

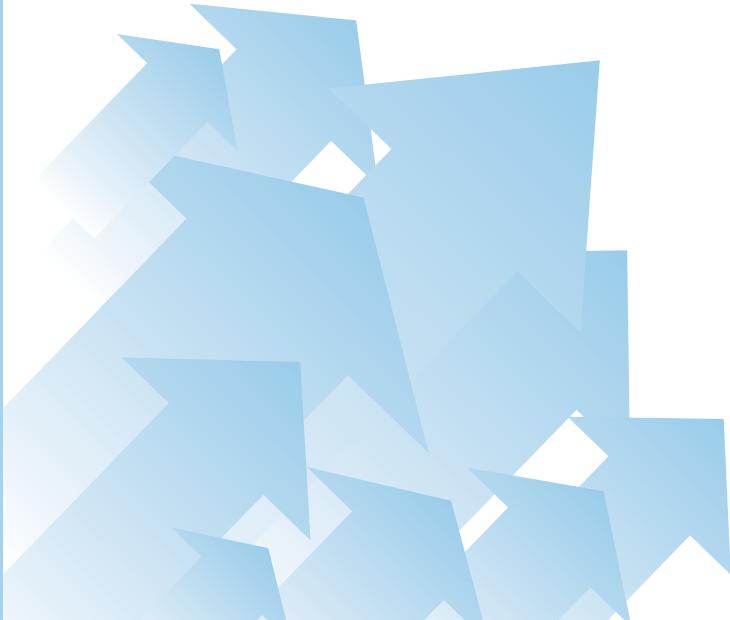
Reihe 12

Verkehrstechnik/
Fahrzeugtechnik

Nr. 804

Michael Aeberhard, M.Sc.,
München

Object-Level Fusion for Surround Environment Perception in Automated Driving Applications



Object-Level Fusion for Surround Environment Perception in Automated Driving Applications

DISSERTATION

submitted in partial fulfillment
of the requirements for the degree

Doktor Ingenieur
(Doctor of Engineering)

in the

Faculty of Electrical Engineering and Information Technology
at Technische Universität Dortmund

by

M.Sc. Michael Aeberhard
Lausanne, Switzerland

Date of approval: May 31st, 2017

First examiner: Univ.-Prof. Dr.-Ing. Prof. h.c. Dr. h.c. Torsten Bertram
Second examiner: Univ.-Prof. Dr.-Ing. Hans-Joachim Wünsche

Fortschritt-Berichte VDI

Reihe 12

Verkehrstechnik/
Fahrzeugtechnik

Michael Aeberhard, M.Sc.,
München

Nr. 804

Object-Level Fusion for
Surround Environment
Perception in Automated
Driving Applications

VDI verlag

Aeberhard, Michael

Object-Level Fusion for Surround Environment Perception in Automated Driving Applications

Fortschr.-Ber. VDI Reihe 12 Nr. 804. Düsseldorf: VDI Verlag 2017.

214 Seiten, 79 Bilder, 21 Tabellen.

ISBN 978-3-18-380412-2, ISSN 0178-9449,

€ 76,00/VDI-Mitgliederpreis € 68,50.

Keywords: Sensor Fusion – Perception – Autonomous Driving – Driver Assistance – Track-to-Track Fusion – Tracking – Object Detection

Driver assistance systems have increasingly relied on more sensors for new functions. As advanced driver assistance system continue to improve towards automated driving, new methods are required for processing the data in an efficient and economical manner from the sensors for such complex systems. In this thesis, an environment model approach for the detection of dynamic objects is presented in order to realize an effective method for sensor data fusion. A scalable high-level fusion architecture is developed for fusing object data from several sensors in a single system. The developed high-level sensor data fusion architecture and its algorithms are evaluated using a prototype vehicle equipped with 12 sensors for surround environment perception. The work presented in this thesis has been extensively used in several research projects as the dynamic object detection platform for automated driving applications on highways in real traffic.

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 2017

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 0178-9449

ISBN 978-3-18-380412-2

Acknowledgments

This thesis and the corresponding research was completed with the Technische Universität Dortmund in cooperation with the BMW Group Research and Technology in Munich, Germany.

First and foremost I would like to thank Univ.-Prof. Dr.-Ing. Prof. h.c. Dr. h.c. Torsten Bertram for advising this thesis and guiding me through the process of undergoing the research and writing the thesis. I am grateful for his many insights, advice and suggestions while completing the thesis. Additionally I would like to thank Univ.-Prof. Dr.-Ing. Hans-Joachim Wünsche of the Universität der Bundeswehr for taking over the role as second examiner.

I would like to thank Dr.-Ing. Dirk Wisselmann, Dr.-Ing. Helmut Spannheimer and Dr.-Ing. Nico Kaempchen for giving me the chance to write my thesis in cooperation with the BMW Group and giving me the opportunity to begin my career in the exciting and fulfilling field of autonomous driving. My sincere thanks go in particular to Dr.-Ing. Nico Kaempchen, who served as my technical adviser at BMW during the time as a doctoral student. Without his guidance, insights, experience and encouragement during the scores of meetings, discussions and test drives, this thesis would not have been possible.

Additionally I would like to thank my fellow colleagues at BMW with whom many exciting projects were completed: Michael Ardel, Mohammad Bahram, Martin Friedl, Thomas Hofmann, Florian Homm, Pei-Shih Huang, Werner Huber, Horst Klöden, Thomas Kühbeck, Yves Pilat, Andreas Rauch, Sebastian Rauch, Bernhard Seidl, Georg Tanzmeister, Julian Thomas, Peter Waldmann and Moritz Werling. I am also grateful for the excellent contributions of all my bachelor/master/diploma thesis students: Christopher Bayer, Sebastian Dingler, Sascha Paul, Marcin Rabiega, Stefan Schlüchthärle and Jinquan Zheng.

My experience with BMW began at the manufacturing plant in Spartanburg, South Carolina as an intern while studying at the Georgia Institute of Technology in Atlanta, GA. For this opportunity, I am thankful to Russell Levesque, my adviser during the internship. I am also thankful to Prof. Dr. Markus Krug, now a Professor at the University of Applied Sciences Munich, for giving me the opportunity to do an international internship at BMW Motorsport in Munich, Germany, which sparked my interest in working in Germany. I would also like to thank Dr.-Ing. Marc Muntzinger for giving me the opportunity to complete my master thesis at Daimler AG in Ulm, Germany, where I first gained experience in the field of driver assistance systems.

I am very grateful and forever indebted to my parents, Brigitte Aeberhard and Peter Aeberhard, for their continued support throughout my life and always believing in me during my endeavors. Last but not least I would like to thank my wife Rabea for her love, support and encouragement during the final stretches of completing this thesis.

Munich, 2017

Michael Aeberhard

66 For once you have tasted flight you will walk the earth with your eyes turned skywards, for there you have been and there you will long to return. 99

Leonardo da Vinci

Contents

Abbreviations	VIII
List of Symbols	X
Abstract	XV
1 Introduction	1
1.1 Motivation	2
1.2 Automation in Driver Assistance and Safety Systems	3
1.2.1 Level 0 – No Automation	6
1.2.2 Level 1 – Driver Assistance	7
1.2.3 Level 2 – Partial Automation	8
1.2.4 Level 3 – Conditional Automation	9
1.2.5 Levels 4 and 5 – Towards Fully Automated Driving	15
1.3 Problem of Object Detection	21
1.4 Contribution and Outline of the Thesis	23
2 Sensor Data Fusion Architectures	27
2.1 Overview	27
2.1.1 Low-Level	28
2.1.2 High-Level	31
2.1.3 Hybrid	32
2.1.4 Comparison	33
2.2 Proposed Modular Sensor Data Fusion Architecture	38
2.2.1 Object Model	39
2.2.2 Sensor-Level	41
2.2.3 Fusion-Level	42
2.2.4 Application-Level	43
3 Fusion Strategy and Object Association	46
3.1 Data Alignment	46
3.1.1 Spatial	46
3.1.2 Temporal	47
3.2 Fusion Strategy	48
3.2.1 Sensor-to-Sensor	48
3.2.2 Sensor-to-Global	49
3.3 Association	50
3.3.1 Architecture	51
3.3.2 Feature Selection	52
3.3.3 State Vector	56
3.3.4 Geometrical	58

3.3.5	Association Validation	60
3.3.6	Multi-Object Association	60
4	State and Covariance	64
4.1	Sensor-Level Processing with Tracking Algorithms	64
4.1.1	Feature Extraction	65
4.1.2	Data Association	66
4.1.3	Filtering	66
4.1.4	Track Management	68
4.1.5	Kinematic Models	68
4.2	Correlation and Sequence of Sensor Data	69
4.2.1	Process Noise	70
4.2.2	Common Information History	71
4.2.3	Out-of-Sequence Data	72
4.3	Track-to-Track Fusion with the Common State	73
4.3.1	Adapted Kalman Filter	74
4.3.2	Covariance Intersection	76
4.3.3	Information Matrix Fusion	77
4.3.4	Comparison	79
4.4	Geometrical Fusion using the Object Model	86
4.4.1	Dimension Estimation	87
4.4.2	Extraction of Fused Coordinates	90
5	Existence Probability	93
5.1	Sensor-Level Processing	93
5.1.1	Existence Prediction	94
5.1.2	Existence Update	95
5.1.3	Generalized Bayes Extension	97
5.1.4	Modeling the Parameters	98
5.1.5	Object Management	104
5.2	Fusion	105
5.2.1	Architecture	105
5.2.2	Modeling with Dempster-Shafer Evidence Theory	105
5.2.3	Extension for Occlusion Modeling	110
5.2.4	Modeling the Trust Probability	114
6	Classification	116
6.1	Sensor-Level Processing	117
6.1.1	Measurement Classification	117
6.1.2	Temporal Filtering	124
6.2	Fusion	124
6.2.1	Modeling with the Dempster-Shafer Evidence Theory	125
6.2.2	Modeling the Trust Probability	130
7	Evaluation	133
7.1	Test Vehicle and Sensor Configuration	133

7.2	Overtaking Maneuver with Ground Truth	135
7.2.1	Ground Truth Calculation	136
7.2.2	State Estimation	136
7.2.3	Existence	140
7.2.4	Classification	140
7.3	Performance in Real Traffic Scenarios	141
7.3.1	Detection Rate	144
7.3.2	Classification Performance	146
7.3.3	Integration in Automated Driving and ADAS Projects	149
8	Conclusion and Discussion	152
A	Synchronous Track-to-Track Fusion Algorithms	155
A.1	Simple Weighted Fusion	155
A.2	Use of Cross-Covariance	157
A.3	Covariance Intersection	158
A.4	Comparison	159
B	Information Matrix Fusion Derivation	162
C	Determining the Trust Probability	164
C.1	Existence	164
C.2	Classification	165
D	Evaluation Scenario Descriptions	167
D.1	Training Data	167
D.2	Evaluation Data	167
D.2.1	Test Track	167
D.2.2	Real Traffic	168
References		172

Abbreviations

ABS	Anti-Lock Brakes.
ACC	Active Cruise Control.
ADAS	Advanced Driver Assistance Systems.
ALA	Active Lane Assist.
ANIS	Average Normalized Innovation Squared.
AUC	Area Under the Curve.
BAST	<i>Bundesanstalt für Straßenwesen.</i>
BBA	Basic Belief Assignment.
BSD	Blind Spot Detection.
CAN	Controller Area Network.
DARPA	Defense Advanced Research Projects Agency.
DSC	Dynamic Stability Control.
DST	Dempster-Shafer Evidence Theory.
EBA	Emergency Brake Assist.
ESP	Electronic Stability Program.
FCW	Forward Collision Warning.
FISST	Finite Set Statistics.
GDA	Gaussian Discriminant Analysis.
GPS	Global Positioning System.
IMM	Interacting Multiple Model.
IPDA	Integrated Probabilistic Data Association.
JIPDA	Joint Integrated Probabilistic Data Association.
JPDA	Joint Probabilistic Data Association.
LDW	Lane Departure Warning.

LKA	Lane Keeping Assist.
MHT	Multiple Hypothesis Tracking.
NEES	Normalized Estimation Error Squared.
NHTSA	National Highway Traffic Safety Administration.
NIS	Normalized Innovation Squared.
PDA	Probabilistic Data Association.
PHD	Probability Hypothesis Density.
RMSE	Root Mean Squared Error.
ROC	Receiver Operating Characteristic.
SAE	Society of Automotive Engineers.
SVM	Support Vector Machines.
TJA	Traffic Jam Assist.
V2V	Vehicle-to-Vehicle Communication.
VRU	Vulnerable Road User.

List of Symbols

General Notation

a	Scalar
\mathbf{a}	Vector
\mathbf{A}	Matrix
\mathbf{A}'	Transpose of matrix \mathbf{A}
\mathbf{A}^{-1}	Inverse of matrix \mathbf{A}
$(\hat{\cdot})$	Estimate of the true value of (\cdot)
$(\tilde{\cdot})$	Error between the estimate $(\hat{\cdot})$ and the true value (\cdot)
$(\bar{\cdot})$	Complement of (\cdot)
$(\cdot)(k)$	Value of (\cdot) at the discrete time step k
$(\cdot)_k$	Value of (\cdot) at the discrete time step k
$(\cdot)(k \mid k)$	Value of (\cdot) at the discrete time step k conditioned on information from the current time step k
$(\cdot)_{k k}$	Value of (\cdot) at the discrete time step k conditioned on information from the current time step k
$(\cdot)(k \mid k - i)$	Value of (\cdot) at the discrete time step k conditioned on information from a previous discrete time step $k - i$
$(\cdot)_{k k-i}$	Value of (\cdot) at the discrete time step k conditioned on information from a previous discrete time step $k - i$
$(\cdot)(k, k - i)$	Transition from $k - i$ to k with (\cdot)
$(\cdot)(t)$	Value of (\cdot) at the continuous time t
$(\cdot)(t - \tau)$	Value of (\cdot) at a previous continuous time $t - \tau$
$\{(\cdot)\}(t)$	Set of (\cdot) at the continuous time t
$\{(\cdot)\}_a^b$	Complete set of (\cdot) from time a up to time b
$\text{Bel}((\cdot))$	Belief function
$\text{BetP}((\cdot))$	Pignistic transformation of (\cdot)

$E[(.)]$	Expected value of (.)
$F_{(.)}^{-1}$	Inverse cumulative distribution function for the (.) distribution
$m((.))$	Dempster-Shafer evidence theory basic belief assignment
$Pl((.))$	Plausibility function

Latin Letters

\mathcal{C}	Set of classification hypothesis
\mathcal{D}	Generic representation for some data
\mathcal{E}	Environment model
\mathcal{G}	Generic representation for spatial-based, or grid-based, objects/obstacles
\mathcal{I}	Generic representation for information
\mathcal{I}^*	Generic representation for a-priori information
\mathcal{L}	Log odds ratio
\mathcal{M}	Generic representation for digital map information
\mathcal{O}	Object list
\mathcal{R}	Generic representation for road infrastructure information
\mathcal{S}	Generic representation for data perceived from a sensor
\mathcal{T}	Training set
\mathcal{U}	Generic representation for control information from the host vehicle platform
\mathcal{X}	Generic representation for host vehicle localization and pose
\mathbf{c}	Classification vector of an object
\mathbf{d}	Dimension vector of an object
\mathbf{d}_{σ^2}	Dimension uncertainty vector of an object
\mathbf{f}	Feature vector of an object
\mathbf{m}	1-dimensional grid map for geometrical dimension estimation
\mathbf{p}	Position vector in a Cartesian coordinate system
\mathbf{u}	Host system control vector
\mathbf{w}	Normal vector to a decision boundary
\mathbf{x}	State vector of an object
\mathbf{x}_a	State vector subset of \mathbf{x} of an object used for association

y	Attribute vector for classification
z	Measurement vector
A	Object association matrix
B	Control transformation matrix
C	Association cost matrix in the auction algorithm
F	State transition matrix
H	State-space transformation matrix
I	Identity matrix
K	Kalman gain
S	Innovation covariance matrix
P	Covariance matrix of a state estimate $\hat{\mathbf{x}}$
P ^{ab}	Cross-covariance between the state estimates $\hat{\mathbf{x}}^a$ and $\hat{\mathbf{x}}^b$
P _{ab}	Cross-covariance matrices with retrodicted states
Q	Process noise covariance matrix
R	Covariance matrix of a measurement z
W	Kalman gain for an out-of-sequence measurement
<i>a</i>	Acceleration of an object
<i>a</i> _{i,j}	The element of the association matrix A in the <i>i</i> th row and <i>j</i> th column
<i>w</i>	Width of an object
<i>b</i>	Bias parameter
<i>d</i>	Geometrical dimension of an object
<i>d</i> ²	Mahalanobis distance
<i>g</i>	Boolean result from geometrical association
<i>l</i>	Length of an object
<i>m</i>	Single cell of the 1-dimensional map m
<i>n</i> _{a}	Number of elements, or dimension, of vector a
<i>p</i>	Bid price for assignment in the auction algorithm
<i>r</i>	Range in a polar coordinate system
<i>v</i>	Velocity of an object
<i>x</i>	Position of an object on the <i>x</i> -axis in a Cartesian coordinate system
<i>y</i>	Position of an object on the <i>y</i> -axis in a Cartesian coordinate system

C_i	Object class i , where i corresponds to the i th element of \mathbf{c} or \mathcal{C}
D^2	Extended Mahalanobis distance
G	Gating threshold during object association
H	Object association hypothesis
O_i	The i th object in an object list \mathcal{O}
Z^i	List of measurements from sensor i

Greek Letters

γ	Dempster-Shafer evidence theory prediction weight
δ	Offset/translation of a sensor's placement on the vehicle
$\Delta(\cdot)$	Difference of (\cdot) between two values
ϵ	Normalized Estimation Error Squared
η	Normalization factor
θ	Orientation of a sensor's mounting position on the vehicle
Θ	Dempster-Shafer evidence theory frame of discernment
λ	Rate parameter of a Poisson process
μ	Mean
ρ	Correlation weighting factor
σ	Standard deviation
σ^2	Variance
ϕ	Angle in a 2-dimensional polar coordinate system
ψ	Orientation angle of an object
$\dot{\psi}$	Orientation velocity of an object
ω	Covariance intersection weighting factor

Subscripts and Superscripts

$(\cdot)^{S_i}$	(\cdot) originates from sensor S_i
$(\cdot)^G$	(\cdot) results from a global fusion algorithm
$(\cdot)^{\text{obj}}$	(\cdot) is in the object coordinate system
$(\cdot)^{\text{sensor}}$	(\cdot) is in the sensor coordinate system
$(\cdot)^{\text{veh}}$	(\cdot) is in the host vehicle coordinate system

$(.)_f$	Value of $(.)$ corresponds to the feature f
$(.)_x$	Scalar corresponding to the x component of $(.)$ in a Cartesian coordinate system
$(.)_y$	Scalar corresponding to the y component of $(.)$ in a Cartesian coordinate system
$(.)_{a \rightarrow b}$	Transformation from a to b

Probabilities

$p(a)$	Continuous probability density function of the random variable a
$p(a b)$	Continuous conditional probability density of the random variable a conditioned on b
$p(\exists \mathbf{x})$	Existence probability of an object
$p(\nexists \mathbf{x})$	Non-existence probability of an object
p_b	Birth probability
p_c	Clutter probability
p_d	Detection probability
p_p	Persistence probability
p_{trust}	Trust probability
$P_{(.)}$	Scalar probability value

Abstract

Driver assistance systems have increasingly relied on more sensors for new functions. As advanced driver assistance system continue to improve towards automated driving, new methods are required for processing the data in an efficient and economical manner from the sensors for such complex systems. The detection of dynamic objects is one of the most important aspects required by advanced driver assistance systems and automated driving. In this thesis, an environment model approach for the detection of dynamic objects is presented in order to realize an effective method for sensor data fusion. A scalable high-level fusion architecture is developed for fusing object data from several sensors in a single system, where processing occurs in three levels: sensor, fusion and application. A complete and consistent object model which includes the object's dynamic state, existence probability and classification is defined as a sensor-independent and generic interface for sensor data fusion across all three processing levels. Novel algorithms are developed for object data association and fusion at the fusion-level of the architecture. An asynchronous sensor-to-global fusion strategy is applied in order to process sensor data immediately within the high-level fusion architecture, giving driver assistance systems the most up-to-date information about the vehicle's environment. Track-to-track fusion algorithms are uniquely applied for dynamic state fusion, where the information matrix fusion algorithm produces results comparable to a low-level central Kalman filter approach. The existence probability of an object is fused using a novel approach based on the Dempster-Shafer evidence theory, where the individual sensor's existence estimation performance is considered during the fusion process. A similar novel approach with the Dempster-Shafer evidence theory is also applied to the fusion of an object's classification. The developed high-level sensor data fusion architecture and its algorithms are evaluated using a prototype vehicle equipped with 12 sensors for surround environment perception. A thorough evaluation of the complete object model is performed on a closed test track using vehicles equipped with hardware for generating an accurate ground truth. Existence and classification performance is evaluated using labeled data sets from real traffic scenarios. The evaluation demonstrates the accuracy and effectiveness of the proposed sensor data fusion approach. The work presented in this thesis has additionally been extensively used in several research projects as the dynamic object detection platform for automated driving applications on highways in real traffic.

