HYBRID FASTSLAM APPROACH USING GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION FOR ROBOTIC PATH PLANNING

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ABSTRACT

Simultaneous Localization and Mapping (SLAM) is an algorithmic technique being used for mobile robot to build and create a relative map in an unknown environment. FastSLAM is one of the SLAM algorithms, which is capable of speeding up convergence in robot's path planning and environment map estimation. Besides, it is popular for its higher accuracy compared to other SLAM algorithms. However, the FastSLAM algorithm suffers from inconsistent results due to particle depletion problem over time. This research study aims to minimize the inconsistency in FastSLAM algorithm using two soft computing techniques, which are particle swarm optimization (PSO) and genetic algorithm (GA). To achieve this goal, a new hybrid approach based on the mentioned soft computing techniques is developed and integrated into the FastSLAM algorithm to improve its consistency. GA is used to optimize particle weight while PSO is used to optimize the robot's estimation in generating an environment map to minimize particle depletion in FastSLAM algorithm. The performance of the proposed hybrid approach is evaluated using root mean square error (RMSE) analysis to measure degree of error during estimation of robot and landmark position. The results are verified using margin error analysis. With the percentage error analysis results, the new hybrid approach is able to minimize the problems in FastSLAM algorithm and managed to reduce the errors up to 33.373% for robot position and 27.482% for landmark set position.

ABSTRAK

Penempatan dan Pemetaan Serentak (SLAM) adalah satu teknik algoritma yang digunakan untuk robot mudah alih dalam membina dan membuat peta dari persekitaran yang tidak diketahuinya. Algoritma FastSLAM adalah salah satu algoritma SLAM yang digunakan bagi mempercepatkan penumpuan semasa merancang laluan robot dan menganggar peta persekitaran. Ia juga popular kerana mempunyai ketepatan yang lebih tinggi berbanding algoritma SLAM yang lain. Walaubagaimanapun, algoritma FastSLAM mengalami masalah kekurangan zarah dari masa ke masa yang menyebabkan keputusan yang dihasilkannya tidak selaras. Kajian ini bertujuan bagi mengurangkan masalah ketidakselarasan yang berlaku didalam algoritma FastSLAM dengan menggunakan dua teknik pengkomputeran lembut iaitu pengoptimuman kawanan zarah (PSO) dan algoritma genetik (GA). Bagi mencapai matlamat ini, pendekatan hibrid yang baru berdasarkan teknik-teknik pengkomputeran lembut tersebut telah dibangunkan dan digunakan ke dalam algoritma FastSLAM bagi meningkatkan prestasinya. GA digunakan untuk mengoptimumkan nilai berat zarah manakala PSO digunakan untuk mengoptimumkan anggaran yang dibuat oleh robot mudah alih dalam menjana peta persekitaran bagi mengurangkan masalah pengurangan zarah didalam algoritma FastSLAM. Prestasi pendekatan hibrid yang dicadangkan ini telah dinilai menggunakan analisis punca min ralat persegi (RMSE) bagi mengukur tahap ralat semasa robot menganggar kedudukannya dan objek halangan didalam persekitaran. Keputusan ini telah disahkan dengan menggunakan analisis ralat margin. Berdasarkan keputusan daripada analisis peratusan ralat, pendekatan hibrid baru ini telah berjaya mengurangkan masalah yang berlaku didalam FastSLAM algoritma dengan mengurangkan ralat sehingga 33.373% bagi kedudukan robot dan 27.482% bagi kedudukam objek.

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LIST OF ABBREVIATIONS

ABBREVIATION

EKF	-	Extended Kalman Filter
GA	-	Genetic Algorithm
KF	-	Kalman Filter
PF	-	Particle Filter
PSO	-	Particle Swarm Optimization
SLAM	-	Simultaneous Localization and Mapping
UFastSLAM	-	Unscented FastSLAM

LIST OF SYMBOLS

s_t	-	Pose of the robot at time t
s^t	-	Complete path of the robot $\{s_1, s_2, s_3, \ldots, s_t\}$
θ_n	-	Position of the n-th landmark
θ	-	Map, set of all n landmark positions
z_t	-	Sensor observation at time t
z^t	-	Set of all observations $\{ z_1, z_2, z_3, \ldots, z_t\}$
u_t	-	Robot control at time t
u^t	-	Set of all controls $\{ u_1, u_2, u_3, \ldots, u_t\}$
n_t	-	Data association of observation at time t
n^t	-	Set of all data association $\{ n_1, n_2, n_3, \ldots, n_t\}$
$h(s_{t-1}, u_t)$	-	Vehicle motion model
P_t	-	Linearized vehicle motion noise
$g(s_t, \theta, n_t)$	-	Vehicle measurement model
R_t	-	Linearized vehicle measurement noise
$\hat{z}_{nt}$	-	Expected measurement of n_t-th landmark
z_t - $\hat{z}_{nt}$	-	Measurement innovation
Z_t	-	Innovation covariance matrix
G_θ	-	Jacobian of measurement model with respect to landmark pose
G_{st}	-	Jacobian of measurement model with respect to robot pose
S_t	-	FastSLAM particle set at time t
$S_t^{[m]}$	-	m-th FastSLAM particle at time t
$\mu_{n,t}^{[m]}, \Sigma_{n,t}^{[m]}$	-	n-th landmark EKF (mean, covariance) in the m-th particle
$N(x; \mu, \Sigma)$	-	Normal distribution over x with mean μ and covariance Σ
$w_t^{[m]}$	-	Importance weight of the m-th particle
N	-	Total number of landmarks
M	-	Total number of FastSLAM particles

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CHAPTER 1

INTRODUCTION

1.0 Introduction

In robotics, a mobile robot that is able to autonomously navigate, move and explore throughout an unknown environment, such as subsea, disaster area and another planet has become a popular topic in recent artificial intelligent robotic development. The mobile robot that is capable to think by itself when exploring the unknown environment without prior knowledge on such environment becomes a promising approach. This is useful since the environment may be possibly harmful or unreachable for human beings. As an example, before people can explore the disaster areas, such as an earthquake region, a mobile robot is used to observe and gain knowledge about the area. Hence, it provides useful information to people before they can start to explore the area, and thus avoiding any possible dangerous situation.

1.1 Problem Background

An autonomous robot that is able to perform designated tasks without intervention from human beings becomes highly desirable, especially in artificial intelligent navigation system. The tasks, such as self-exploration in an unknown environment become a trend in recent robotic development. Exploration in an unknown planet, disaster area, seabed, or any environment which are unreachable and potentially harmful to human beings can be done by the autonomous robot.

It should be a robot that is able to perform the designated tasks by itself without human intervention. It is scientifically known as artificial intelligent robot as it is able to 'think' before making decision and 'act' accordingly then. This research focuses on the autonomous mobile robot that is able to move into an unknown environment. The robot must 'think' how it should move. According to Pirahansiah *et al.* (2013), the challenges faced by autonomous robot are the environment factors, its capability to explore, navigate without any knowledge on the unknown environment and generates its own map for the environment. Another challenge faced by the robot is its capabilities to recognize its own position, landmark and any obstacles, and making decision based on the new environment data and is able to navigate through the environment without human intervention.

The most notable solution ever being introduced is called simultaneous localization and mapping (SLAM). SLAM is an algorithm where a mobile robot simultaneously generates a map of environment (mapping) and uses the map to locate its own position within the environment (localization) (Durrant-Whyte and Bailey, 2006a). Both mapping and localization are done simultaneously and recursively as it navigates and explores in the unknown environment. In theoretical view, a SLAM is considered as perfect or solved solution, but in practice, there are certain issues arise in making the mobile robot truly autonomous (Pascal and Kuhn, 2013). There are several SLAM algorithms and one of them is called FastSLAM algorithm, introduced by Montemerlo *et al.* (2002). The FastSLAM is popular for its good data accuracy compared to other SLAM algorithms. However, it suffers from sample degradation over time, due to particle depletion which degrades its overall performance.

Many conducted studies focused on improving robot's performance during estimation and most of them often measure the distance between estimated and true location of the robot and landmarks based on a given map (Burgard *et al.*, 2009). The robot's task is to make itself accurately recognizes its own position, surrounding landmarks and is able to make an appropriate path planning based on the given map. The difficulty is, when SLAM is implemented in real environment, the geographical structures are usually very complex. The robot might encounter numerous difficulties and thus unable to perform its designated tasks as expected. The difficulties are how the robot accurately estimates its own position, surrounding landmarks (obstacles) and make an appropriate path planning within the environment map it created. Hence, it can be say that even the robot manages to locate its own position and surrounding landmarks but the estimated position might deviates from actual position.

A perfect SLAM algorithm should estimate robot's position and landmarks position without any errors. The errors are the distance of estimated robot and landmarks position which deviates from actual position and surrounding landmarks. The longer the distance between the estimated position and actual position, the larger the error would be. However, it is impossible to achieve zero error, due to several limitations, such as noisy received data from hardware and algorithm's computational complexity.

This study are trying to understand the structure of FastSLAM algorithm and the problems it faces in detail. Then, this research are attempting to minimize the problem by providing a promising solution. Among the introduced solutions, the most interesting one is implementing a soft computing technique into the FastSLAM algorithm. The idea of soft computing technique into the FastSLAM algorithm is not something new since previous works have done before. For example, previous work done by Xia and Yang (2011), who implemented genetic algorithm in FastSLAM algorithm and work done by Heon-Cheol*et al.* (2009) who implemented particle swarm optimization in FastSLAM algorithm. They will be further explained in Chapter 2.

The implementation of soft computing technique indeed provides a promising solution in minimizing the problem during robot estimation. For example, work done by Xia and Yang (2011), which implements genetic algorithm in FastSLAM algorithm. The algorithm uses a particle filter to estimate robot's landmark position. Hence, the particles can be used by genetic algorithm as search operator to perform its task in optimizing the FastSLAM algorithm.

One concerned issue is the effectiveness of the solution when being used in different maps. Different researchers used different map representations to evaluate their own developed solutions. Xia and Yang (2011) and Heon-Cheol *et al.* (2009), both use different maps to evaluate their own solutions. Hence, there isn't any standardized or benchmarked map environment to analyze performance of the proposed solution since different maps yield different results. The real question here: Does the solution work well in different maps and environment?

1.2 Problem Statements

Problem statements of this research:-

1) What are the significant SLAM parameters and their setting values required for the proposed simulation model of selected SLAM map environment?

2) What is the best approach to minimize errors in robot estimation in FastSLAM algorithm?

3) How to improve the performance of a new hybrid approach in terms of error rate in robot position and landmark position estimations?

1.3 Research Goal and Objectives

The research goals:-

> "To introduce a new hybrid approach by implementing soft computing technique into FastSLAM algorithm using a standardized parameters and its setting values that is capable to improve FastSLAM performance by minimizing error rate in estimation"

The research objectives were identified and stated as follows:-

1) To analyze and identify significant SLAM parameters and their setting values for the proposed simulation model of the selected SLAM map environment.

2) To implement a new hybrid approach into FastSLAM algorithm using genetic algorithm (GA) and particle swarm optimization (PSO).

3) To improve performance of the new hybrid approach for error rate in robot position and landmark position estimations.

1.4 Research Scope

1) Existing SLAM Algorithms and Hybrid Approach

In this research, an existing SLAM method, i.e. the FastSLAM algorithm is used. Other existing hybrid approaches using soft computing technique in FastSLAM algorithm are also used for reference. The existing hybrid algorithm approach will be compared with the FastSLAM algorithm and developed hybrid approach to calculate the robot's estimation capability. It will be further explained in Chapter 2.

i. FastSLAM algorithm :-
An existing SLAM algorithm introduced by Montemerlo *et al.* (2002), is used in developing the proposed hybrid approach.

ii. FastSLAM algorithm with GA :-
It was introduced by Xia and Yang (2011) who implemented the genetic algorithm (GA) in FastSLAM algorithm.

iii. FastSLAM algorithm with PSO :-
It was introduced by Heon-Cheol *et al.* (2009) who implemented the particle swarm optimization (PSO) approach in FastSLAM algorithm.

iv. FastSLAM algorithm with GA and PSO:-

These hybrid approaches are the research proposed hybrid approach which implements GA and PSO in FastSLAM algorithm.

2) Simulation Model and Data Structure

The experiment is conducted in a simulated two-dimensional sparse map environment. The map is generated from the SLAM toolbox. This research reconstruct the environment map used by Heon-Cheol *et al.* (2009). Figure 1.1 shows the reconstructed simulated environment map.

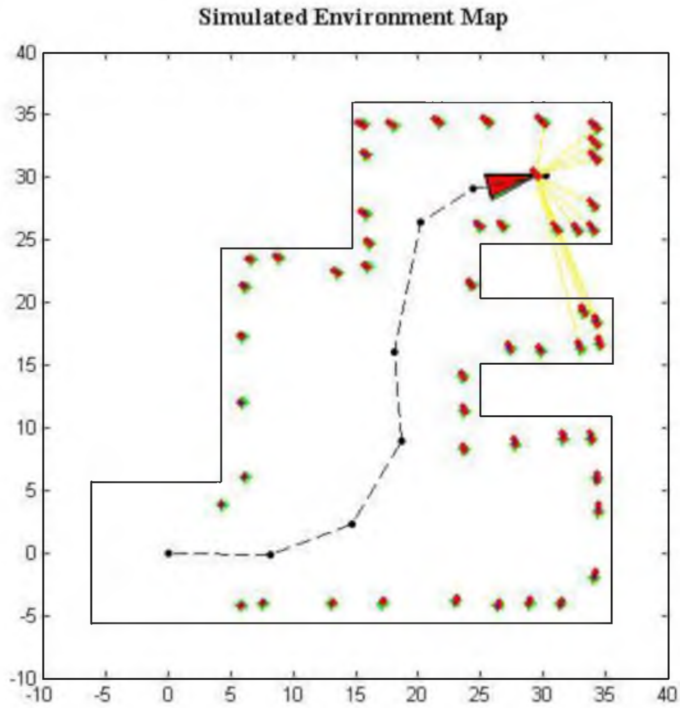

Figure 1.1 : Reconstructed simulated environment maps

In Figure 1.1, before the simulation started, significant parameters were set and required configuration data must be properly set up. Once the simulation begins, the virtual robot starts to explore the environment map by following the assigned waypoint. As the virtual robot moves, it estimates its current position in the environment map and detects landmarks location using its virtual sensors. The exploration completed when it reaches the last checkpoints of the assigned waypoints. This will be explained in detail in Chapter 2, 3 and 4.

3) Parameter Determination and Setting Values

Parameter determination and its setting value are conducted to ensure that the results are consistent and avoid any unexpected errors in experiments. Several parameters have been selected (Refer chapter 4, section 4.2.2). To select suitable parameters, it should not heavily affect the experiment process in terms of computational complexity. Computational complexity is the time taken for one occurrence. For that, some parameters are selected based on best average by considering computational complexity of the experiment. For some parameters that are not affected by the computational complexity, the values selection is based on the lowest error values of robot or landmark position. A validation has also been conducted to observe the pattern of experiment result produced by the experiment. From the validation, the pattern produced is the same and consistent (Refer chapter 4, section 4.2.4.1).

4) Performance and Data Analysis

In this study, the performance of the developed hybrid approach are analyzed based on the error occurs during estimation process. Root mean square error (RMSE) analysis is used to calculate the errors. The error is calculated based on two indicators, i.e. robot and landmark set position. To verify the results produce in RMSE analysis, margin error analysis is used. Percentage error analysis is used to measure capabilities of the developed hybrid approach in minimizing the error rate in FastSLAM algorithm. It will be explained in detail in Chapter 3 at section 3.6.

5) Software and Tools

Matlab is used as platform to conduct the research experiments. For the used tools is SLAM toolbox which developed by Tim Bailey (3 April 2015) to observe and validate the developed hybrid approach. For the performance and data analysis, Matlab is also used to calculate the data results (i.e. RMSE, margin error and percentage error analysis). OriginPro is used to visualize the calculated data for RMSE and margin error analysis.

1.5 Significance of Research

The significance of the research is as follows:-

1) The propose hybrid approach is able to provide a promising solution to improve the performance of FastSLAM algorithm by minimizing errors in robot position and landmark estimation.

2) Introduction of implementation of more than one soft computing technique for solving problems in FastSLAM algorithm.

1.6 Chapter Outline

This thesis consists of six main chapters. Chapter one is the introduction that briefly summarizes and provides general overview of this research. Chapter two gives literature review that discusses about research results and findings of this research. Chapter three mentions the research methodology that explains research framework and how the research is conducted. Chapter four is the proposed hybrid approach. It explained about this research experiment process and the proposed hybrid approach which is GA-PSO-FastSLAM. Chapter five are analysis that explained about this research results and findings. And lastly, Chapter six describes the conclusions of the research.

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