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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

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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.

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> *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.*
>
> Leonardo da Vinci

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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 *Bundesanstalt für Straßenwesen*.

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 $\mathbf{A}$
$\hat{(.)}$	Estimate of the true value of $(.)$
$\tilde{(.)}$	Error between the estimate $\hat{(.)}$ and the true value $(.)$
$\bar{(.)}$	Complement of $(.)$
$(.)(k)$	Value of $(.)$ at the discrete time step k
$(.)_k$	Value of $(.)$ at the discrete time step k
$(.)(k \mid k)$	Value of $(.)$ at the discrete time step k conditioned on information from the current time step k
$(.)_{k\|k}$	Value of $(.)$ at the discrete time step k conditioned on information from the current time step k
$(.)(k \mid k-i)$	Value of $(.)$ at the discrete time step k conditioned on information from a previous discrete time step $k-i$
$(.)_{k\|k-i}$	Value of $(.)$ at the discrete time step k conditioned on information from a previous discrete time step $k-i$
$(.)(k, k-i)$	Transition from $k-i$ to k with $(.)$
$(.)(t)$	Value of $(.)$ at the continuous time t
$(.)(t-\tau)$	Value of $(.)$ at a previous continuous time $t-\tau$
$\{(.)\}(t)$	Set of $(.)$ at the continuous time t
$\{(.)\}_a^b$	Complete set of $(.)$ from time a up to time b
$\mathrm{Bel}((.))$	Belief function
$\mathrm{BetP}((.))$	Pignistic transformation of $(.)$

$\mathrm{E}\left[(.)\right]$	Expected value of (.)
$F_{(.)}^{-1}$	Inverse cumulative distribution function for the (.) distribution
$m((.))$	Dempster-Shafer evidence theory basic belief assignment
$\mathrm{Pl}((.))$	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
$\mathbf{d}_{\sigma^2}$	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
$\mathbf{x}_{\mathrm{a}}$	State vector subset of $\mathbf{x}$ of an object used for association

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

C_i	Object class i, where i corresponds to the ith 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 ith 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
$\Delta(.)$	Difference of $(.)$ 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

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

$(.)_{\mathrm{f}}$	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
$(.)_{\mathrm{a}\to\mathrm{b}}$	Transformation from a to b

Probabilities

$p(a)$	Continuous probability density function of the random variable a
$p(a \mid b)$	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.