CHEMNITZ UNIVERSITY
OF TECHNOLOGY

Non-Parametric Bayesian Filtering for Multiple Object Tracking

von der Fakultät für Elektrotechnik und Informationstechnik
der Technischen Universität Chemnitz

genehmigte

Dissertation

zur Erlangung des akademischen Grades

Doktoringenieur (Dr.-Ing.)

vorgelegt von

Dipl.-Ing. Eric Richter
geboren am 25. März 1978 in Karl-Marx-Stadt (heute Chemnitz)

eingereicht am 13. Februar 2012

Gutachter: Prof. Dr.-Ing. Gerd Wanielik
Prof. Dr.-Ing. Peter Protzel

Tag der Verleihung: 24. Juli 2012

Forschungsberichte der Professur Nachrichtentechnik
herausgegeben von Prof. Dr.-Ing. Gerd Wanielik

Band 8

Eric Richter

Non-Parametric Bayesian Filtering for Multiple Object Tracking

D 93 (Diss. TU Chemnitz)

Shaker Verlag
Aachen 2012

Bibliographic information published by the Deutsche Nationalbibliothek
The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available in the Internet at http://dnb.d-nb.de.

Zugl.: Chemnitz, Techn. Univ., Diss., 2012

Printed in Germany.

ISBN 978-3-8440-1488-4
ISSN 1610-1251

Shaker Verlag GmbH • P.O. BOX 101818 • D-52018 Aachen
Phone: 0049/2407/9596-0 • Telefax: 0049/2407/9596-9
Internet: www.shaker.de • e-mail: info@shaker.de

Acknowledgments

This work has been developed during my employment as a research associate at the professorship of Communications Engineering at Chemnitz University of Technology.
I would like to thank my PhD supervisor Prof. Dr.-Ing. Gerd Wanielik for his excellent expert advises and great support during the last years. Especially, the scientific and technical conditions provided by him gave me the opportunity to continuously research within the field of automotive engineering.
I would also like to thank Prof. Dr.-Ing. Peter Protzel for his interest in my work and his efforts as a reviewer of this thesis.
Robin, I am very grateful for our numerous scientific and non-scientific conversations. I thank you and Dr. Ulrich Neubert for reading this thesis and for your critical feedback.
Marcus, thank you for your steadily research support which helped a lot for successfully finishing this thesis.

Summary

Advanced driver assistance systems increase the comfort, efficiency, and safety of nowadays and future automobiles. Especially if these systems need to derive a safety critical decision like an emergency brake they require a reliable and precise environment recognition in order to keep the false triggering rate close to zero.

In this work, environment recognition means to recursively estimate both the time varying number of objects in a scene and their parameters like position and velocity—so called multiple object tracking. The thesis summarizes typical state of the art multiple object tracking approaches which classically consist of separate detection, observation association, and estimation stages. Often, the detection and association steps derive decisions which are hardly reversible during the tracking process. Additionally, the majority of current multiple object tracking systems insufficiently model the spatial extension of objects though high resolution sensors like laser scanner can observe it.

The scope of this work is to overcome these limitations by integrating dynamic as well as *a priori* knowledge into one Bayes filter, which is implemented by a reversible jump Markov chain Monte Carlo sampling approach. By that, it is possible to track spatially extended objects without dedicated detection and association steps. Instead, several models are combined in an integrated Bayesian estimation process. These models include how objects look like and move, where they are expected to appear and disappear, and how they interact with each other. By that, the approach contributes to the field of spatially extended object tracking and provides many connection points for further investigation.

The resulting multiple object tracking system rigorously utilizes the Bayesian framework to cope with the uncertainties occurring in different domains. This includes association ambiguities as well as observation and system process noises. Furthermore, a track management is included in a statistical fashion.

The work demonstrates three case studies of multiple spatially extended object tracking utilizing different sensors and algorithmic approaches. At first, a data fusion system combining a radar and a camera sensor using a classical multiple object tracking method is shown. Hereafter, a lidar based system is demonstrated which uses advanced occupancy grid methods in order to detect and track spatially extended objects. Finally, an implementation of the reversible jump Markov chain Monte Carlo sampling approach for a lidar based tracking of spatially extended objects is shown.

Contents

Glossary

Greek letters

α	Unscented Kalman filter parameter
$\beta_{0\ldots M}$	IPDA weights
β	Unscented Kalman filter parameter
γ	Unscented Kalman filter scaling parameter
κ	Unscented Kalman filter parameter
χ	Sigma points
Υ	Transformed sigma points
ϵ	Random walk process noise
η	Normalization constant
Γ	Gamma function
λ	Parameter of the Poisson distribution
$\omega(x)$	Weight of x
Σ	Covariance matrix
σ	Standard deviation

Measurement and state space variables

a	Acceleration
Δx	x component of the ego motion between $k-1$ and k
Δx	y component of the ego motion between $k-1$ and k
$\Delta\theta$	θ component of the ego motion between $k-1$ and k
ω	Object yaw rate
ϕ	Radar beam angle
$\dot{r}$	Radar range rate
r	Radar range
θ	Object heading
v	Velocity
l	Object length
w	Object width
x	Position x
y	Position y

Probabilistic expressions and operators

$\delta_\mu(\cdot)$	Delta distribution at μ

$\mathcal{N}(x, \hat{x}, S)$	Gaussian PDF of x with mean $\hat{x}$ and variance S
π	Stationary probability density function
$\mathcal{U}(x_{\mathbf{min}}, x_{\mathbf{max}})$	Uniform PDF of x with lower and upper bound $x_{\min}$, $x_{\max}$
$p(z_k\|x_k)$	Likelihood function of z at time k
$p(x_k\|Z_k)$	*A posteriori* PDF of x at time k
$p(x_k\|Z_{k-1})$	*A priori* PDF of x at time k
$p(x_k\|x_{k-1})$	Transition PDF of x at time k
$\|$	Conditioned on
$\propto$	Proportional to
$\sim$	Distributed according to
$\exists m$	Existence random variable of object m
$\exists$	Object exists
$\nexists$	Object does not exist
p_D	Detection probability
p_F	False alarm probability
p_B	Object birth probability
p_P	Object persistence probability

Roman letters

$\mathbf{A}$	Camera calibration matrix
a	Acceptance rate
A_{ad}	Appearing and disappearing area
A_o	Constant object number area
B	Number of beams
b	Beam index
$c^{(i,j)}$	Grid cell at index i, j
d	Mahalanobis distance
d_b	Distance at beam b
ΔT	Timespan between t_{k-1} and t_k
d_f	Observed distance at feature f
$f(\cdot)$	State transition function
f	Feature
$\mathbf{F}$	State transition matrix
H_n	Normalized entropy
$h(\cdot)$	Observation function
$\mathbf{H}$	Observation matrix
$\mathbf{K}$	Kalman gain
k	Discrete time
M	Number of objects/observations
m	Observation index
s, e, r, l, m	Object index

N	Number of samples
n	Sample index
$O(\cdot)$	Upper bound on the growth rate of a function
$\mathbf{P}$	Covariance matrix of the state
$p(\cdot)$	Probability density function
$p^*(\cdot)$	Non-normalized probability density function
$\mathbf{Q}$	Covariance matrix of the process noise
$\mathbf{R}$	Covariance matrix of the observation noise
W	Unscented Kalman filter weights
$q(\cdot)$	Proposal density function
q_r	Proposal ratio
$\mathbf{R}$	Rotation matrix of a homogeneous transformation
$\mathbf{r}_x$	Grid resolution in x direction
$\mathbf{r}_y$	Grid resolution in y direction
$\mathbf{T}$	Translation matrix of a homogeneous transformation
t	Time
U	Logarithmic existence probability ratio
$\mathbf{U}$	Covariance matrix of the expected observation
V	Hyper volume of the gate
S	Variance of x
$\hat{x}$	Mean of x
${}^{\mathbf{i}}w$	Width in image coordinates
${}^{\mathbf{i}}x$	Image x coordinate
${}^{\mathbf{i}}y$	Image y coordinate
$\mathbf{x}$	State space
x_k	Probably multidimensional state of a system at time k
x'	Proposal sample
x	Probably multidimensional random variable
x_0	Grid position offset in x direction
x_t	State of a Markov chain at t
$x^{(n)}$	Sample n
y_0	Grid position offset in y direction
z	Probably multidimensional random variable
Z_k	Set of all observations until time k
z_k	Probably multidimensional observation at time k

Set expressions and auxiliary operators

$\mathcal{C}$	Occupancy grid cells, current object set
$\|\mathcal{S}\|$	Cardinality of $\mathcal{S}$
$\sqrt{\mathbf{P}}$	Cholesky decomposition of $\mathbf{P}$
$\|\mathbf{P}\|$	Determinant of $\mathbf{P}$

$\mathbb{E}(\cdot)$	Expectation value operator
$\mathcal{F}$	Feature pool
$\mathcal{F}_a$	Assignable features
$\mathcal{F}_o$	Assigned features
$\mathbf{P}^{-1}$	Inverse of $\mathbf{P}$
$\mathbb{N}$	Set of natural numbers
$\mathcal{E}$	Entering objects
$\emptyset$	Empty set
$\mathcal{L}$	Leaving objects
$\mathcal{R}$	Set of objects that stay
$\mathcal{S}$	Set of objects
$\mathcal{X}$	Set of samples

List of Acronyms

ACC	Adaptive cruise control
ADAS	Advanced driver assistance systems
CDF	Cumulative density function
CTRA	Constant turn rate and acceleration
EKF	Extended Kalman filter
FIR	Far infrared
FMCW	Frequency modulated continuous wave
GNSS	Global navigation satellite system
HMI	Human machine interface
INS	Inertial navigation system
IPDA	Integrated probabilistic data association
JIPDA	Joined integrated probabilistic data association
LDW	Lane departure warning
MAP	Maximum *a posteriori* approximation
MCMC	Markov chain Monte Carlo
MHT	Multiple hypothesis tracking
MIT	Most important target
MOT	Multiple object tracking
OSPA	Optimal subpattern assignment

PDA	Probabilistic data association
PDF	Probability density function
RJMCMC	Reversible jump Markov chain Monte Carlo
ROI	Region of interest
SIR	Sampling-Importance-Resampling
SIS	Sequential importance sampling
SPRT	Sequential probability ratio testing
TBD	Track-before-detect
UKF	Unscented Kalman filter