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Abstract

Position information has become an elementary part of the daily life, devices like mobile phones or navigation systems using it extensively. Furthermore, upcoming automotive technologies such as vehicle-to-vehicle communication process this kind of data as well. However, the accuracy and availability of position information obtained from affordable off-the-shelf GPS receivers is limited due to physical constraints. At the same time, a more accurate positioning would offer new possibilities for vehicle-related applications like comfort and safety systems.

The work at hand describes novel measurement models for the localization of vehicles in urban environments. The system utilizes different sensors which are mounted to a vehicle: A gray scale camera, vehicle motion sensors and a GPS receiver. Moreover, digital maps are used as additional source of information. The innovation of the presented method is in the novel kind of incorporation of the image data delivered by a camera sensor into the process of estimating the vehicle's position. In contrast to state-of-the-art approaches, the models proposed by the author are able to include entire image areas instead of only distinct features limited in terms of space. The approaches use different means of representing the digital map data. On the one hand, data equivalent to standardized map databases can be utilized. On the other hand, aerial images can be used as well.

The presented approaches are evaluated using real-world data. For this purpose, measurements were provided by a test vehicle and an extensive test drive. The results of the algorithm are compared to a ground-truth reference. It is shown that the approach proposed by the author can achieve lane-level accuracy of the position information in urban environments using the given sensors. This enables new kinds of applications, at the same time keeping the costs for such system feasible.

Furthermore, the work at hand presents two additional approaches for solving relevant partial problems in the domain of vehicle localization. One method aims to remove systematic errors of vehicle motion sensors in the process of estimating a vehicle's ego motion. To achieve that, GPS information is fused with motion data of a vehicle. The second application derives accuracy requirements for a relative positioning system which is used for cooperative localization in urban environments. It simulates vehicle-to-vehicle communication and utilizes vehicle motion data as well as data of a standardized digital map.

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Glossary

Acronyms

ABS	Anti-lock braking system
ADAS	Advanced driver assistance system
AOA	Angle-of-arrival
BN	Bayesian network
C2C	Car-to-car
CCA	Constant curvature and acceleration
CEP	Circular error probable
CSW	Cumulative sum of normalized particle weights
CTRV	Constant turn rate and velocity
DGPS	Differential GPS
ESC	Electronic stability control
FFT	Fast-Fourier transform
FOV	Field of view
GDF	Geographic Data File
GNSS	Global navigation satellite system
GPS	Global Positioning System
HSI	Hue, Saturation, Intensity
i.i.d	independent and identically distributed
INS	Inertial navigation system
IQR	Interquartile range

ITS	Intelligent transportation system
KF	Kalman filter
LDM	Local Dynamic Map
LOS	Line-of-sight
MAP	Maximum a posteriori
MC	Monte Carlo
MCL	Monte Carlo localization
MEMS	Micro-electromechanical system
MHT	Multi-hypothesis tracking
ML	Maximum likelihood
MMSE	Minimum mean-square error
MOT	Multi-object tracker
MW	Maximum weight
NLOS	Non-line-of-sight
pdf	Probability density function
PF	Particle filter
RTK	Real-time kinematik
SIS	Sequential importance sampling
SLAM	Simultaneous localization and mapping
SMC	Sequential Monte Carlo
SNR	Signal-to-noise ratio
SPKF	Sigma-point Kalman filter
TDOA	Time-difference-of-arrival
TOA	Time-of-arrival

TOF	Time-of-flight
UKF	Unscented Kalman filter
UTM	Universal Transverse Mercator
UWB	Ultra-wide band
V2V	Vehicle-to-vehicle
WGS	World Geodetic System
WSN	Wireless sensor network

Greek letters

ΔT	Time difference between t_k and t_{k-1}
γ	Attitude of a vehicle
μ	Magnitude of \mathbf{o}
ω	Yaw rate of a vehicle
ϕ	Orientation of \mathbf{o}
Ψ	Tangent angle

Roman letters

a	Acceleration of a vehicle
\mathcal{C}	Set of classes of the world representation
$^{cc}(\dots)$	Camera coordinates
C	Curvature of circle arc for feature estimation
c	Curvature of circle arc for motion model
c_c	Coherency value of the structure tensor
$E\{f(x)\}$	Expectation value of $f(x)$
\mathbf{f}	State transition function at time k
\mathbf{h}	Measurement model

${}^{cam}\mathbf{H}$	Camera calibration matrix
${}^{int}\mathbf{H}$	Intrinsic camera parameters
\mathbf{I}	Intensity value of the structure tensor
${}^{ic}(\dots)$	Image coordinates
\mathbf{J}	Structure tensor
\mathbf{K}	Kalman gain
k	Time index
\mathbf{m}	Set of features of a digital map
$\mathcal{N}(x; \mu, \sigma^2)$	Normally distributed random variable x with mean value μ and variance σ^2
\mathbf{o}	Orientation vector of the structure tensor
\mathcal{P}	Image of classes \mathcal{C}
P	Covariance matrix
$p(\mathbf{x})$	Probability density function of \mathbf{x}
s	Scale factor of a wheel velocity sensor
\mathbf{T}	Matrix for transformation of coordinates
\mathcal{T}	Structure tensor representation of an image
${}^{ext}\mathbf{T}$	Extrinsic camera parameters
t_k	Time at time index k
\mathbf{u}	Control input vector
\mathbf{U}_k	Sequence of control inputs \mathbf{u}_0 to \mathbf{u}_k
\mathbf{v}	Process noise vector
${}^{vc}(\dots)$	Vehicle coordinates
$v(\dots)$	Quantity of a vehicle

v	Velocity of a vehicle
v_{gnd}	Velocity over ground
\mathbf{w}	Measurement noise vector
$w^c(\dots)$	World coordinates
$w(\mathbf{x}^i)$	Weight of i -th sample of a particle set
x	x-coordinate of a vehicle
\mathbf{x}	State vector
$\hat{\mathbf{x}}_k$	Mean value of $p(\mathbf{x}_k)$
y	y-coordinate of a vehicle
y_t	Tangent offset
\mathbf{z}	Measurement vector
\mathbf{Z}_k	Sequence of measurements \mathbf{z}_0 to \mathbf{z}_k