HYBRID GENETIC ALGORITHM AND PARTICLE FILTER OPTIMIZATION MODEL FOR SIMULTANEOUS LOCALIZATION AND MAPPING PROBLEMS

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I would like to dedicate this to my late mother.

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ABSTRACT

Determining position of a robot and knowing position of the required objects on the map in unknown environments such as underwater, other planets and the remaining areas of natural disasters has led to the development of efficient algorithms for Simultaneous Localization and Mapping (SLAM). The current solutions for solving the SLAM have some drawbacks. For example, the solutions based on Extended Kalman Filter (EKF) are faced with limitation in non-linear models and non-Gaussian errors which are causes for decrease of accuracy. The solutions based on particle filter are also suffering from high memory complexity and time complexity. One of the major approaches to solve the SLAM problem is the approach based on Evolutionary Algorithm (EA). The main advantage of the EA is that it can be used in search space which is too large to be used with high convergence while its disadvantage is high time and computational complexity. This thesis proposes two optimization models in solving SLAM problem namely Hybrid Optimization Model (HOM) and Lined-Based Genetic Algorithm Optimization Model (LBGAOM). These models do not have the limitations of EKF, memory complexity of particle filter, and disadvantages of EA in search space. When the results of HOM compared with original EA, it showed an increase of accuracy based on presented fitness function. The best fitness in original EA was 16.36 but in HOM has reached to 16.68. Both models applied a proposed new representation model. The representation model is designed and used to represent the robot and its environment and is based on occupancy grid and genetic algorithm. There are two types of representation models proposed in this thesis namely Layer 1 and Layer 2. For each layer, related fitness function is created to evaluate the accuracy of map in the model that was tested with some different parameters. The proposed HOM is designed based on genetic algorithm and particle filter by creating a new mutation model inspired by particle filter. The search space is reduced and only suitable space will be explored based on proposed functions. The proposed LBGAOM is a new optimization model based on extraction line from laser sensor data to increase the speed. In this model, search space in the map is a set of lines instead of pixel by pixel and it makes searching time faster. The evaluation of the proposed representation model shows that Layer 2 has better fitness value than Layer 1. The HOM has better performance compared to original GA Layer 1. The LBGAOM has decreased the search space compared to pixel based model. In conclusion, the proposed optimization models have good performance in solving the SLAM problem in terms of speed and accuracy.

ABSTRAK

Menentukan posisi sesebuah robot dan mengetahui posisi objek yang dikehendaki di atas peta, di persekitaran yang tidak diketahui seperti di bawah paras laut, planet lain dan di lokasi bencana alam telah mendorong kepada pembangunan algorithma yang efisien bagi Pemetaan dan Penempatan Serentak (SLAM). Penyelesaian terkini bagi menyelesaikan SLAM mempunyai beberapa kelemahan. Antaranya adalah penyelesaian berdasarkan Penapis Kalman yang Dilanjutlcan (EKF) berhadapan dengan had yang terdapat dalam model bukan linear dan ralat bukan-Gaussion yang menjadi sebab untuk mengurangkan ketepatan. Penyelesaian berdasarkan saringan partikel berhadapan dengan masalah storan tinggi yang kompleks. Salah satu pendekatan utama untuk menyelesaikan permasalahan SLAM adalah pendekatan berdasarkan Algoritma Berevolusi (EA). Kelebihan utama EA adalah ianya boleh digunakan dalam ruang carian yang sangat besar dengan tumpuan yang tinggi manakala kelemahannya pula adalah dari segi masa yang lama dan pengkomputeran yang kompleks. Tesis ini mencadangkan dua model pengoptimuman dalam menyelesaikan permasalahan SLAM iaitu Model Pengoptimuman Hibrid (HOM) dan Model Pengoptimuman Algoritma Genetik Berasaskan Garisan (LBGAOM). Kedua-dua model tidak mempunyai had EKF, memori yang kompleks bagi saringan partikel dan kelemahan EA dalam ruang carian. . Apabila keputusan HOM dibandingkan dengan EA yang asal, ia menunjukkan ketepatan keputusan meningkat berdasarkan fungsi kecergasan yang dihitung. Kecergasan terbaik dalam EA asal adalah 16.36 tetapi dalam HOM telah mencapai ke 16.68. Kedua-dua model mencadangkan perwakilan model yang baru. Perwakilan model tersebut direka dan digunakan untuk mewakili robot dan persekitarannya, dan adalah berdasarkan penggunaan grid dan algoritma genetik. Terdapat dua jenis perwakilan model yang dicadangkan di dalam tesis ini iaitu Lapisan 1 dan Lapisan 2. Bagi setiap lapisan, fungsi padanan yang berkaitan dibina untuk menilai ketepatan peta bagi sesuatu model yang kemudiannya diuji menggunakan beberapa parameter yang berlainan. HOM yang dicadangkan, direka bentuk berdasarkan algoritma genetik dan saringan partikel dengan membina suatu model mutasi baru yang diilhamkan oleh saringan partikel. Ruang carian dikecilkan dan hanya ruang yang bersesuaian sahaja dijelajah berdasarkan fungsi-fungsi yang telah dicadangkan. LBGAOM yang dicadangkan adalah sebuah model pengoptimuman baru, berdasarkan garisan ekstrak dari data imbasan laser, bertujuan meningkatkan kelajuan. Dalam model ini, ruang carian dalam peta adalah satu set garisan dan bukannya piksel yang mana menjadikan masa carian lebih pantas. Penilaian model perwakilan yang dicadangkan, menunjukkan bahawa Lapisan 2 mempunyai nilai padanan yang lebih baik dari Lapisan 1. HOM mempunyai prestasi yang lebih baik berbanding Lapisan 1 GA yang asal. LBGAOM pula telah mengecilkan ruang carian berbanding model berasaskan piksel. Sebagai kesimpulan, model-model pengoptimuman yang telah dicadangkan memiliki prestasi yang baik dalam menyelesaikan permasalahan SLAM dari segi kelajuan dan ketepatan.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

DP-SLAM	-	Distributed Particle Simultaneous Localization and Mapping
EA	-	Evolutionary Algorithm
EKF	-	Extended Kalman Filter
ELF	-	Evolutionary Localization Filter
GA	-	Genetic Algorithm
HOM	-	Hybrid Optimization Model
KF	-	Kalman Filter
LBGAOM	-	Line-Based Genetic Algorithm Optimization Model
PF	-	Particle Filter
PSO	-	Particle Swarm Optimization
SLAM	-	Simultaneous Localization and Mapping

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Overview

With current technological advances in the science of robotics, we have seen robots built to work autonomously on other planets, under seas and oceans and other unknown environments. Considering that the robots do not have any information about the environment, they should have the ability to build an environment map on the move and to estimate its location on that map correctly.

Mapping is to obtain a model of the robot environment, and localization is to estimate the position of robot in obtained map. For building map, we need to acknowledge the location of robot and for localization we need to map (chicken and egg problem) so solving these problems simultaneously is reasonable: simultaneous localization and mapping (SLAM) (Thrun, 2003; Bailey, *et al.*, 2006; Thrun, 2008).

Maps are often used for guidance and localization, thus for mapping, robots must be equipped with several sensors. Sensors that are commonly used for this work are sonar sensors to measure the distance, laser, radar, infrared, GPS, camera etc. (Karlsson, 2010). It should be noted that all sensors have at least a bit of measurement error and most sensors have a limited operating range. Because of these limitations, robots for building the map should move in the environment and use sophisticated methods (Thrun, 2003; Frese, 2006). In order to perform their duties, robot need to identify their surroundings and estimate their location with high precision. This action is called simultaneous localization and mapping (SLAM). Because robot do not have any information about environment that they have entered, they begin to construct a map and to find its location in that map using of its odometer and sensor data (Durrant-Whyte, *et al.*, 2006).

It is natural that in such a case we are faced with a large search space. For exact performance of the robot and with reasonable speed, we need a solution that the robot can use to cover a large search space in shortest possible time and in the best way. Mapping has a long history. In the 80's and early 90's, mapping was mostly divided in two categories: metric and topologic. One example of the first category is occupancy grid that represents the map with a network of some full as well as empty cells. The topologic maps represent the environment with a list of important locations that are connected by some arcs. These arcs contain information about how robot navigate between different locations (Thrun, *et al.*, 1998; Thrun, 2003).

In simultaneous localization and mapping, the mobile robot captures data from the environment with own sensors, interprets this date and after building an appropriate map, determines its location in that map. Obtaining an unknown environment model must respond to three activities: mapping, localization and motion control. Mapping is shaping the collected data from robot sensors to the desired form. Localization is estimating the robot position and motion control answers this question; how to navigate the robot to favourite location or proposed path (Huang, *et al.*, 2004; Dissanayake, *et al.*, 2001).

Figure 1.1, shows the shared domain of these three activities. Active localization involves navigating the robot to special places in the map for enhancement of position estimation. Other methods use robot navigation in unknown environments and explore the environment. The central region of the figure shows an integrated strategy: SLAM and motion control.

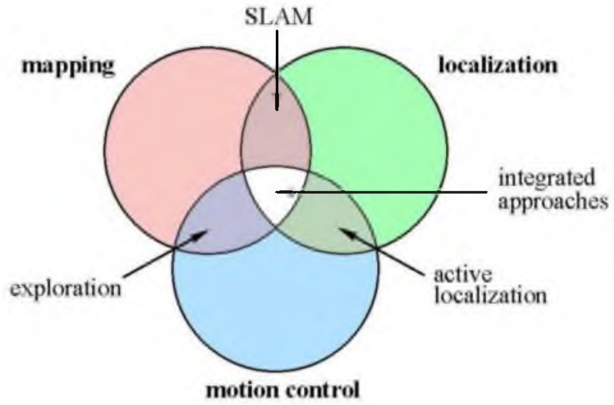

Figure 1.1 Activities that must be performed to obtain an accurate model of the environment (Makarenko, 2002).

Note that the robot should do the localization and mapping simultaneously, and should determine its path during the mapping. Typically the robot motion operation is called exploration. Although it is easy to move around a completely modelled environment, the explorer robots are face uncertainties and inefficient models. Thus each successful exploration process should have the ability to deal with unpredictable and unexpected situations, thus the issues in this case should be solved with heuristic solutions. The correct position estimation is necessary for data correct correlation. It means that we should determine if the measurements that have been done up to now match with our built map. So building maps are necessary for robot navigation in unknown environments, is needed for other activities such as localization, path planning, interaction with manipulators, and interaction with operator. As said before, this activity is called SLAM and it is a hard problem because the same, noisy sensor data must be used for both mapping and localization (Carrillo, *et al.*, 2012; Blanco, *et al.*, 2008). Sources of uncertainty in solving this problem can be divided in to two major categories:

1. The continuous uncertainties in the localization of the robot and the robot observations from environment (e.g., due to sensor noise, error in execution of commands in motors and manipulators, etc.)

2. The synthetic problem of data association (e.g., landmark extractions, feature recognition, place labelling, etc.) in which a correspondence must be detected between sensor measurements and observed features in the map.

Most of current solutions for solving the SLAM problem consider only the first category of uncertainty, and assume that the data association problem will be solved when observations are integrated into the map (e.g., it is typical to assume that all landmarks can be identified uniquely). However, this assumption is doomed to fail sooner or later for modern robots activities in unknown environments (Kang, *et al.*, 2012). In brief, failure in data association will input error in localization, which can lead to catastrophic errors in the map. Otherwise, the robot must somehow doing the search in space of possible maps. So the SLAM problem can be defined as a global optimization problem in which the objective is to search the space of possible robot maps (Duckett, 2003; Pegden, *et al.*, 1980; Kollar, *et al.*, 2008).

1.2 Problem Background

SLAM is the process by which a mobile robot can build a map of an environment and at the same time use this map to compute its own location. The past decade has seen rapid and exciting progress in solving the SLAM problem together with many compelling implementations of SLAM methods. Two famous and useful methods are extended Kalman filter (EKF) and particle filter.

The Extended Kalman Filter (EKF) is one of the first probabilistic SLAM algorithms that solve the SLAM problem using a linearized Kalman filter and this is the most important drawback of EKF. It means that the EKF should transfer all non-linear equations to a linear equation (for example with Taylor series). However, this method uses only uni-modal Gaussians to model non-Gaussian probability density function. Another disadvantage of EKF is O(N3) matrix inversion required for its calculations (Castellanos, *et al.*, 2004; Paz, *et al.*, 2006; Hui-Ping, *et al.*, 2009).

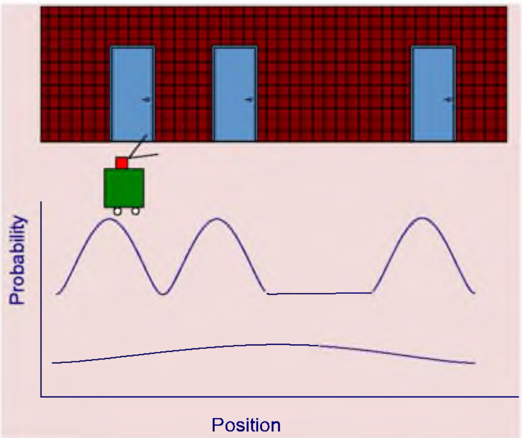

Figure 1.2 Model extraction by robot based on features (doors) and transfer to uni-modal Gaussian diagram for use in EKF.

Another method for solving the SLAM problem is particle filter. Particle filter represents probability distribution as a set of discrete particles which occupy the state space. This method can represent multi-modal distributions.

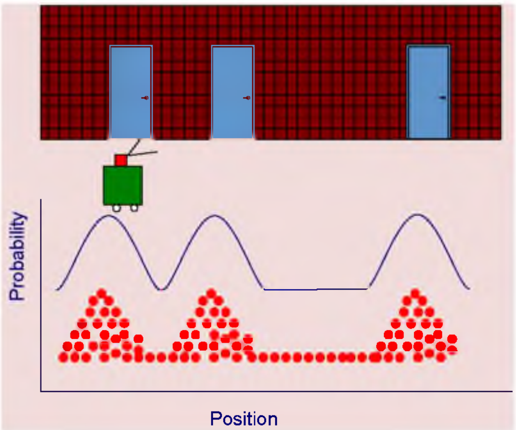

Figure 1.3 Model extraction by robot based on features (doors) and showing the number of particles in high probability places

Two problems with this method are that the number of particles grows exponentially with the dimensionality of the state space and high memory complexity (Thrun, 2002; Törnqvist, *et al.*, 2009; Gustafsson, 2010).

One of the major approaches to solve the SLAM problem is the approach based on evolutionary algorithm like Genetic Algorithm (GA). The proposed optimization model in this study is in the same category. GA is a class of search algorithm that inspired by the style evolution of living beings have arisen. The main advantage of the evolutionary algorithm is that these algorithms can be used to search space which is too large to be used with high convergence. A number of solutions are using the GA for solving the SLAM problem like Duckett solution, Begum solution or Shiry solution. Each of these solutions has some problems and drawbacks that are explained by detail in Chapter 2. Generally the main problem of solutions based on GA is connected to high computational complexity and time complexity (Begum, *et al.*, 2006; Begum, *et al.*, 2007). GA has three kind of operators for keeping the diversity and variety which are selection, mutation and crossover. Each of these operators also have some kind or model of implementations like uniform and two point model for crossover operation or Roulette wheel and Q-tournament model for selection operation. Choosing the appreciate model for each operators is very effective in time and computational complexity based on desired optimization problem. So for increase the speed of GA and decrease the time and computational complexity of that, the new ideas and contributions should be applied in these operators or have contribution in procedure of GA based on fitness function and other parameters of GA. The most important operator is mutation because if the pattern of response doesn't exists in initial population, the GA couldn't coverage to optimal answer. In original mutation selection of a gen for mutation is completely random and this is one on the problems of mutation because there is not any control in selection of gen and it is completely random. So because this operation is not targeted, the searching time will be increased and the speed of GA will be decreased consequently (Duckett, 2003).

1.3 Problem Statement

As discussed in the previous section, two methods for solving the SLAM problem, EKF and particle filter, have faced some drawbacks. In EKF, the main problem connected to this method is working solely with linear systems and uni-modal

Gaussians equations. In addition, for solving the aforementioned problem, EKF needs to convert non-linear equations to linear equations using for example Taylor series which causes additional errors to the system. In the particle filter, the main problem is the high memory and computation time required when increasing the number of particles. Although genetic algorithm demonstrates very good performance with large search spaces, it has some weaknesses and drawbacks such as computational and time complexity which result in low speed. There are two main causes of low speed in GA: the first is untargeted search involving replacement or adding a fixed value for mutation operation and the second is large search space. In brief, the problem can be stated as below:

"Low speed and accuracy in solutions based on Genetic Algorithm for solving the SLAM problem in mobile robots"

For study on solving the SLAM problem in mobile robots, a map representation as experimental setup and test bed is needed as preprocessing. Thus a new representation model based on Genetic Algorithm should first be designed and developed for implementation of new models and then comparison of the obtained results. For this propose, in each step the best values for GA parameters should be found (parameter tuning) for better comparison of original GA and hybrid optimization model.

The following research questions will be answered in this research:

I. How can a new representation model based on occupancy grid be modified for represent the robot and its environment?
II. How can the genetic algorithm be hybrid with particle filter by increasing the accuracy perspective?
III. How can reduce the search space in SLAM problem for increase the speed?

1.4 Purpose of Study

To propose new optimization model in increase the speed and accuracy of SLAM problem using new hybrid of particle filter and GA algorithm for avoidance of random selection in mutation step.

To increase the speed of optimization model with a line based GA and a new representation of occupancy grid for decrease the search space.

1.5 Objectives

Objectives of this research are as follows:

1. To propose and design simulation model of new representation model of occupancy grid based on Genetic algorithm.
2. To develop a hybrid optimization model (HOM) of GA and Particle filter on the proposed representation model.
3. To develop a line based genetic algorithm optimization model (LBGAOM) on the proposed representation model.

1.6 Research Scope

In this study, the scope of the optimization model is mainly based on the following items:

1. The proposed algorithm is based on raw data of robot odometer movement and received data from its laser sensors in a static environment which obstacles are static.
2. In the new representation model of occupancy grid, the map representation performance will be checked with presented fitness functions.
3. The hybrid optimization model (HOB) target is to investigate the increased convergence and speed.
4. The proposed LBGA optimization model is for working in indoor environments only.
5. The new optimization model will be implemented on some simulated maps and the accuracy of model will be evaluated with presented fitness functions.
6. MATLAB software and some related software are used for simulation.

1.7 Significance of Research

The significance of this project is to propose an enhanced optimization model for solving the simultaneous localization and mapping (SLAM) problem by covering the weaknesses of representation of occupancy grid. Another significance of this project is that the solutions based on Kalman filter are highly dependent on the motion model while in this study the presented optimization model is completely independent from motion model. Thus the benefit of this research is the increase in accuracy of SLAM algorithm and improved performance of occupancy grid for map representation. In detail, some significant algorithms are listed below:

1. Two new representation model of occupancy grid for using solving the SLAM problem are presented (Layer 1 and Layer 2) and two new fitness functions are designed and used for each model also.

2. An hybrid optimization model (HOM) based on genetic algorithm and particle filter are presented and new chromosome model and desired fitness function for use in model are designed and presented also.
3. A Line-based genetic algorithm optimization model (LBGAOM) for reduce the search space and increase the speed is presented and new chromosome model and desired fitness function for use in model are designed and presented also.

1.8 Thesis Overview

This research consists of seven chapters. In Chapter 1 an introduction, problem background, problem statement, Purpose of Study, objectives, scope and significant of this research are presented.

In Chapter 2, some basic background about SLAM is presented then some mapping models and localization algorithms are presented. The effective parameters and existing methods and tools for solving the SLAM problem are introduced and compared. Finally the existing solutions based on each methods or hybrid of some methods are presented and compared.

In Chapter 3 methodology which is used in this research discussed.

In Chapter 4 a development of a new representation of occupancy grid based on GA and tune the parameters for comparison in other Chapters, is presented. In this chapter a new representation model with a new fitness function is presented which has best performance in increase the accuracy.

The Chapter 5 is about develop a hybrid model of genetic algorithm and particle filter for solving the problem of mutation operation in genetic algorithm with particle filter concept and avoidance of random selection and adding a fixed value to chromosome.

In Chapter 6 a line base genetic algorithm optimization model is develop for decrease the search space and increase the speed consequently. Finally, Chapter 7 is contained the conclusion and future work of this research

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