

Vector Distance Transform Maps for Autonomous Mobile Robot Navigation

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the degree of

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under the supervision of
Prof. Gamini Dissanayake and Dr. Ravindra Ranasinghe

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Certificate of Original Authorship

I, Janindu Sithumini Arukgoda declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

Robot localization, where the position and the orientation of a mobile robot is estimated based on an *a priori* map, is a fundamental problem in autonomous mobile robot navigation. In this thesis, we present how environments can be represented using the vector distance transform for mobile robot localization, and show that it is a superior representation compared to alternatives such as occupancy grid maps and other distance transform variants such as the unsigned distance transform and the signed distance transform.

We propose an approach based on non-linear least squares optimization for robot localization on environments represented by vector distance transform maps, that also captures the uncertainty of the position estimate. We also propose an approach based on extended Kalman filter for robot localization on environments represented by vector distance transform maps. Using simulations, public domain data and real world experiments, the proposed localization approaches are evaluated and compared with existing localization techniques in multiple robot platforms including both ground and aerial robots navigating in 2D and 3D environments using a series of sensors including LiDARs and cameras.

We propose an information filtering based approach for mobile robot localization where a single endpoint range sensor can be used to accurately localize a mobile robot in motion by rotating it in a direction that will improve its position estimate and the corresponding uncertainty. The proposed approach is evaluated using simulations and real world experiments.

Occupancy grid maps, the most popular type of map for robot localization using a range-bearing sensor, are assumed perfect when used for localization. It is a discrete representation of the environment and the probability of occupancy of each cell is independent from its neighbors. Given a set of robot poses and corresponding range-bearing measurements, both incorporated with uncertainty, a representation of environment based on the vector distance transform using non-linear least squares optimization that is both continuous and uncertain is proposed for robot localization. Simulations are used to demonstrate the accuracy of the map and its uncertainties.

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Acronyms & Abbreviations

1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
AMCL	Adaptive Monte Carlo Localization
AML	Active Markov Localization
CAS	Centre for Autonomous Systems
EKF	Extended Kalman Filter
GPs	Gaussian Processes
GPS	Global Positioning System
IMU	Inertial Measurement Unit
LRF	Laser Range Finder
NDT	Normal Distribution Transform
OGM	Occupancy Grid Map
PDE	Partial Differential Equation
RTK-GPS	Real-Time Kinematics GPS
SDF	Signed Distance Function
SDT	Signed Distance Transform

SLAM	Simultaneous Localization and Mapping
UAV	unmanned aerial vehicle
UDF	Unsigned Distance Function
UDT	Unsigned Distance Transform
UTS	University of Technology Sydney
UWB	Ultra-wideband
VCD	Vector Chamfer Distance
VDF	Vector Distance Function
VDT	Vector Distance Transform

Nomenclature

General Notations

t	Time (continuous)
k	Time (discrete step)
DT_u	Unsigned Distance Transform
DT_s	Signed Distance Transform
DT_v	Vector Distance Transform
DT_x	x component of the Vector Distance Transform
DT_y	y component of the Vector Distance Transform
DT_z	z component of the Vector Distance Transform
d_{VCD}	Vector Chamfer Distance
d_{VDT}	Disparity vector between the observation and the Vector Distance Transform
r_i	i^{th} range measurement
σ_r	Standard deviation of range measurement noise
θ_i	i^{th} bearing measurement
Z	Space of all possible observations
z_i	i^{th} observation, $z_i \in Z$
X_o	Observation vector
J	Jacobian matrix
H	Hessian matrix

\mathbf{X}_R	Robot pose
$\hat{\mathbf{X}}_R$	Robot pose estimate
P	Robot pose covariance matrix
$g(\cdot, \cdot)$	Motion model
$h(\cdot, \cdot)$	Observation model
∇G_{\square}	Jacobian of the motion model with respect to \square
∇H_{\square}	Jacobian of the observation model with respect to \square
v	Linear velocity
ω	Angular velocity
ν	Innovation vector
K	Kalman Gain
\square_{k-1}	Previous state
$\square_{k k-1}$	Predicted current state
\square_k	Updated current state
$cov(\cdot)$	Covariance matrix
$diag(\cdot)$	Diagonal matrix
$trace(\cdot)$	Trace of a matrix
$\Sigma(\cdot)$	Summation
\int	Integral operator
∂	Partial differentiation operator