ with mean $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{P}$

$p(\boldsymbol{x}_k \mid \boldsymbol{z}_{1:k})$	Filtering distribution
$p(\boldsymbol{x}_k \mid \boldsymbol{x}_{k-1})$	Transition density
$p(\boldsymbol{z}_k \mid \boldsymbol{x}_k)$	Measurement likelihood
$p(X \mid \boldsymbol{z}_k)$	Inverse sensor model

Symbols

Latin Capital Letters

$A_{\mathrm{b,min}}$	Area of minimum oriented bounding rectangle
A_{f}	Area of newly free rectangle
A_{h}	Area of free space hole
A_{o}	Area of newly occupied rectangle
A_{th}	Threshold on area quotient in merging step
$\boldsymbol{A}$	System matrix of a discrete-time system
$\boldsymbol{A}_{\mathrm{c}}$	System matrix of a continuous-time system
$B(s)$	B-spline basis function with curve parameter s
$\boldsymbol{B}$	Input matrix of a discrete-time system
$\boldsymbol{B}_{\mathrm{c}}$	Input matrix of a continuous-time system
$C_{\mathrm{I},k}(T_{\mathrm{P}})$	Collision event for time instant $k + T_{\mathrm{P}}$
$C_k(T_{\mathrm{P}})$	Combined collision event for prediction horizon $\{k : k + T_{\mathrm{P}}\}$
$C_{\mathrm{PFS},k}(T_{\mathrm{P}})$	Collision event for prediction horizon $\{k : k + T_{\mathrm{P}}\}$ with respect to PFS map
$C_{\mathrm{V}_i,k}(T_{\mathrm{P}})$	Collision event for prediction horizon $\{k : k + T_{\mathrm{P}}\}$ with respect to i-th vehicle
$\boldsymbol{C}$	Cross covariance matrix between predicted measurements and states
$\mathcal{D}_{\mathcal{S}}(\mathcal{F}')$	Dilated set of $\mathcal{F}'$ with structuring element $\mathcal{S}$
E	Ego vehicle
$\mathcal{E}_{\mathcal{S}}(\mathcal{F})$	Eroded set of $\mathcal{F}$ with structuring element $\mathcal{S}$
$\mathcal{F}$	Set of free cells
$\mathcal{F}'$	Relevant eroded subset of free cells
$\boldsymbol{H}$	Measurement matrix
$\boldsymbol{I}$	Information matrix
$\boldsymbol{K}$	Kalman gain
L	Number of spline spans
M	Motion mode; Driving maneuver
M_{c}	Center of circular arc in TU maneuver

$\mathcal{M}$	Model set
$\mathcal{M}_\mathrm{s}$	Model subset
N	Number of Monte Carlo samples
N_b	Number of B-spline basis functions in PFS map
N_c	Number of circles in PFS map
N_DB	Minimal point number in DBSCAN
N_k	Number of B-spline knots
N_min	Minimum number of detections
N_p	Number of outer boundary cells for B-spline tracking
N_r	Number of oriented rectangles in PFS map
N_v	Number of validated measurements
N_z	Number of measurements in tracking
$\mathbb{N}$	Set of non-zero natural numbers
$\mathbb{N}^0$	Set of natural numbers including zero
$\mathcal{O}_\mathcal{S}(\mathcal{F})$	Opened set of $\mathcal{F}$ with structuring element $\mathcal{S}$
P_D	Detection probability
P_G	Gate probability
P_{y_R}	Variance in Ornstein-Uhlenbeck process
$\boldsymbol{P}$	Error covariance matrix
$\boldsymbol{P}^\star$	Mixed initial covariance matrix in IMM Filter
Q_n	Noise intensity
$\boldsymbol{Q}$	Process noise covariance matrix
$\boldsymbol{Q}_\mathrm{n}$	Noise intensity matrix
$\mathbb{R}$	Set of real numbers
$\boldsymbol{R}$	Measurement noise covariance matrix
S	Spline span
S_M	Neighborhood size of median filter
$\mathcal{S}_{\boldsymbol{p}}$	Structuring element with origin placed at $\boldsymbol{p}$
$\mathcal{S}(\boldsymbol{x})$	Set of occupied points of an object with configuration $\boldsymbol{x} = (x, y, \psi)^T$
$\mathcal{S}(\boldsymbol{x}_\mathrm{PFS})$	Set of occupied points of a PFS map with configuration $\boldsymbol{x}_\mathrm{PFS}$
$\boldsymbol{S}$	Innovation covariance matrix
T	Sampling time
T_c	Time constant in Ornstein-Uhlenbeck process
T_P	Prediction time steps
T_r	Reference maneuver time in LC maneuver
$\boldsymbol{U}(s)$	Matrix of concatenated B-spline basis function vectors with curve parameter s

V	Volume of the validation region; Vehicle
$V_{\mathrm{U}}(q)$	Volume of the q-dimensional unit hypersphere
$\mathcal{V}$	Validation region
$\boldsymbol{\mathcal{X}}$	Matrix of sigma points in UKF state prediction
$\boldsymbol{\mathcal{X}}^*$	Matrix of sigma points in UKF state prediction
$\mathcal{Z}$	Measurement set
$\mathcal{Z}_{\mathrm{v}}$	Validated measurement set
$\boldsymbol{\mathcal{Z}}$	Matrix of sigma points in UKF measurement prediction

Latin Lowercase Letters

a	Acceleration in driving direction
a_{max}	Maximum acceleration
a_{min}	Minimum acceleration
$a_{\mathrm{c,max}}$	Maximum centripetal acceleration in TU maneuver
$a_{\mathrm{f,max}}$	Maximum acceleration in FV maneuver
$a_{\mathrm{f,min}}$	Minimum acceleration in FV maneuver
$a_{\mathrm{R,lat}}$	Lateral acceleration perpendicular to road course
$a_{\mathrm{R,lon}}$	Longitudinal acceleration along road course
$a_{\mathrm{R,lon,r}}$	Longitudinal reference acceleration along road course
b	Abbreviation in PDA
$\boldsymbol{b}(s)$	Vector of B-spline basis functions
c	Cell length
c_{m}	Roundness metric
C	Vehicle corner point
d	B-spline order
Δd	Safety distance in TB maneuver
d_{fo}	Distance between newly free and occupied rectangle
d_{r}	Reference safety distance in TB maneuver
$d_{\mathrm{R,fro}}$	Distance to vehicle in front along road course
$d_{\mathrm{R,TU}}$	Distance to turn in TU maneuver
d_{th}	Distance threshold in merging step
e	Abbreviation in PDA
f	Number of vehicles except ego vehicle
$\boldsymbol{i}$	Information vector
i	Running index
j	Running index
k	Time step; Knot position
l	Object length in tracking

l_n	Ray length along normals of free space curve
l_r	Reference maneuver length in LC maneuver
$\boldsymbol{l}$	Line segment
m	Running index
m_i	Grid cell i
m_th	Threshold on free probability for grid segmentation
$\boldsymbol{m}$	Conventional occupancy grid map
$\boldsymbol{m}_\mathrm{opt}$	Optimized occupancy grid map
n	State vector dimension
$\boldsymbol{n}(s)$	Normal vector of B-spline curve with curve parameter s
p	Input vector dimension
p_h	Perimeter of free space hole
$p(m_i)$	Occupancy probability of i-th grid cell
p_o	Percentage of occupied cells in merging step
p_th	Threshold on occupied cell percentage in merging step
q	Measurement vector dimension
q_th	Threshold on temporal difference grid map
$\boldsymbol{q}$	De Boor point
q_x	De Boor point x-coordinate
q_y	De Boor point y-coordinate
r	Number of prediction models
r_c	Turn radius in TU maneuver
r_m	Rectangularity metric
r_DB	Neighborhood radius in DBSCAN
r_SE	Radius of disc-shaped structuring element
$\boldsymbol{r}(s)$	B-Spline curve with curve parameter s
s	Laplace variable; Curve parameter
u	Input scalar
$\boldsymbol{u}$	Input vector
v	Velocity in driving direction
v_rel	Relative velocity to object in front
$v_\mathrm{R,lat}$	Lateral velocity perpendicular to road course
$v_\mathrm{R,lon}$	Longitudinal velocity along road course
$v_\mathrm{R,lon,max}$	Maximum velocity in TU maneuver
$\boldsymbol{v}$	Measurement noise vector; Innovation vector
w	Process noise scalar; Object width in tracking
w_c	Continuous-time process noise scalar
w_L	Lane width
w_V	Vehicle width

$w_i^{(m)}, w_i^{(c)}$	Weights of i-th sigma point in UKF
$\boldsymbol{w}$	Process noise vector
$\boldsymbol{w}_\mathrm{c}$	Continuous-time process noise vector
x	x-coordinate of object center in map-fixed system (Tracking) or global system (Prediction)
x_I	Intersection point road coordinate between road tangents in TU maneuver
x_R	x-coordinate of vehicle center in road-fixed system
$x_\mathrm{R,s}$	Maneuver start coordinate in LC maneuver
$\boldsymbol{x}$	State vector
$\boldsymbol{x}^\star$	Mixed initial state vector in IMM Filter
$\boldsymbol{x}_\mathrm{c}$	State vector of circles in PFS map
$\boldsymbol{x}_\mathrm{P}$	B-Spline control vector in PFS map
$\boldsymbol{x}_\mathrm{PFS}$	State vector of PFS map
$\boldsymbol{x}_\mathrm{r}$	State vector of oriented rectangles in PFS map
y	y-coordinate of object center in map-fixed system (Tracking) or global system (Prediction)
y_R	y-coordinate of vehicle center in road-fixed system
$\boldsymbol{z}$	Measurement vector

Greek Letters

α	Angle in TU maneuver
α_U	Sigma point scaling parameter in UKF
β	Measurement-to-target association probability
β_U	Sigma point scaling parameter in UKF
γ_G	Gate threshold
γ_U	Sigma point scaling parameter in UKF
$\boldsymbol{\gamma}$	Noise gain vector
θ	Association event in PDA
κ	Kulpa's perimeter correction factor
κ_U	Sigma point scaling parameter in UKF
λ	Model likelihood
λ_U	Sigma point scaling parameter in UKF
μ	Mode probability
$\mu_{i\|j}$	Mixing probability
μ_th	Mode probability threshold
$\boldsymbol{\mu}$	Mode probability vector
$\boldsymbol{\Pi}$	Model transition probability matrix

$\sigma_{\Delta a}$	Standard deviation of acceleration increments in discrete-time CTRA model
$\sigma_{\Delta a_{\mathrm{R,lon}}}$	Standard deviation of acceleration increments in discrete-time CA model
$\sigma_{\Delta\omega}$	Standard deviation of yaw rate increments in discrete-time CTRA model
$\sigma_{\psi_{\mathrm{R}}}$	Standard deviation of yaw angle
$\sigma_{y_{\mathrm{R}}}$	Limiting standard deviation in Ornstein-Uhlenbeck process
$\sigma_{y_{\mathrm{R,s}}}$	Standard deviation of lateral maneuver origin in LC maneuver
τ	Time gap in FV maneuver
τ_{r}	Reference time gap in FV maneuver
ϕ_{f}	Angle of newly free rectangle
ϕ_{o}	Angle of newly occupied rectangle
ϕ_{th}	Threshold on angle difference in merging step
ψ	Yaw angle with respect to global coordinate system
ψ_{R}	Yaw angle with respect to road course
ω	Yaw rate

Abstract

Advanced Driver Assistance Systems (ADAS) already make a major contribution to driving safety. To further increase this contribution, it is, however, vital that future intelligent vehicles perceive, predict, and assess their environment more comprehensively. In this context, the present dissertation approaches the questions i) how to represent the driving environment adequately within an environment model, ii) how to obtain such a representation, and iii) how to predict the future traffic scene evolution for proper criticality assessment. Bayesian inference provides the common theoretical framework of all designed methods.

Based on the shortcomings of existing environment representations, a novel parametric representation of general driving environments is first introduced in this work. It consists of a combination of dynamic object maps for moving objects and so-called Parametric Free Space (PFS) maps for static environment structures. PFS maps model the environment by a closed curve around the vehicle, which encloses relevant drivable free space. The representation compactly describes all essential information contained in common occupancy grid maps, suppresses irrelevant details, and consistently separates between static and dynamic environment objects.

A novel method for grid mapping in dynamic road environments provides the basis to realize this representation. Therein, dynamic cell hypothesis are detected, clustered, and subsequently tracked and classified with an adaptive Bayesian multiple model filter for jump Markov nonlinear systems – the so-called Interacting Multiple Model Unscented Kalman Probabilistic Data Association Filter (IMM-UK-PDAF). The intermediate result is a dynamic object map and an optimized grid of the static driving environment. From the optimized grid, relevant free space is then extracted by methods of image analysis, and robustly converted to a PFS map in a final B-Spline contour tracking step. Evaluations and experiments, which were performed with an experimental vehicle equipped with radars and a stereo camera in real driving environments, confirm the advantages of the real-time capable approach.

The so-obtained representation additionally forms the basis of a novel method for long-term trajectory prediction and criticality assessment.

Therein, a three-layered Bayesian network is used to infer current driving maneuvers of traffic participants initially. A trash maneuver class allows the detection of irrational driving behavior and the seamless application from highly-structured to non-structured environments. Subsequently, maneuver-based prediction models in form of stochastic processes are presented and employed to predict the vehicle configurations under consideration of uncertainties in the maneuver executions. Finally, the criticality time metric Time-To-Critical-Collision-Probability (TTCCP) is introduced as a generalization of the time metric Time-To-Collision (TTC) for arbitrary, uncertain, multi-object driving environments and longer prediction horizons. The TTCCP considers all uncertain, maneuver-based predictions and is estimated via Monte Carlo simulations. Simulations confirm its potential to suppress false warnings, to generate timely true warnings, and to generate warnings in critical almost-collision situations effectively.

All methods are part of the driver assistance system PRORETA 3, which has been co-developed in the context of this thesis. It constitutes a novel, integrated approach to collision avoidance and vehicle automation and thereby makes a valuable contribution to realize the Vision Zero – the vision of a future without traffic deaths.

Kurzfassung

Fahrerassistenzsysteme leisten bereits heute einen bedeutenden Beitrag zur Sicherheit im Straßenverkehr. Um diesen Beitrag weiter zu erhöhen, müssen zukünftige intelligente Fahrzeuge ihre Umgebung jedoch noch eingehender wahrnehmen, prädizieren und bewerten. In diesem Kontext behandelt die vorliegende Dissertation die Fragen, i) wie die Fahrumgebung geeignet in einem Umfeldmodell repräsentiert werden kann, ii) wie eine solche Repräsentation realisierbar ist und iii) wie die zukünftige Entwicklung der Verkehrssituation sowie deren Kritikalität abgeschätzt werden kann. Bayessche Inferenzverfahren bilden das gemeinsame theoretische Gerüst aller hierzu entworfenen Methoden.

Ausgehend von den Limitierungen bestehender Umgebungsrepräsentationen wird in dieser Arbeit zunächst eine neue parametrische Repräsentation allgemeiner Fahrumgebungen eingeführt. Sie besteht aus einer Kombination aus dynamischen Objektkarten für sich bewegende Objekte und sogenannten parametrischen Freiraumkarten für statische Umgebungsstrukturen. Letztere modellieren die Umgebung mittels einer geschlossenen Kurve, die das Fahrzeug umgibt und die relevante befahrbare Freiräume einschließt. Die Repräsentation stellt alle wesentlichen Informationen, die auch in den verbreiteten Belegungsgitterkarten enthalten sind, kompakt dar, unterdrückt irrelevante Details und unterscheidet konsistent zwischen dynamischen und statischen Objekten.

Eine neue Methode zur Erstellung von Belegungsgitterkarten in dynamischen Fahrumgebungen bildet die Basis zur Realisierung dieser Repräsentation. Hierbei werden dynamische Zellhypothesen detektiert, gruppiert und objektbasiert mit einem adaptiven Bayesschen Mehrmodellfilter für nichtlineare Markov-Sprungprozesse – dem sogenannten Interacting Multiple Model Unscented Kalman Probabilistic Data Association Filter (IMM-UK-PDAF) – zeitlich verfolgt und klassifiziert. Das Zwischenresultat ist eine dynamische Objektkarte sowie eine optimierte Belegungsgitterkarte der statischen Umgebung. Aus der optimierten Gitterkarte werden daraufhin relevante Freiräume mit Methoden der Bildverarbeitung extrahiert und im Rahmen eines nachgeschalteten B-Spline-Konturverfolgungsschritts robust in eine parametrische Frei-

raumkarte überführt. Evaluationen und Experimente, die in realen Fahrumgebungen mit einem mit Radarsensoren und Stereokamera ausgerüsteten Versuchsfahrzeug ausgeführt wurden, bestätigen die Vorteile des echtzeitfähigen Ansatzes.

Die so erzeugte Umgebungsrepräsentation dient darüber hinaus als Basis für ein neues Langzeit-Trajektorienprädiktions- und Kritikalitätsbewertungsverfahren. Den Ausgangspunkt hierfür bildet ein dreischichtiges Bayessches Netz, das genutzt wird, um auf die aktuellen Fahrmanöver der Verkehrsteilnehmer zu schließen. Eine Restmanöverklasse erlaubt zusätzlich die Erkennung irrationaler Fahrerhandlungen sowie die nahtlose Anwendbarkeit von hochstrukturierten bis hin zu unstrukturierten Fahrumgebungen. Weiterhin werden manöverbasierte Prädiktionsmodelle in Form stochastischer Prozesse vorgestellt und zur Vorhersage der Fahrzeugkonfigurationen unter Berücksichtigung von Unsicherheiten in der Manöverausführung genutzt. Abschließend wird das Kritikalitätszeitmaß Time-To-Critical-Collision-Probability (TTCCP) als Erweiterung des Zeitmaßes Time-To-Collision (TTC) für beliebige unsichere Fahrumgebungen mit mehreren Objekten eingeführt, das auch für längere Prädiktionshorizonte geeignet ist. Die TTCCP bezieht alle unsicheren, manöverbasierten Vorhersagen mit ein und wird mittels einer Monte-Carlo-Simulation geschätzt. Simulationen bestätigen das Potential des Ansatzes Fehlwarnungen zu unterdrücken, korrekte Warnungen frühzeitig zu erzeugen sowie auch in kritischen Beinahezusammenstoßsituationen effektiv zu warnen.

Anwendung finden die Methoden im Assistenzsystem PRORETA 3, das im Rahmen dieser Arbeit mitentwickelt wurde. Dieses stellt einen integralen Ansatz zur Kollisionsvermeidung und Fahrzeugautomatisierung dar und leistet damit seinerseits einen wertvollen Beitrag zur Realisierung der Vision Zero – der Vision einer Zukunft ohne Verkehrstote.