DEVELOPMENT OF A ROOM RECOGNITION SYSTEM USING A CATADIOPTRIC SENSOR AND ARTIFICIAL NEURAL NETWORK

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DEVELOPMENT OF A ROOM RECOGNITION SYSTEM USING A CATADIOPTRIC SENSOR AND ARTIFICIAL NEURAL NETWORK

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A thesis submitted in fulfilment of the
requirements for the award of the degree of
Master of Engineering (Electrical)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

JANUARY 2006

DEDICATION

Dedicated to my beloved family and my dearest, Che Fai.

ACKNOWLEDGEMENT

First and foremost, my most sincere appreciation to my project supervisor, Professor Dr. Shamsudin Hj. Mohd. Amin, who sets a noble example of a devoted educator. His encouragement and constant support will always be treasured.

A big thank you to my co-supervisor, Associate Professor Dr. Rosbi Mamat, for his kind guidance and invaluable advice.

My deepest gratitude to Yeong Che Fai, for his continuous motivation, technical assistance and most importantly, his insightful counsel throughout the entire period of this project. I can never thank him enough for the inspiration, for his patience and for always being there as my pillar of strength.

To my dearest family members for their love, care and prayers. Thank you for persevering with me.

To everyone who assisted me in one way or another, be it through advice or words of encouragement - my dedicated friends, thanks for making this possible.

A special thanks to Universiti Teknologi Malaysia, especially the Department of Mechatronics and Robotics, for providing financial support and excellent facilities to complete my research.

Above all, I thank God for everything that He has given and planned for me.

ABSTRACT

Robot localization has been a challenging issue in robot navigation. In recent years, there has been increasing interest in topological localization. One popular approach for vision based topological localization is the appearance based method, where the image can be used for recognition in its basic form without extracting local features. The general aim of this work is to develop a room recognition system using appearance-based method for topological localization. In this work, the room recognition is achieved by matching color histogram of image using the Artificial Neural Network. A hardware module and a software module have been developed for this project. The hardware module consists of a catadioptric sensor system implemented on a mobile platform. The software module encompasses several sub modules namely image acquisition; image pre-processing; histogram plotting; histogram filtering, sampling and normalization; neural network for offline training and testing, and finally real time room recognition. A few experiments have been conducted to evaluate the performance of the system and the results have been favorable. Testing for suitable network setting was also carried out and a recommendable setting was proposed.

ABSTRAK

Lokalisasi robot merupakan satu isu yang mencabar dalam navigasi robot. Sejak kebelakangan ini, terdapat perhatian yang meningkat terhadap lokalisasi secara topologikal. Salah satu kaedah yang popular bagi lokalisasi topologikal menggunakan 'penglihatan' adalah melalui pendekatan berasaskan penampilan, di mana imej dapat digunakan untuk pengenalan dalam bentuk asas tanpa mengekstrak ciri-ciri tempatan. Objektif keseluruhan projek ini adalah untuk menghasilkan satu sistem pengenalan bilik yang menggunakan kaedah berasaskan penampilan bagi lokalisasi topologikal. Dalam projek ini, pengenalan bilik dicapai dengan memadankan histogram warna menggunakan Jaringan Neural Buatan (*Artificial Neural Network*). Satu modul perkakasan dan satu modul perisian telah dihasilkan bagi projek ini. Modul perkakasan merangkumi sistem penderia *catadioptric* yang diimplementasikan atas platform bergerak. Modul perisian pula merangkumi beberapa sub-modul iaitu pengambilan imej; pra-pemprosesan imej; pemplotan histogram; penapisan histogram; pensampelan; normalisasi; jaringan neural untuk latihan dan pengujian secara *offline*; dan akhir sekali, pengenalan bilik secara nyata. Beberapa eksperimen telah dijalankan untuk mengevaluasi pencapaian sistem ini dan keputusan yang diperoleh adalah memuaskan. Pengujian turut dilaksanakan untuk mendapatkan aturan yang bersesuaian dan satu aturan saranan telah dicadangkan.

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LIST OF ABBREVIATIONS

2D	-	Two dimensional
3D	-	Three dimensional
ANN	-	Artificial Neural Network
B	-	Blue
BeMR	-	Bluetooth enabled Mobile Robot
BP	-	Back Propagation
CAD	-	Computer Aided Design
CCD	-	Charge-coupled Device
DGPS	-	Differential Global Positioning System
G	-	Green
GPS	-	Global Positioning System
GUI	-	Graphical User Interface
MLP	-	Multi Layer Perceptron
MSE	-	Mean Square Error
NASA	-	National Aeronautics and Space Administrations
PCA	-	Principal Components Analysis
PDA	-	Personal Digital Assistant
R	-	Red
RGB	-	Red, Green, Blue
SA	-	Selective Availability
ZPR	-	Zero Phase Representation

CHAPTER 1

INTRODUCTION

Autonomous mobile robots designed to move freely in the world have the same problems as humans when navigating. The world is a complex environment and if robots only move around without 'looking' at where their action takes them, they might get lost due to the imperfections in their moving mechanisms and the environment. The research here therefore, focuses on a topological localization strategy that employs vision and neural network for the robot to 'see' its surroundings and then estimate its own location.

1.1 Challenges in Mobile Robot Navigation

In order for a mobile robot to perform its assigned tasks, it often requires a representation of its environment, a knowledge of how to navigate in its environment, and a method for determining its position in the environment. These problems have been characterized by the three fundamental questions of mobile robotics, which are "Where am I?", "Where am I going?" and "How can I get there?' (Leonard and Durrant-Whyte, 1991).

The first question is one of localization. The robot has to know where it is in a given environment based on what it sees and what it was previously told. The second and third questions are essentially those of specifying a goal and being able to plan a path to achieve that goal. Therefore, finding a robust and reliable solution to the first question of localization is a precursor to answering the remaining two questions. This can be related with the example of going into a bookshop. You will firstly need to know where you are standing (localization) and where is your destination relative to your current position (identifying goal) so that you can plan which direction you should take in order to reach your destination (path planning). This is why many researchers (Duckett and Nehmzow , 2001; Cox and Wilfong, 1990; Fox, 1998; Borenstein *et al.,*1996) maintained that localization is one of the most fundamental problems in mobile robotics.

1.2 An Overview of Robot Localization

Robot localization is the problem of estimating a robot's pose relative to a map of its environment (Fox *et al.,* 1999). A wide variety of localization methods have been proposed and a number of successful laboratory prototypes have been developed. Some of these systems have been validated in larger environments, generally consisting of enclosed areas within public buildings (Yamauchi and Langley, 1997; Weiss and von Puttkamer, 1995; Burgard *et al.,* 1998; Thrun *et al.*, 2000; Duckett and Nehmzow, 2000) and some attempts have been made for localization in outdoor environments (Kweon and Kanade, 1991; Takeuchi and Herbert 1998).

The localization issue can usually be categorized as being geometric or topological (Andreasson and Duckett, 2004, Ulrich and Nourbakhsh, 2000). Geometric approaches attempt to estimate the position of the robot as accurately as possible (x, y, θ) with respect to the map's coordinate system. Topological localization gives a more abstract position estimate, for example "This is the coffee room".

The task of localization can again be divided into two sub-problems: position tracking and global localization. In position tracking, a robot knows its initial position and only has to accommodate small errors in its odometry as it moves (Fox *et al.,* 1999). The global localization is the ability to estimate the position of the robot without knowledge of its initial location and the ability to relocalize if its position is lost (Fox, 1998). Global localization hence, has to solve a much more difficult localization problem, that of estimating its position from scratch. This includes the kidnapped robot problem where the robot is all of a sudden transferred or 'kidnapped' to another location without the robot being aware of this.

Some researchers, however, categorize the localization tasks using different terms. Yamauchi *et al*. (1998) divided the localization tasks to that of continuous localization and place recognition. Continuous localization is like driving downtown without getting lost which is similar to position tracking. In contrast, place recognition is like waking up in a hotel room and trying to determine which city one is in. In place recognition approaches, accurate coordinates are not needed and thus, place recognition approaches are normally used in topological localization.

In determining its location, a robot needs access to two kinds of information. First is the information or map, either gathered by the robot itself or supplied by an external source during the training or initialization phase. This map specifies certain features of the environment that are time-invariant and thus can be used to determine a location. The second kind of information is the navigational information which the robot gathers from its sensors during navigation. Generally, when a map or information of the environment is available, the robot position is computed thanks to a matching technique applied between currently observed part of the environment and the global map.

1.3 Problem Background

Over the past few years, there has been tremendous scientific interest in algorithms for estimating a robot's location from sensor data. Many different approaches have been introduced to handle various challenges in the robot localization problem. A few challenges have been identified as dynamism of environment, noise and errors, computational cost and ease of use.

A robot may be confronted with the problem of dynamic environment. Due to the changes of furniture arrangement, the environment may look different from the representation of a robot's initial map. This raises the question of how to make a robot localization method robust against such dynamic effects.

A general factor that complicates the robot localization is the existence of noise and errors, particularly in the sensor readings. To perceive changes in the environment, the robot has to sense repeatedly and often. However, knowledge gained via sensing is incomplete, inaccurate and uncertain. One example is the use of odometry sensors which count the revolutions that the wheels make while moving and turning. The readings can be used to help in estimating the displacement over the floor to give an indication of the location of the robot. Due to wheel slippage and irregularities of the floor texture, the odometer readings may give inaccurate results. With more revolutions, the cumulative error increases.

Another issue in localization system for robot is computational power. For a robot to accurately determine its location, a detailed metric map will be a good input. However, this type of maps requires extremely large memory and for the matching algorithms to quickly determine a robot's location in such a detailed map, a very fast processing is needed. The computational cost is even higher if the robot is to do real time image processing. Often, a two-dimensional map is used to avoid the computation and space explosion that a three-dimensional representation may entail (Kaelbling *et al.,* 1998; Nourbakhsh *et al.,* 1995; Schultz *et al.,* 1999; Simmons and Koenig, 1995). Statistical sampling is also used to alleviate this computational burden at the cost of completeness (Dellaert *et al.,* 1999).

Some approaches for robot localization face the problems in terms of ease of use when a robot is transferred to a new domain. It will require a period of initialization or retraining. Methods of localization which involve artificial landmarks or beacons need a lot of additional engineering effort and modification of the environment when a robot has to change or expand its environment. Localization method which employs metric mapping will even need a new set of representation.

1.4 Project Objectives

The objective of this work is therefore to design a topological localization strategy which can potentially help a robot recognize its surroundings despite the dynamism, errors and computational limitations. Strategically, the system should require no or little alteration when used in a new domain.

The objectives of this project are:

1. To develop a room recognition system using vision sensor and artificial neural network
   a. To develop hardware combination for color based sensing.
   b. To develop an algorithm for room recognition using color histogram.
   c. To implement Multi Layer Perceptron (MLP) network as recognition engine.
2. To evaluate the performance of the room recognition system.
3. To propose a suitable setting for the room recognition system.

1.5 Outline of the Proposed Approach

The interest of this work is primarily in the place recognition aspect of the topological localization problem. Putting together the issues to be solved, a room recognition method employing vision and neural network for robot topological localization is introduced. The proposed approach can be outlined as follows:

1. Adopting topological map as the world representation.
2. Room recognition (global localization) using visual information obtained from camera.
3. Image matching using Artificial Neural Network.
4. Testing and evaluating this combination of sensor and techniques in an unmodified indoor environment.

In this approach, the topological representation of the world is chosen because creating such map takes little effort as there is no need to measure the dimensions of the environment. By nature of their compactness, it has the potential for representing environments which are several magnitudes larger than those which can be tractably navigated using metric maps. Topological localization uses a graph representation that captures the connectivity of a set of features in the environment. Nodes of the graph represent locations while arcs represent the connectivity between the locations. The topological map of a section of the P08 Robotics Building is shown in Figure 1. This map and section of the building were used during testing.

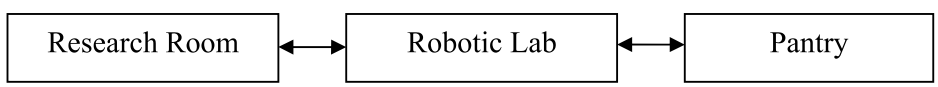

Figure 1.1 Topological map of the indoor environment

A robust localization system requires a sensor that provides rich information in order to allow the system to reliably distinguish between adjacent locations. For this reason, a color web camera is used as the sensor. The images captured during the training stage need to be representative of the environment. In order to keep the number of necessary reference images low, the ‘fish-eye’ camera set-up which provides a 360° circular image of its surroundings is implemented (Greiner and Isukapalli, 1994; Betke and Gurvits, 1997). An example of fish-eye field of view image is shown in Figure 1.2.

Figure 1.2 Sample image of fish-eye field of view

This vision-based localization system must be trained before it can be used in an environment. During training, representative images are captured from the environment and associated with corresponding locations. Classification of images is done through the Multi Layer back propagation technique. At runtime, the acquired image is compared to the map's reference images. The location whose reference image best matches the input image is then considered to be currently visible location. Image matching is achieved through the same neural network.

For validation, this localization system is tested in an indoor environment. All tests were performed in unmodified environments.

1.6 Outline of Thesis

The remainder of this thesis is organized in four main chapters. Chapter 2 reviews related works on robot localization and existing methods for vision-based system focusing on appearance based method. Chapter 3 describes the development methodology and guidelines in designing an appearance based room recognition system for robot localization. Chapter 4 explains the theory and concept of the appearance based room recognition system design. Chapter 5 describes the hardware and software implementation of the system. Chapter 6 presents the experimental results of the system performance analysis. Finally, Chapter 7 concludes the thesis with summary of contributions and suggestions for future development.

Designing a robot that can navigate and operate in a real world environment is a challenging task. The most fundamental competence it should have is the localization capability. To localize, a robot needs to have external sensor information and be able to give an estimate of its location. Localization is made complicated due to a few factors such dynamism of environment, noise and errors, limitations in computational resources and the ease of use of the system. Various techniques and sensors have been introduced to tackle these issues. In this work, a vision-based topological localization system is developed and investigated for an unmodified, indoor environment.

enhancement, the system can be made to return several fuzzy states of answers for Room A – for example, CONFIDENT RIGHT for (0.9, 0.01, 0.0) ; NOT CONFIDENT RIGHT for (0.4, 0.0,0.0) ; CONFUSED for (0.4, 0.4, 0.0) or WRONG for (0.0,0.9,0.0). When in NOT CONFIDENT or CONFUSED states, a dynamic voting system can be designed to vote for a confident answer to hopefully increase confidence and recognition rate.

4. The aluminium rod which serves as a mounting platform for the webcam, reflector ball and shade is generating some occlusion factor in the system. The rod can be replaced with a transparent glass cylinder. Ideally, the items can be mounted within the transparent glass cylinder to avoid any occlusion in the view. Then, the system can be fused with orientation tracking sensors such as magnetic compass to determine a robot's current heading position.

5. The software module can be modified to incorporate multiple color spaces for future investigations in color and recognition.

6. Currently, the laptop used for this room recognition work is different from the laptop used to control the BeMR in previous work by Yeong (2005). The integration of both systems on the same laptop will be excellent to present a multi purpose service robot with global localization capability that can be controlled with a portable device.

The appearance based room recognition system successfully developed in this work offers a partial solution to the problem of mobile robot localization in an unmodified indoor environment. Many improvements can still be carried out to improve the system with more capabilities and higher accuracy.

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