Navigation and Control for Assistive Robotics

by

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A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

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Certificate of Original Authorship

I certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

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Abstract

In this thesis, we address the problem of navigation and control for assistive robots. Autonomously creating a suitable representation of the environment (a map) and having the ability to localise a robot in that environment are considered to be the cornerstones of autonomous robot navigation. We present a distance function based framework to represent the occupancy of two-dimensional environments and a chamfer distance based sensor model to relate measurements captured from a sensor mounted on the robot to the environment representation. Employing the proposed representation and the sensor model, we propose two novel strategies to localise the robot on the map using an extended Kalman filter and an optimisation based method. These methods are computationally more efficient and are free of environment dependent tuning, which are necessities for assistive robots to operate in different environments ranging from small households to large shopping centres. We also demonstrate an adaptation of the popular particle filter based localisation algorithm using the distance function representation.

A mapping algorithm that utilises the proposed distance function based framework, which can be used to create maps of considerably large scale crowded indoor environments with low error accumulation is also presented. Although we do not consider the effect of sensor uncertainties, we demonstrate that the algorithm can efficiently build high-quality maps that can be used in practical scenarios of importance associated with assistive robots.

We present experiments conducted using simulations, public domain datasets, and experimental datasets we collected in real environments to evaluate and compare these algorithms.

The control strategy used in an assistive robot needs to be specifically designed to suit the task that the robot is expected to perform. Using standard user centred design methods often result in complicated, unintuitive control interfaces for assistive robots, which are difficult to be integrated into the daily activities of the end users.

We demonstrate that design approaches based on the principles of cooperative design can be used to alleviate the complexities in the design process. We propose and develop a control system based on admittance control for a robotic hoist, and evaluate it using user studies to experimentally illustrate that this design framework could be used for developing controllers for assistive robots in general.

The analysis of electromyographic measurements and forces exerted by the end users while using the robotic hoist confirm that the robot has the potential to reduce musculoskeletal injuries amongst care workers in the aged and disabled care sector, by providing assistance during the patient transfer process. As a result of the cooperative design process, the control interface became simple, intuitive, and easy to use, which made the robot readily incorporable to the work-flow of care facility.

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Contents

List of Figures

Acronyms & Abbreviations

1D	One-dimensional
2D	Two-dimensional
3D	Three-dimensional
AMCL	Adaptive Monte-Carlo localisation
AR	Assistive robotics
BMI	Body Mass Index
C-LOG	A Chamfer Distance Based Method for Localisation in Occupancy Grid-maps
CAS	Centre for Autonomous Systems
CD	Chamfer distance
CPU	Central Processing Unit
DARPA	Defense Advanced Research Projects Agency
DF	Distance function
DT	Distance transform
EKF	Extended Kalman filter
EMG	Electromyography
EP	End Point
FEA	Finite Element Analysis

GP	Gaussian process
GPS	Global Positioning System
GPU	Graphics Processing Unit
GUI	Graphical User Interface
ICL	Iterative Closest Line
ICP	Iterative Closest Point
ICS	Iterative Closest Surface
IF	Information Filter
IRT	Illawarra Retirement Trust
KL	Kullback-Leibler
LiDAR	Light detection and ranging
LRF	Laser range finder
MCL	Monte-Carlo Localisation
ML	Maximum Likelihood
MVC	Maximum Voluntary Contraction
NEES	Normalised estimation error squared
NDT	Normal distribution transform
ND	Normal distribution
OG	Occupancy Grid
OGM	Occupancy Grid Map
PF	Particle filter
RBPF	Rao-Blackwellized particle filter

RGB	Red, Green, and Blue
RGBD	Red, Green, Blue, and Depth
RMS	Root-mean-square
ROS	Robot Operating System
SDF	Signed Distance Function
SLAM	Simultaneous Localisation And Mapping
SLS	Selective Laser Sintering
SVD	Singular Value Decomposition
TREC	Terrestrial Robotics and Control Laboratory
TSDF	Truncated Signed Distance Function
UCD	User Centred Design
UI	User Interface
UPS	Uninterruptible Power Supply
UTS	University of Technology, Sydney
VSDF	Volumetric Signed Distance Function
WSN	Wireless sensor networks

Nomenclature

	General Notations
t	Time (continuous)
k	Time (discrete step)
$\square$	Denotes any variable
α	Direction of linear force.
C	Coefficient of damping, linear motion.
C_ω	Coefficient of damping, angular motion.
$C(\cdot,\ \cdot)$	A cost function.
DF	A distance function matrix obtained by transforming a binary image or an OGM
d_{DF}	Abbreviation for $DF(\mathbf{x}_o)$
d_{CD}	Abbreviation for $d_{CD}(\mathbf{z} \mid \mathbf{x},\ DF)$
δ_{ij}	Spatial relation between the pose at i^{th} and j^{th} locations.
ϵ_k	NEES metric.
$\bar{\epsilon}_k$	Average-NEES metric.
$\varepsilon(\cdot)$	Error between pose relations (SLAM benchmarking metric).
$\bar{\varepsilon}(\cdot)$	Mean error between pose relations (SLAM benchmarking metric).
η	Normalisation constant.
η_r	Noise of a range measurement.
F	Linear force.
$F(\cdot)$	Control function.
f_{ex}	Feature extraction function.

γ	Threshold for association of NDs.
$h(\cdot,\ \cdot)$	Observation function.
I	Moment of inertia
$J_\square$	Jacobian matrix with respect to $\square$.
K	Kalman gain
m	Mass.
$\mathbf{m}$	Map of the environment.
$\nabla F_\square$	Jacobian of the control function with respect to $\square$.
$\nabla h_\square$	Jacobian of the observation function with respect to $\square$.
$\mathcal{O}(\cdot)$	Big O notation.
ω	Angular velocity.
$P_{\square\vert\square}$	Covariance matrix of the state vector.
${}^{\{B\}}_{\{A\}}\mathbf{p}$	Relative transform between two coordinate frames.
ϕ	Orientation of the robot.
Q_k	Covariance matrix of control noise at time k.
r_i	The i^{th} range reading.
S	The space of all possible sensor readings.
$\Sigma_\square$	Covariance matrix.
σ_r	Standard deviation of range noise.
$\mathbf{s}$	$\mathbf{s} \in S$, a single observation at a certain state of the robot, $\mathbf{x}$
τ	Torque.
θ_i	The bearing of the i^{th} sensor reading.
u_k	Control command at time k.
v	Linear velocity.
$\mathbf{x}$	Robot Pose vector in 2D space. Consists of the position components $x,\ y$ and the orientation component ϕ.
$\mathbf{x}_o$	Observation coordinates. In the case of a laser range finder sensor, consists of n readings of range r_i and bearing θ_i. Can be translated into global Cartesian coordinates x_{o_i} and y_{o_i} using (2.8).
Z	Space of all possible observations.
$\mathbf{z}$	Observation vector, $\mathbf{z} \in Z$.

Coordinate Frames & Transforms

${}^{\{C\}}\square$	Camera coordinate frame.
${}^{\{G\}}\square$	Global coordinate frame.
${}^{\{I\}}\square$	Image coordinate frame.
${}^{\{R\}}\square$	Robot coordinate frame.
${}^{\{A\}}_{\{B\}}R$	Rotation matrix between the coordinate system A to coordinate system B.
${}^{\{A\}}_{\{B\}}T$	Homogeneous transform matrix from the coordinate system A to coordinate system B.
${}^{\{A\}}_{\{B\}}t$	Translation matrix between the coordinate system A to coordinate system B.

Distributions

$\mathcal{F}$	Folded normal distribution.
$\mathcal{N}$	Normal distribution.
$\mathcal{U}$	Uniform distribution.

Operations

$\dot{\square}$	The first derivative of $\square$.
$\oplus$	The standard motion composition operator.
$\ominus$	Inverse of the standard motion composition operator.
$CD(\cdot,\ \cdot)$	Chamfer distance between a template and a reference.
$DF(\mathbf{x}_o)$	Value of the distance function at the observation coordinate $\mathbf{x}_o$.
$R(\theta)$	2D rotation matrix for an orientation change of θ.
$\prod(\cdot)$	Product.
$\sum(\cdot)$	Summation.

State Transitions

$\square_{k-1\|k-1}$	Previous state.
$\square_{k\|k-1}$	Predicted current state.
$\square_{k\|k}$	Updated current state.