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Dipl.-Ing. Georg Tanzmeister,
München

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Grid-based Environment Estimation for Local Autonomous Vehicle Navigation

Lehrstuhl für Steuerungs- und Regelungstechnik
Technische Universität München
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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.

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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.

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Munich, 2015 Georg Tanzmeister

Contents

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 $(a, b, \ldots)$. *Matrices* are denoted by upper case letters in italic type $(A, B, \ldots)$. *Functions* are denoted by lower case letters $(f, g, \ldots)$. *Curves* and *angles* are denoted by lower case Greek letters $(\tau, \omega, \ldots)$. Number sets are denoted by upper case letters. Special number set, such as the set of natural numbers, are denoted by blackboard bold letters $(\mathbb{N}, \mathbb{R}, \ldots)$. Other sets are denoted by standard calligraphic letters $(\mathcal{A}, \mathcal{B}, \ldots)$. 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 $p(x_1, x_2, \ldots, x_t)$ 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
$\mathrm{diag}(a, b)$	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
$\mathrm{O}(\cdot)$	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
$()_{[\cdot]}$	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 *dynamic*
F	subset of frame of discernment denoting *free*
$m(A)$	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
$n_\chi^{i,\max}$	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 $\chi_{[k]}$
$p_{\text{surv}}^{\max}$	maximum survival probability
$p_{\text{surv}}^{\min}$	minimum survival probability
r	radius of circle on which vehicle rotates in local grid
S	subset of frame of discernment denoting *static*
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
$\overline{\mathcal{X}}_t$	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
$\vartheta_{\min}$	minimum uncertainty
Θ	frame of discernment
$\mathrm{bel}(\cdot)$	belief
$\mathrm{betP}(\cdot)$	pignistic probability distribution
$\mathrm{pl}(\cdot)$	plausibility
$\oplus^{\mathrm{C}}$	conjunctive rule of combination
$\oplus^{\mathrm{D}}$	Dempster's rule of combination
$\oplus^{\mathrm{J}}$	Jøsang'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
$\mathcal{C}_{\mathrm{costs}}$	configuration space costs
$\mathcal{C}_{\mathrm{free}}$	set of collision-free configurations
$\mathcal{C}_{\mathrm{obs}}$	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
$\mathcal{L}_{\mathrm{closed}}$	closed list
$\mathcal{L}_{\mathrm{goal}}$	goal list
$\mathcal{L}_{\mathrm{open}}$	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
$n_{\mathrm{iter}}^{\max}$	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 $\mathcal{C}_{\text{obs}}$ 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
$\mathcal{T}_{\text{rep}}$	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
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
$\text{pred}(\tau, \tau')$	path equivalence predicate between τ and τ'
$\text{proj}_{\mathcal{W}}(\cdot)$	workspace projection
$\oplus$	morphological dilation
$\ominus$	morphological erosion

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 Manöveroptionen 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.