

Reihe 8

Mess-,
Steuerungs- und
Regelungstechnik

Nr. 1246

Dipl.-Ing. Georg Tanzmeister,
München

Grid-based Environment Estimation for Local Autonomous Vehicle Navigation

<https://doi.org/10.51202/9783186246080-1>

Generiert durch IP '18.226.214.194' am 15.06.2024, 15:54:31.
Das Erstellen und Weitergeben von Kopien dieses PDFs ist nicht zulässig.

Lehrstuhl für Steuerungs- und Regelungstechnik
Technische Universität München
Univ.-Prof. Dr.-Ing./Univ. Tokio Martin Buss

Grid-based Environment Estimation for Local Autonomous Vehicle Navigation

Georg Tanzmeister

Vollständiger Abdruck der von der Fakultät für Elektrotechnik und Informationstechnik der Technischen Universität München zur Erlangung des akademischen Grades eines

Doktor-Ingenieurs (Dr.-Ing.)

genehmigten Dissertation.

Vorsitzender: Jun.-Prof. Dr. rer. nat. Martin Kleinstaubler

Prüfer der Dissertation:

1. Univ.-Prof. Dr.-Ing. habil. Dirk Wollherr
2. Univ.-Prof. Dr.-Ing. Hans-Joachim Wünsche

Die Dissertation wurde am 13.04.2015 bei der Technischen Universität München eingereicht und durch die Fakultät für Elektrotechnik und Informationstechnik am 21.12.2015 angenommen.

Fortschritt-Berichte VDI

Reihe 8

Mess-, Steuerungs-
und Regelungstechnik

Dipl.-Ing. Georg Tanzmeister,
München

Nr. 1246

Grid-based Environment
Estimation for Local
Autonomous Vehicle
Navigation

VDI verlag

Tanzmeister, Georg

Grid-based Environment Estimation for Local Autonomous Vehicle Navigation

Fortschr.-Ber. VDI Reihe 8 Nr. 1246. Düsseldorf: VDI Verlag 2016.

166 Seiten, 54 Bilder, 8 Tabellen.

ISBN 978-3-18-524608-1, ISSN 0178-9546,

€ 62,00/VDI-Mitgliederpreis € 55,80.

Keywords: Autonomous Vehicles – Environment Model – Grids – Mapping – Tracking – Navigation – Road Boundary – Collision Checking and Cost Evaluations – Laser Scanners – Radar Sensors

This dissertation is focused on the environment model for automated vehicles. A reliable model of the local environment available in real-time is a prerequisite to enable almost any useful activity performed by a robot, such as planning motions to fulfill tasks. It is particularly important in safety critical applications, such as for autonomous vehicles in regular traffic. In this thesis, novel concepts for local mapping, tracking, the detection of principal moving directions, cost evaluations in motion planning, and road course estimation have been developed. An object and sensor-independent grid representation forms the basis of all presented methods enabling a generic and robust estimation of the environment. All approaches have been evaluated with sensor data from real road scenarios, and their performance has been experimentally demonstrated with a test vehicle.

Bibliographische Information der Deutschen Bibliothek

Die Deutsche Bibliothek verzeichnet diese Publikation in der Deutschen Nationalbibliographie; detaillierte bibliographische Daten sind im Internet unter <http://dnb.ddb.de> abrufbar.

Bibliographic information published by the Deutsche Bibliothek

(German National Library)

The Deutsche Bibliothek lists this publication in the Deutsche Nationalbibliographie (German National Bibliography); detailed bibliographic data is available via Internet at <http://dnb.ddb.de>.

© VDI Verlag GmbH · Düsseldorf 2016

Alle Rechte, auch das des auszugsweisen Nachdruckes, der auszugsweisen oder vollständigen Wiedergabe (Fotokopie, Mikrokopie), der Speicherung in Datenverarbeitungsanlagen, im Internet und das der Übersetzung, vorbehalten.

Als Manuskript gedruckt. Printed in Germany.

ISSN 0178-9546

ISBN 978-3-18-524608-1

Foreword

This thesis summarizes my research as a doctoral student at the Institute of Automatic Control Engineering (LSR) of the Technische Universität München and at the Department of Automated Driving, Active Safety, and Sensors of the BMW Group Research and Technology in Munich.

First, I want to thank Prof. Dirk Wollherr for supervising my thesis. It would not have been possible without him and I am grateful for the scientific freedom and the trust he has always given me to follow my own ideas. From the BMW Group, I want to thank first of all Martin Friedl, Werner Huber, Nico Kämpchen, and Helmut Spannheimer, for the extraordinary pleasant work environment, for giving me the opportunity to pursue this thesis, and for the support in every regard.

I would also like to thank all my colleagues at the BMW Group Research and Technology, in particular, Moritz Werling, Yves Pilat, Michael Aeberhard, Mohammad Bahram, Sebastian Rauch, Benjamin Gutjahr, and Thomas Hofmann, as well as all my colleagues at the LSR, in particular, Andreas Lawitzky, Daniel Carton, and Daniel Althoff, for the detailed and long discussions that often led to new ideas, but especially for the wonderful time we shared.

This thesis has been supported by the student projects of Sascha Steyer, Michael Schreibauer, Matthias Beck, Julian Thomas, and Eduard Feicho. I want to thank all of them for their work and their commitment.

Finally, my greatest thanks go to my parents for their constant support throughout my entire education, to my sister for her always encouraging words, and to my friends in Vienna who are keeping our friendship, as if we still lived in the same city.

Munich, 2015

Georg Tanzmeister

Contents

Notations	VIII
Abstract	XIII
Zusammenfassung	XIV
1 Introduction	1
1.1 Prior Knowledge for Autonomous Navigation in Road Scenarios	2
1.1.1 High Prior Knowledge Navigation	2
1.1.2 Sensor-based Navigation	4
1.1.3 Low Prior Knowledge Navigation	5
1.2 Environment Model	6
1.3 Main Contributions and Outline of the Thesis	8
2 Grid-based Tracking and Mapping	10
2.1 Introduction	10
2.1.1 State of the Art	10
2.1.2 Approach and Contribution	12
2.2 Fundamentals	13
2.2.1 Dempster–Shafer Environment Model	13
2.2.2 GTAM Overview	15
2.2.3 Scan Grid Generation and Fusion	16
2.3 The Particle Map	21
2.3.1 Estimating Cell Velocity Distributions using Particle Filters	21
2.3.2 Particle Creation and Sampling	22
2.3.3 Particle Weighting and Resampling	26
2.3.4 Belief Mass Derivation	29
2.4 The Dempster–Shafer Theory Map	30
2.4.1 Filtering over Time	30
2.4.2 Deriving Static Bayesian Maps	32
2.5 Results	34
2.6 Summary	39
3 Detection of Principal Moving Directions	40
3.1 Introduction	40
3.1.1 State of the Art	41
3.1.2 Approach and Contribution	44
3.2 Local Path Planning with Unknown Goal Poses	45
3.2.1 Problem Formulation	45
3.2.2 Velocity-dependent Reachability Graph	46

3.2.3	Path Cost and Heuristic with Unknown Goal Poses	48
3.2.4	A*-RRT Motion Primitive Path Planner	48
3.3	Environment-based Trajectory Clustering	52
3.3.1	Equivalence for Local Trajectories	52
3.3.2	Clustering with a Binary Equivalence Predicate	54
3.3.3	Trajectory Clustering with Overlapping Clusters	56
3.4	Results	58
3.5	Summary	63
4	Configuration Space Costs: Cost Evaluation on Workspace Cost Maps	64
4.1	Introduction	64
4.1.1	State of the Art	64
4.1.2	Approach and Contribution	66
4.2	Grid-based Collision Checking and Cost Evaluation	66
4.2.1	Collision Checking Fundamentals	67
4.2.2	Extending Collision Checking to Cost Evaluation	69
4.3	Fast Approximate Calculation of the Configuration Space Costs for Arbitrary Footprints with FAMOD	71
4.3.1	Calculation of Grayscale Dilation with Convolution	72
4.3.2	Practical Considerations	73
4.4	Efficient Exact Calculation of the Configuration Space Costs for Rectangular Footprints with vHGW-360	74
4.4.1	Reducing Computations by Exploiting Symmetry	74
4.4.2	The vHGW Algorithm	75
4.4.3	Practical Considerations	76
4.5	Evaluating Continuous Paths on Discrete Grids	77
4.5.1	Calculating Path Costs with the Configuration Space Costs	77
4.5.2	Determining Look-Up Positions	78
4.6	Results	79
4.7	Summary	86
5	Road Course and Road Boundary Estimation	87
5.1	Introduction	87
5.1.1	State of the Art	87
5.1.2	Approach and Contribution	89
5.2	Overview	90
5.3	Path-based Road Boundary Estimation	92
5.3.1	The Effects of Path Clustering	92
5.3.2	Road Boundary Estimation	93
5.4	Road Course Validation	94
5.4.1	Single Frame Validation	94
5.4.2	Recursive Bayesian Validation	96
5.5	Road Course Tracking	97
5.5.1	Tracking Road Courses based on Paths	97
5.5.2	Path Association	98

5.6	Results	99
5.7	Summary	101
6	Evaluation	102
6.1	Evaluation of the Grid-based Tracking and Mapping	102
6.1.1	Particle Convergence with Static Particle Sampling	102
6.1.2	Parameter Evaluation	103
6.1.3	Classification	108
6.1.4	Estimated Velocities	109
6.2	Evaluation of the Road Course Estimation	113
6.2.1	Road Course Validation	113
6.2.2	Boundary Estimation Accuracy	115
6.2.3	Comparison to Predicted Vehicle Path	115
6.2.4	Autonomous Navigation in an Unmapped Road Scenario	116
6.3	Qualitative Evaluation of the Road Course Estimation with GTAM	119
6.4	Summary	122
7	Conclusion	123
A	Appendix	127
A.1	Prototype Vehicle and Sensor Setup	127
A.2	Hardware and Software Computing Platform	129
A.3	Local Grid Mapping	129
A.4	Path Smoothing	131
A.5	Data Sets	133
A.5.1	Grid-based Tracking and Mapping	133
A.5.2	Road Course Estimation	133
	Own Publications	136
	Bibliography	137

Notations

Abbreviations

CUDA	Compute Unified Device Architecture by Nvidia
DGPS	Differential Global Positioning System
DST	Dempster–Shafer Theory of Evidence
DSTMap	Dempster–Shafer Theory Map
FAMOD	Fast Approximate Morphological Grayscale Dilation
FOV	Field of View
GTAM	Grid-based Tracking And Mapping
MGCS	Map Grid Coordinate System
PMap	Particle Map
RCE	Road Course Estimation
ROC	Receiver Operating Characteristic
RRT	Rapidly Exploring Random Tree
SCS	Sensor Coordinate System
SGCS	Scan Grid Coordinate System
SLAM	Simultaneous Localization And Mapping
VCS	Vehicle Coordinate System
vHGW	van Herk-Gil-Werman Algorithm
vHGW-360	Modified van Herk-Gil-Werman Algorithm
WCS	World Coordinate System

Conventions

Scalars and *vectors* are denoted by lower case letters in italic type (a, b, \dots). *Matrices* are denoted by upper case letters in italic type (A, B, \dots). *Functions* are denoted by lower case letters (f, g, \dots). *Curves* and *angles* are denoted by lower case Greek letters (τ, ω, \dots). Number sets are denoted by upper case letters. Special number set, such as the set of natural numbers, are denoted by blackboard bold letters ($\mathbb{N}, \mathbb{R}, \dots$). Other sets are denoted by standard calligraphic letters ($\mathcal{A}, \mathcal{B}, \dots$). Note that in this thesis, it does not make a difference if the indices are superscripts or subscripts, e.g., $x_{ijk} = x_{ij}^k$. Probability density functions are denoted by $p(\cdot)$. The probability that a random variable Y has value y is denoted by $p(Y = y)$, but will be abbreviated as $p(y)$. The joint probability $p(x_1, x_2, \dots, x_t)$ is denoted by $p(x_{1:t})$. The belief mass $m(\{A\})$ of the set $\{A\}$ in the Dempster–Shafer theory of evidence is abbreviated as $m(A)$. Single variables within this thesis may deviate from this notation to be conform with standard notation or to reduce ambiguities. These

deviations are, however, clearly highlighted. The mathematical notation that is used is given in the following:

A^T	transpose of matrix A
A^{-1}	inverse of matrix A
$\det(A)$	determinant of matrix A
$\det(a, b)$	determinant of matrix build by vectors a and b
$\text{diag}(a, b)$	diagonal matrix with scalar entries a and b
$\ x\ $	Euclidean norm of vector x
$ x $	absolute value of scalar x
$ \mathcal{X} $	cardinality of set \mathcal{X}
$a b$	scalar or component-wise vector multiplication of a and b
$a \cdot b$	inner (dot) product of two vectors a and b
\emptyset	empty set
$\sphericalangle a, b$	angle between two vectors a and b

Symbols

General

$f(\cdot), g(\cdot), h(\cdot)$	functions
i, j, k	index or integer number
l	length index
n_x	number of entities x
$\mathcal{N}(\mu, \sigma)$	normal distribution with mean μ and variance σ
$\mathcal{N}(x; \mu, \sigma)$	normal distribution with mean μ and variance σ evaluated at x
$O(\cdot)$	big O notation; Landau notation
q	robot configuration
R_α	rotation matrix of α degrees
t	time index
$\mathcal{U}(x, y)$	uniform distribution with lower bound x and upper bound y
w	weight
x	robot state

ε	small arbitrary number
η	normalizer
μ	mean
θ	orientation of the robot
σ	standard deviation

\mathbb{B}	set of boolean values
\mathbb{N}	set of natural numbers
\mathbb{R}	set of real-valued numbers
\mathbb{R}_0^+	set of non-negative real-valued numbers

Subscripts

$()_l, ()_r$	referring to the left and right
$()_{\min}, ()_{\max}$	referring to the minimum and maximum
$()_R, ()_T$	referring to the radial and tangential component
$()_S, ()_G$	referring to the start and goal
$()_t$	referring to the time instance t
$()_v$	referring to the velocity component
$()_x, ()_y$	referring to the position component; to the x and y component
$()_{[]}$	referring to the particle

Mapping and Tracking

a, b	scalar parameter
c	scalar conflict in Dempster's rule of combination
D	subset of frame of discernment denoting <i>dynamic</i>
F	subset of frame of discernment denoting <i>free</i>
$m(A)$	belief mass of set A in Dempster–Shafer theory
m_p	map grid representing belief masses from particle map
m_{s_i}	scan grid representing belief masses of sensor s_i
m_s	scan grid representing belief masses after sensor data fusion
m_t	map grid representing final belief masses at time instance t
n_{cells}	number of grid cells per dimension
n_{χ}^i	actual number of particles in cell i
$n_{\chi}^{i,\text{des}}$	desired number of particles in cell i
$n_{\chi}^{i,\text{max}}$	maximum number of particles per cell
o_t^{MGCS}	origin of map grid coordinate system at time t
$p_{\text{surv}}(\chi_{[k]})$	survival probability of particle $\chi_{[k]}$
$p_{\text{surv}}^{\text{max}}$	maximum survival probability
$p_{\text{surv}}^{\text{min}}$	minimum survival probability
r	radius of circle on which vehicle rotates in local grid
S	subset of frame of discernment denoting <i>static</i>
v	2-D velocity vector
v_{max}	maximum velocity
v^*	true 2-D velocity vector
$v_{[k]}$	velocity component of k -th particle
V	multivariate random variable denoting 2-D velocity vectors
w_{rand}	probability of sampling a random particle during resampling
$x_{[k]}$	position component of k -th particle
\mathcal{X}_t	set of particles at time instance t
\mathcal{X}_S^i	set of static particles in cell i
\mathcal{X}_D^i	set of dynamic particles in cell i
$\bar{\mathcal{X}}_t$	predicted set of particles from \mathcal{X}_{t-1}

z	sensor measurement
α	angle
$\chi_{[k]}$	k -th particle
$\delta(x; y)$	Dirac delta distribution at y evaluated at x
ν_t	grid map of velocity vectors at time t
ν_t^i	cell i of map ν_t
ϑ_{\min}	minimum uncertainty
Θ	frame of discernment
<hr/>	
$\text{bel}(\cdot)$	belief
$\text{betP}(\cdot)$	pignistic probability distribution
$\text{pl}(\cdot)$	plausibility
\oplus^{C}	conjunctive rule of combination
\oplus^{D}	Dempster's rule of combination
\oplus^{J}	Jøssang's cumulative rule of combination

Motion Planning and Road Course Estimation

$b_{\{l,r\}}$	boundary element of left/right boundary
B	binary obstacle grid map
$\mathcal{B}_{\{l,r\}}$	set of left/right road boundary cells
c	cost
C_i	cluster i , i.e., set of trajectories that are in i -th cluster
\mathcal{C}	configuration space
$\mathcal{C}_{\text{costs}}$	configuration space costs
$\mathcal{C}_{\text{free}}$	set of collision-free configurations
\mathcal{C}_{obs}	configuration space obstacles
$d, d(\cdot, \cdot)$	distance; if not explicitly stated, standard Euclidean distance
$f_c(\tau)$	function yielding cluster of a path/trajectory τ
$f_m(q, u), f_m(x, u)$	motion model
$f_w(\cdot)$	weight function
\mathcal{F}_w	set of weight functions
l_a	axis length
\mathcal{L}	list of states
$\mathcal{L}_{\text{closed}}$	closed list
$\mathcal{L}_{\text{goal}}$	goal list
$\mathcal{L}_{\text{open}}$	open list
M	grayscale grid map
n_c	number of clusters
n_{checks}	number of cost/collision evaluations
n_{cols}	number of columns of image/matrix
$n_{\text{iter}}^{\text{max}}$	maximum number of iterations
n_o	number of objects
n_{pixels}	number of pixels of image

n_{prim}	number of motion primitives
n_{rows}	number of rows of image/matrix
n_{slices}	number of layers of \mathcal{C}_{obs} or $\mathcal{C}_{\text{costs}}$
n_{τ}	number of paths
o	occupied cell
\mathcal{O}	obstacle region; set of occupied cells
$\mathcal{O}_{\{l,r\}}$	set of occupied grid cells that are left/right of some separator
P	set of parameter
\mathcal{P}	polygon
\mathcal{R}	set of road courses
S	structural element; robot mask
\mathcal{T}	set of paths/trajectories
\mathcal{T}_{rep}	set of cluster representatives, i.e., the principal moving directions
u	action
U	action space
v	vector
v_{road}	estimated drivable velocity
\mathcal{W}	work space
<hr/>	
α	steering angle of wheels of vehicle
β	semantic continuous road boundary
$\delta(\cdot)$	discretization function
φ	alternative symbol for road course
γ	generalized Voronoi diagram of semantic road boundaries
κ	curvature
$\lambda(\cdot)$	log odds ratio
π	alternative symbol for path/trajectory
ρ	road course
τ	path/trajectory
τ^c	path cells
τ^n	path nodes
τ_p	primary path
τ_s	smoothed path
ω	action trajectory
Ω	set of action trajectories
ξ	plausibility criterion
ψ	angle
<hr/>	
$\text{pred}(\tau, \tau')$	path equivalence predicate between τ and τ'
$\text{proj}_{\mathcal{W}}(\cdot)$	workspace projection
\oplus	morphological dilation
\ominus	morphological erosion
<hr/>	

Abstract

A reliable model of the local environment available in real-time is a prerequisite to enable almost any useful activity performed by a robot, such as planning motions to fulfill tasks. It is particularly important in safety critical applications, such as for autonomous vehicles in regular traffic. In this thesis, novel concepts for mapping, tracking, the detection of principal moving directions, cost evaluations in motion planning, and road course estimation have been developed. An object- and sensor-independent grid representation forms the basis of all presented methods enabling a generic and robust environment estimation.

Grid-based Tracking and Mapping (GTAM), a low-level approach for the simultaneous estimation of the dynamic and the static obstacles and their velocities is presented. Uncertainties are incorporated in a Dempster-Shafer environment model. The method overcomes the drawback of widely-used occupancy grid mapping, which is only defined for static environments and leads to artifacts, if applied when dynamic objects are in the perceptual field of the robot. The grid map of the static world from GTAM forms the basis of the subsequently presented methods.

The *principal moving directions* through the environment represent the main possible maneuvers of the vehicle for local navigation. They are detected by a path planning and path clustering approach. Two path planner families are combined in order to efficiently sample a set of collision-free paths. A path equivalence definition is provided to cluster the paths, which is motivated by path homotopy but does not require that all paths end at the same point.

The costs of paths often arise due to the particular workspace, such as the distances to the nearest obstacles in order to prefer high clearance. The concept of configuration space obstacles is generalized to *configuration space costs*, which allow costs and collisions to be performed in the configuration space, i.e., incorporating the robot shape. Furthermore, two algorithms for their efficient calculation on graphics hardware are presented.

The methods from above form the basis of an indirect approach to *road course estimation*. The road topology is extracted using the principal moving directions as boundary separators, and the road boundaries are individually estimated for each detected roadway given the grid map.

All developed methods have been evaluated with sensor data from real road environments and their performance has been experimentally demonstrated with a test vehicle.

Zusammenfassung

Ein aktuelles und zuverlässiges Umfeldmodell ist Kernkomponente praktisch jedes realen Robotersystems und unverzichtbar in sicherheitskritischen Anwendungen wie bei autonomen Fahrzeugen. Ein Roboter wird dadurch erst befähigt sinnvolle Aufgaben, wie beispielsweise einen bestimmten Ort zu erreichen, durchzuführen. In der vorliegenden Dissertation werden neuartige Konzepte für die lokale Kartierung, die Verfolgung von dynamischen Objekten, die Erkennung der Hauptbewegungsrichtungen, die Kostenevaluierung für Pfad- und Trajektorienplanung sowie die Schätzung des Fahrbahnverlaufs vorgestellt. Ihnen allen liegt eine gitterbasierte Darstellung zu Grunde, welche ohne objekt- und sensorspezifische Annahmen auskommt und dadurch eine sowohl generische als auch robuste Schätzung des Umfeldmodells ermöglicht.

Die Arbeit beginnt mit der Präsentation von *GTAM*, ein Verfahren bei dem gleichzeitig sowohl die statische als auch die dynamische Umgebung anhand von Sensordaten geschätzt wird. Im Gegensatz zu klassischen Belegungskarten, welche nur für statische Umgebungen definiert sind und bei denen dynamische Objekte zu ungewollten Artefakten führen, liefert das Verfahren ein einheitliches und konsistentes Abbild der Umgebung inklusive Geschwindigkeitsinformationen. Die Belegungskarte der statischen Umgebung bildet die Basis für die im Weiteren vorgestellten Methoden.

Die *Hauptbewegungsrichtungen* durch die lokale Umgebung repräsentieren die Manöroptionen des Fahrzeugs. Sie werden durch eine Kombination aus Pfadplanung und -gruppierung erkannt. Dazu werden zwei verschiedene Pfadplanungsfamilien kombiniert und ein Äquivalenzkriterium definiert, welches durch die Pfadhomotopie motiviert ist.

Bei der kostenabhängigen Pfad- und Trajektorienplanung sind die Kosten oftmals durch die lokale Umgebung gegeben wie etwa Abstand zu Hindernissen. Um Form und Ausdehnung des Roboters für die Kostenberechnung, welche die Kollisionsprüfung miteinschließt, berücksichtigen zu können, wird das Konzept der Konfigurationsraumobjekte auf *Konfigurationsraumkosten* erweitert sowie zwei effiziente Algorithmen für deren Berechnung auf Grafikkarten vorgestellt.

Die obigen Ansätze bilden die Basis eines indirekten Verfahrens für die *Schätzung des Fahrbahnverlaufs*. Hierbei wird die lokale Topologie der Straße anhand der Hauptbewegungsrichtungen extrahiert und für jede erkannte Fahrbahn die zugehörige Randbebauung geschätzt.

Alle entwickelten Methoden wurden mit Realdaten aus Fahrten mit einem Versuchsfahrzeug in diversen Verkehrsszenarien evaluiert und deren Performanz demonstriert.