Locating Senior Walking Frame Users in Crowded Indoor Environments

by

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A thesis submitted in partial fulfilment for the
degree of Master of Engineering (Research)

at the
Centre for Autonomous Systems
Faculty of Engineering and Information Technology
University of Technology Sydney

October 2017

Declaration of 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

This thesis presents a low cost indoor localization system, primarily intended for use by professional elder care supervisors for tracking elderly people in their excursions to a crowded shopping centre. The main requirement is that the system provides an approximate locations of multiple elderly people during an excursion to a crowded shopping centre. The residents are to use walking frames for locomotion, thus their motion is relatively slow and predictable. The resolution of localization is considered adequate if the care supervisor is able to locate a given person through visual contact relative to the estimated location. This thesis presents two novel localization methods that make use of these simplifying constraints and provides an industry strength implementation of one of these strategies.

The first method described is an image based place recognition technique that employs the Bag of Words model for generating image descriptors and a three layer feedforward neural network for producing location estimates. Shop fronts and their corresponding neighbourhood areas are used as classes for training the neural network. The performance of this approach that was evaluated in a real shopping centre environment is presented. Although the system developed performs well, it was found to require the user cooperation in crowded areas and was deemed to have potential privacy concerns.

An alternative solution, a Wi-Fi based indoor localization method is also presented. It estimates the current location of a subject using the Wi-Fi signal strengths received by a sensor module mounted on a walking frame. The environment is modelled as a collection of cells with sizes sufficiently small for locating a person through eye contact. A motion model, based on the knowledge of the floor plan of the environment is described. A probabilistic framework using the Bayes rule in combination with a Kernel Density method for estimating the probability density functions of received signal strengths at the cells is developed.

The Wi-Fi based indoor localization method was implemented on a unit that measures strengths of Wi-Fi signals received from the access points present in an environment,

computes the location and transmits it using the telephone network to a tablet held by a carer. An application on the tablet for visualizing the location of multiple walkers was also developed. The performance of this system was evaluated by conducting multiple trials, including a shopping centre excursion organized by a professional elder care provider named IRT.

From the localization accuracies obtained through the test trials, it could be concluded that the presented Wi-Fi based localization method is adequate to fulfil the requirement of IRT, which is locating elderly people in a crowded indoor environment. It is also found that the floor plan based motion model enables the localization algorithm to produce reliable location estimates, given the relatively slow motion of elderly people.

Acknowledgements

I would like to express my immense gratitude to the people who have supported me in many ways throughout my research.

Firstly, I thank my principal supervisor, Professor Gamini Dissanayake for his continuous support and supervision provided throughout this work, which eventually led to the completion of a quality thesis. His broad scope of knowledge and experience, as well as the patience and understanding nature helped me immensely to complete my research successfully. I'm also grateful to my co-supervisor, Doctor Ravindra Ranasinghe for the support and guidance provided to me. His experience and enthusiasm was invaluable for the completion of this work.

My thanks also go to the staff and residents in Illawarra Retirement Trust (IRT) care facility based in Sydney, for their collaboration in the designing, developing and evaluating processes of the indoor localization system proposed in this work.

I would also like to extend my gratitude to Doctor Lakshitha Danthanarayane, Doctor Michael Behrens and Janindu Arukgoda for their contributions to this work. Their assistance in various software and hardware related development tasks made this work a reality.

I also thank all my colleagues in Centre for Autonomous Systems (CAS), who made my stay in the lab wonderful and joyful. I was extremely fortunate to be a part of CAS circle.

Last, but not least, I would like to thank my loving family: Heartfelt thanks go to my wife Nilakshika, who stayed with me in all the good times and bad times. Thank you for your patience and understanding. I extend my sincere gratitudes to my parents, who made immense sacrifices to bring me to this state. Without your effort, nothing would have been possible.

Contents

List of Figures

Acronyms & Abbreviations

1D	One-Dimensional
2D	Two-Dimensional
3D	Three-Dimensional
CAS	Centre for Autonomous Systems
UTS	University of Technology, Sydney
IRT	Illawarra Retirement Trust
GPU	Graphics Processing Units
RGB	Red Green Blue
RGB-D	Red Green Blue Depth
KDE	Kernel Density Estimation
LRF	Laser Range Finder
BoW	Bag of Words
RFID	Radio Frequency Identification
AMCL	Adaptive Monte-Carlo Localization
SLAM	Simultaneous Localization and Mapping
EKF	Extended Kalman Filter

MCL Monte Carlo Localization

IMU Inertial Measurement Unit

CNN Convolutional Neural Network

SVM Support Vector Machine

SURF Speeded Up Robust Features

KLT Kanade-Lucas-Tomasi

RANSAC Random Sample Consensus

HOUP Histogram of Oriented Uniform Patterns

UWB Ultra-Wide Band

BLE Bluetooth Low Energy

RSSI Received Signal Strength Indication

ToF Time of Flight

LoS Line of Sight

FAF Floor Attenuation Factor

WAF Wall Attenuation Factor

AoA Angle of Arrival

TDoA Time Difference of Arrival

KNN K-Nearest Neighbour

IAP Important Access Points

MLP Multi-Layer Perceptron

RBF Radial Basis Function

GRNN Generalized Regression Neural Network

cRBF Clustered Radial Basis Function

DAQ Data Acquisition

MAC Media Access Control

ROS Robot Operation System

Nomenclature

General Notations

$e^{\square}$	Exponential
α	Gain parameter in contrast/brightness function
β	Bias parameter in contrast/brightness function
$W_{\square,\square}$	Weight parameter in neural network
$B_{\square}$	Bias parameter in neural network
f	Frequency
X_g	Normal random variable which reflects the attenuation due to flat fading
γ	Path loss exponent
d	Distance
d_0	Reference distance
$\bar{d}$	estimated distance
FAF	Floor attenuation factor
WAF	Wall attenuation factor
n_w	Number of walls
C_w	Maximum number of walls upto which the attenuation factor makes an effect
$t_{\square,\square}$	Transition from one cells to another
N	Number of cells
M	Number of access points
(x, y)	Geometric x and y coordinates in a 2D plane

$s_{\square}$	Signal strength value of an access point
$\theta_{\square}$	Direct path angle of arrival of an access point
ρ	Case base parameter in *exponential* signal strength representation
ϕ	Case base parameter in *powed* signal strength representation
τ	Signal strength threshold
$F_{\square}$	A given value in floor weight vector
g	Decay constant for floor weight vector

Functions

$O(.,.)$	RGB pixel values at a given spatial coordinate of an output image
$I(.,.)$	RGB pixel values at a given spatial coordinate of an input image
$H(.,.)$	Cross entropy function of two distributions
$K(.)$	Kernel smoothing function
$p(.)$	Probability of a given variable
$P(.)$	Signal power at a given transmitter receiver distance

Operations

$\exp(.)$	Exponential
$\sum(.)$	Summation
$\prod(.)$	Product