



**DESIGN AND DEVELOPMENT OF COOPERATIVE
SIMULTANEOUS LOCALIZATION AND MAPPING
INTEGRATED WITH NEURAL NETWORK FOR MOBILE ROBOT**



MASTER OF SCIENCE IN ELECTRONICS ENGINEERING

2024



**Faculty of Electronics and Computer Technology and
Engineering**

**DESIGN AND DEVELOPMENT OF COOPERATIVE
SIMULTANEOUS LOCALIZATION AND MAPPING INTEGRATED
WITH NEURAL NETWORK FOR MOBILE ROBOT**

اونيورسيتي تيكنيكل مليسيا ملاك

Amirul Bin Jamaludin
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

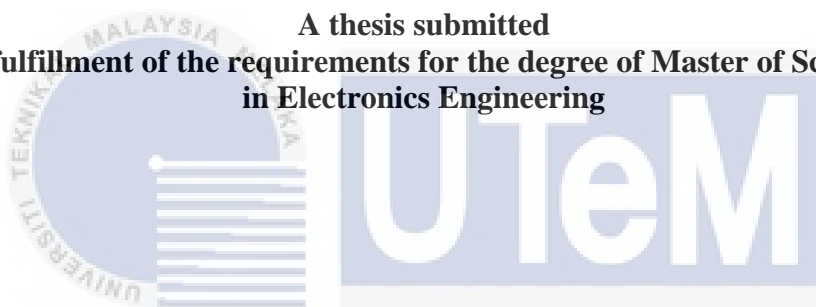
Master of Science of Electronics Engineering

2024

**DESIGN AND DEVELOPMENT OF COOPERATIVE SIMULTANEOUS
LOCALIZATION AND MAPPING INTEGRATED WITH NEURAL NETWORK
FOR MOBILE ROBOT**

AMIRUL BIN JAMALUDIN

**A thesis submitted
in fulfillment of the requirements for the degree of Master of Science
in Electronics Engineering**



اونيورسيتي تيكنيكل مليسيا ملاك

Faculty of Electronics and Computer Technology and Engineering

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

2024

DECLARATION

I declare that this thesis entitled “Design and Development of Cooperative Simultaneous Localization and Mapping Integrated with Neural Network for Mobile Robot” is the result of my own research except as cited in the references. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.

Signature : 
Name : Amirul Bin Jamaludin
Date: 27 May 2024

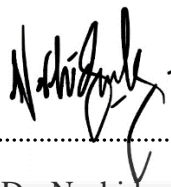


اونيورسيتي تيكنيكل مليسيا ملاك
UNIVERSITI TEKNIKAL MALAYSIA MELAKA

APPROVAL

I hereby declare that I have read this thesis and in my opinion this thesis is sufficient in terms of scope and quality for the award of Master of Science in Electronics Engineering.

Signature

: 

Supervisor Name

: Dr. Norhidayah Binti Mohamad Yatim

Date:

: 27 May 2024



اونيورسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

DEDICATION

This thesis is dedicated to:

My beloved parents, Saripah Kassim and Jamaludin Sulaiman

My beloved siblings

and to all my family.



ABSTRACT

Autonomous cooperating mobile robots is one of technological advancement in enabling autonomy in search and rescue task (SaR). While, simultaneous localization and mapping (SLAM) algorithm is one of a key element to enable autonomous navigation. Many researchers chose to adopt high-end sensors to solve Cooperative SLAM or CSLAM. But this will cause staggering cost for multiple robot system. Thus, the alternative is to implement low-cost sensors with limited sensing to perform CSLAM. However, this approach introduces challenges such as inaccurate robots' sensors measurements and low accuracy cooperative mapping were reported. In this research, an Artificial Neural Network (ANN) is proposed to improve the accuracy of the CSLAM algorithm with low-cost sensors and is evaluated using real robots. Here, the selected methodologies are divided into three important stages to support three objectives defined to solve the stated problem statement. Firstly, the ANN configurations is established to reduce the nonlinearity error of the low-cost sensor measurements for building high accuracy environmental map. By training the ANN using sensor measurements, it learns to model the data and reduce the error or uncertainties present in the measurements obtained from the low-cost sensors. Secondly, a framework of CSLAM algorithm integrated with ANN using Rao-Blackwellized particle filter (RBPF) algorithm for single SLAM robot, and the map merging using random sample consensus (RANSAC) algorithm, is designed and developed. Lastly, the performance of the CSLAM algorithm with ANN is evaluated and validated using measurements from real robot platforms, and compared to that without ANN. From the real-world experiment, CSLAM with ANN has increased the performance of resulting maps by 61.09% compared to without ANN. It shows that, CSLAM integrated with ANN have improved the performance of CSLAM significantly. Moreover, CSLAM integrated with ANN have achieved 3 closed loop condition out of 10 trials for 600 particles compared to without ANN that does not achieve closed loop map out of 10 trials even though, the number of particles is increased. From the results, it can be concluded that the development of CSLAM algorithm integrated with ANN able to improve the performance of CSLAM for mobile robot using low-cost sensor.

REKABENTUK DAN PEMBANGUNAN KOPERATIF PENYETEMPATAN DAN PEMETAAN SERENTAK BERSEPADU DENGAN RANGKAIAN NEURAL BAGI ROBOT MUDAH ALIH

ABSTRAK

Robot-robot bergerak secara autonomi yang bekerjasama merupakan salah satu kemajuan teknologi dalam membolehkan autonomi dalam tugas mencari dan menyelamatkan (SaR). Sementara itu, algoritma penyetempatan dan pemetaan (SLAM) merupakan salah satu elemen utama untuk membolehkan navigasi autonomi. Banyak penyelidik memilih untuk mengadopsi sensor-sensor berkualiti tinggi untuk menyelesaikan Cooperative SLAM atau CSLAM. Namun, ini akan menyebabkan kos yang tinggi untuk sistem robot yang banyak. Oleh itu, alternatifnya adalah mengimplementasikan sensor-sensor berkos rendah dengan penerimaan yang terhad untuk melaksanakan CSLAM. Walau bagaimanapun, pendekatan ini membawa cabaran seperti pengukuran sensor robot yang tidak tepat dan pemetaan koperatif yang kurang tepat dilaporkan. Dalam penyelidikan ini, Jaringan Neural Tiruan (ANN) dicadangkan untuk meningkatkan ketepatan algoritma CSLAM dengan sensor berkos rendah dan dinilai menggunakan robot sebenar. Di sini, metodologi yang dipilih dibahagikan kepada tiga peringkat penting untuk menyokong tiga objektif yang ditakrifkan untuk menyelesaikan kenyataan masalah. Pertama, konfigurasi ANN dibina untuk mengurangkan ralat bukan linear pengukuran sensor berkos rendah untuk membina peta alam sekitar dengan ketepatan tinggi. Dengan melatih ANN pada data sensor, ia mempelajari untuk memodelkan dan mengurangkan ketidaklinearan yang hadir dalam pengukuran yang diperolehi daripada sensor berkos rendah. Kedua, rangkaian algoritma CSLAM yang terintegrasi dengan ANN menggunakan algoritma Rao-Blackwellized particle filter (RBPF) untuk robot SLAM tunggal, dan penggabungan peta menggunakan algoritma random sample consensus (RANSAC), direka dan dibangunkan. Akhirnya, prestasi algoritma CSLAM dengan ANN dinilai dan disahkan menggunakan pengukuran dari platform robot sebenar, dan dibandingkan dengan yang tanpa ANN. Dari eksperimen dunia nyata, CSLAM dengan ANN telah meningkatkan prestasi peta hasil sebanyak 61.09% berbanding tanpa ANN. Ini menunjukkan bahawa CSLAM yang terintegrasi dengan ANN telah meningkatkan prestasi CSLAM secara signifikan. Selain itu, CSLAM yang terintegrasi dengan ANN telah mencapai 3 keadaan litar tertutup daripada 10 percubaan untuk 600 partikel berbanding tanpa ANN yang tidak mencapai peta litar tertutup daripada 10 percubaan walaupun bilangan partikel telah ditingkatkan. Dari hasil ini, dapat disimpulkan bahawa pembangunan algoritma CSLAM yang terintegrasi dengan ANN dapat meningkatkan prestasi CSLAM untuk robot bergerak menggunakan sensor berkos rendah.

ACKNOWLEDGEMENTS

My sincere gratitude to Almighty God who granted me health and long life, without Him I could not have complete this Master's Proposal. His bless and grace is giving me full strength end up untill this stage. First and foremost, I am immeasurably grateful to my parents for believing in me and encouraging me through the hardship not only in the process of preparing this proposal but also for my Master of Science of Electronics Engineering journey.

I would like to express my deepest appreciation to my Master's project supervisor, Dr. Norhidayah Binti Mohamad Yatim, for challenging and supporting me throughout this journey. Her unwavering patience, guidance, and remarkable force enabled me to successfully complete this thesis. She provided invaluable feedback and tips, understanding me even at my lowest points and motivating me until the very end. Additionally, I extend my heartfelt gratitude to Dr. Zarina Binti Mohd Noh, my co-supervisor, for her continuous guidance and support throughout my Master's journey. I want to emphasize that the kindness shown by both Dr. Norhidayah and Dr. Zarina will be remembered for the entirety of my life.

In addition, a special thanks to all my friends, Muhammad Nazmi Bin Zainal Azali, Nurfarah Izzati Binti Ismail, Nur Farahin Binti Abdul Halim, Hee Thien Tack, Nur Fatini Binti Kamaruzaman, Muhammad Afiq Bin Roslin, Hatiqah Anis Binti Harman, Muhammad Afiff Bin Alias and all my friends for their moral support and guidance which helped me to overcome the challenges I faced in completing my thesis. Lastly, I would like to thank all those who directly and indirectly for helping me. I am really obliged for their constant encouragement in completion of this project without them, this project would not have been possible.

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

TABLE OF CONTENTS

	PAGES
DECLARATION	
DEDICATION	
ABSTRACT	i
ABSTRAK	ii
ACKNOWLEDGEMENTS	iii
TABLE OF CONTENTS	iv
LIST OF TABLES	vii
LIST OF FIGURES	viii
LIST OF ABBREVIATIONS	xii
LIST OF PUBLICATIONS	xiv
LIST OF APPENDICES	xv
CHAPTER	
1. INTRODUCTION	1
1.1 Background	1
1.2 Motivation	3
1.3 Problem Statement	4
1.4 Objectives	6
1.5 Research Gap/Contribution	6
1.6 Research Hypothesis	7
1.7 Research Scope	8
2. LITERATURE REVIEW	11
2.1 Introduction	11
2.2 Definition of SLAM	11
2.3 SLAM Algorithms	13
2.3.1 Extended Kalman Filter	14
2.3.2 Particle Filter	16
2.3.3 EIF SLAM	22
2.3.4 Variable Structure Filter (VSF)	25
2.3.5 Summary of SLAM Algorithms	28
2.4 Map Representation	30
2.4.1 Grid Maps	31
2.4.2 Topological Maps	33
2.4.3 Feature Maps	35
2.4.4 Summary of the Map Representation	36
2.5 Map Merging	38
2.5.1 Direct Map Merging	39
2.5.1.1 Robot to Robot Measurements	39
2.5.1.2 Direct Optimization Method	40
2.5.2 Indirect Map Merging	42
2.5.2.1 Hough Transform Method	42
2.5.2.2 Random Sample Consensus (RANSAC) Algorithm	45

2.5.2.3	Probabilistic Generalized Voronoi Diagram (PGVD)	47
2.5.3	Summary of map merging method	50
2.6	Artificial Neural Network Regressor Implementation	52
2.6.1	ANN Training Method	53
2.6.2	Types of the ANN	56
2.6.3	Review of ANN Performance	58
2.7	SLAM Strategy for Multi-robot System	60
2.7.1	Centralized System	60
2.7.2	Decentralized System	61
2.8	Exploration Strategies	65
2.8.1	Frontier Based Strategy	65
2.8.2	Via Visitation Map	66
2.8.3	Manual Control	67
2.9	Sensor Measurements	67
2.9.1	Observation	67
2.9.2	Odometry	70
2.10	Literature Review Summary	71
3.	METHODOLOGY	76
3.1	Introduction	76
3.2	Equipment and Tools	76
3.2.1	Robot Operating System	77
3.2.1.1	Packages in ROS	77
3.2.1.2	Communication in ROS	78
3.2.2	Turtlebot3 Robot Platform	80
3.2.3	LiDAR Sensor	81
3.2.4	Wheel encoder	82
3.2.5	Remote PC	83
3.3	Overall Thesis Methodology Flowchart	83
3.4	Artificial Neural Network Model (Phase 1)	84
3.4.1	Data Collection (LiDAR Data Point)	85
3.4.2	Training the Model of ANN	87
3.4.3	Validation of ANN Model	92
3.5	Design of the Cooperative SLAM Framework (Phase 2)	93
3.5.1	Single SLAM Robot	93
3.5.1.1	Odometry motion model	95
3.5.1.2	Sensor model	98
3.5.1.3	Rao-Blackwellized Particle Filter (RBPF) Algorithms Framework	100
3.5.1.4	Occupancy Grid Mapping	104
3.5.2	Multi-Robot SLAM	105
3.5.3	Map Merging Operation	106
3.5.3.1	Find Intitial Overlapping Maps	106
3.5.3.2	Feature Detection	108
3.5.3.3	Feature Description	109
3.5.3.4	Feature Matching	110
3.5.3.5	RANSAC	111
3.5.3.6	Finding Largest Connected Component	113
3.5.3.7	Final Transformation Estimation	114

3.5.4	Manual Exploration Strategy	115
3.6	Evaluation of Performance	116
3.7	Summary	120
4.	RESULTS AND DISCUSSION	122
4.1	Introduction	122
4.2	Artificial Neural Network Model Establishment (Phase 1)	122
4.3	RBPF integrated with ANN (Phase 2)	128
4.3.1	Single robot	129
4.3.1.1	Accuracy Performance	130
4.3.1.2	Loop-Closure Consistency	136
4.3.1.3	Computational Cost	137
4.3.2	Real-world Experiment – Cooperative robot	138
4.3.2.1	Accuracy Performance	142
4.3.2.2	Loop Closure Consistency	145
4.3.2.3	Computational Cost	151
4.3.2.4	Exploration Time Comparison	153
5.	CONCLUSION AND RECOMMENDATIONS	154
5.1	Conclusion	154
5.2	Future Works	157
	REFERENCES	158
	APPENDICES	171



LIST OF TABLES

TABLE	TITLE	PAGE
Table 2.1	Advantages and disadvantages of SLAM algorithms	28
Table 2.2	Advantages and disadvantages of map representations	37
Table 2.3	Advantages and disadvantages of map merging method	50
Table 2.4	Comparison of ANN Architecture Training Method	56
Table 2.5	Advantages and disadvantages of the multi-robot SLAM strategies	64
Table 3.1	Mean, variance and standard deviation for real-world data	87
Table 3.2	Odometry motion model pseudo-code	97
Table 3.3	Summary of the parameter setting in the methodology	121
Table 4.1	Average Number of Inliers According to Number of Particles	132
Table 4.2	Closed-loop Map Condition According to Number of Particles	136
Table 4.3	Resulting Map Condition According to Number of Particles	142
Table 4.4	Resulting Map Condition According to Number of Particles	150
Table 4.5	Time taken for exploration	153

LIST OF FIGURES

FIGURE	TITLE	PAGE
Figure 2.1	Each particles contains a hypothesis of robot pose and its own map (Yatim and Buniyamin, 2015)	17
Figure 2.2	Observation $pztxt$ and motion model $puxt'.ut$ likelihood (Grisetti, Stachniss and Burgard, 2007)	18
Figure 2.3	(a) End of corridor observation (b) Along the coridor observation (c) No observation (Grisetti, Stachniss and Burgard, 2007)	19
Figure 2.4	With the growing number of robots, the number of particles increases (Saeedi et al., 2016)	22
Figure 2.5	Comparisan between EKF and EIF (top column) with SEIF (bottom column) using simulation with 50 landmarks (Thrun et al., 2004)	24
Figure 2.6	The SVSF fundamental estimating concept (Habibi, 2007)	26
Figure 2.7	Cooperative of SVSF SLAM algorithm framework A new adaptive smooth variable structure filter SLAM algorithm for unmanned vehicle (Demim, Nemra, et al., 2017)	27
Figure 2.8	(a) OGM with raw odometry data (b) OGM with 100 samples of particle filter (Hähnel et al., 2003)	32
Figure 2.9	The sensor-scale cells (i.e. black cells) are marked as occupied and the cells (i.e. white cells) are marked as free (Thrun, 2002)	33
Figure 2.10	(a) A metric map (b) A topological map (Vellucci, 2020)	34
Figure 2.11	Example of feature maps (Tao et al., 2010)	36
Figure 2.12	(a) OGM with line segments (b) same OGM rotated 15° and translated 50 cells (c) Hough images of OGM (a) (d) Hough image of OGM (b) (Saeedi et al., 2014b)	44
Figure 2.13	RANSAC searches and tests the best pairs of points from the function matching stage to transform the map that enables the evaluated map to be merged (Alberto et al., 2020)	46
Figure 2.14	(a) First GVD's map (b) Second GVD's map (Saeedi et al., 2014a)	48
Figure 2.15	(a) First PGVD's map (b) Second PGVD's map (Saeedi et al., 2014a)	49

Figure 2.16	a) Edge number three b) Edge number seven Each cell's grayscale intensity in these edges reflects the cell's likelihood in the PGVD (The probability that it is a valid GVD cell) (Saeedi et al., 2014a)	49
Figure 2.17	(a) E-puck mobile robot is equipped with eight infrared sensors (b) A nine-input ANN consisting of infrared sensors, cell position and heading of the robot (Yatim and Buniyamin, 2017)	55
Figure 2.18	(a) RBPF map with ANN (b) RBPF map without ANN (Yatim et al., 2020)	58
Figure 2.19	(a) Map with ANN process (b) Map without ANN process (Kim, Heon-hui Ha, Yun-Su Jin, 2003)	59
Figure 2.20	(a) Centralized system (b) Decentralized system (Alexandre, 2013)	64
Figure 2.21	Basic time-of-flight principles applied to laser range-finding (Vellucci, 2020)	68
Figure 2.22	The Encoder Block-Diagram (Vellucci, 2020)	70
Figure 3.1	Nodes and topics communication for CSLAM	80
Figure 3.2	Turtlebot3 Burger	81
Figure 3.3	LDS-01 LiDAR sensor	82
Figure 3.4	Overall thesis methodology flowchart	84
Figure 3.5	ANN model flowchart	85
Figure 3.6	(a) Turtlebot3 position ranging from 0.05m to 3.5m (b) Turtlebot3 position at 0°	86
Figure 3.7	Network configuration of ANN for real-world data	88
Figure 3.8	Feedforward backpropagation ANN training flowchart	89
Figure 3.9	Flowchart of single SLAM robot operation	94
Figure 3.10	Odometry model	95
Figure 3.11	Laser scan about cell (0,0). White, gray and black indicate obstacle-free, unknown, and occupied cells, respectively	98
Figure 3.12	Map merging flowchart	107
Figure 3.13	Feature detection using FAST algorithm	109
Figure 3.14	Layout of the Lecturers room, Faculty of Electronics and Computer Engineering, UTeM	116
Figure 3.15	Flowchart of evaluation of performance of CSLAM robots	117

Figure 4.1	Regression graph of ANN model of LDS-01 sensor	123
Figure 4.2	Graph illustration for the data of ANN model testing using real-world LDS-01 sensor measurements data	124
Figure 4.3	Comparison of error of sensor measurement without ANN (green) and with ANN (blue)	125
Figure 4.4	Histogram of LDS sensor measurement at 3 meter distance (without ANN)	125
Figure 4.5	Histogram of LDS sensor measurement at 1 meter distance	126
Figure 4.6	Histogram of LDS sensor measurement at 1 meter distance (with ANN)	127
Figure 4.7	Histogram of LDS sensor measurement at 3 meter distance (with ANN)	127
Figure 4.8	Standard deviation of LDS-01 sensor data using ANN model before and after testing	128
Figure 4.9	(a) Non-closed loop map without ANN (b) Closed loop map with ANN	131
Figure 4.10	Ground truth map of the real-world environment	132
Figure 4.11	Map performance by using number of inliers between resulting map and ground truth map	133
Figure 4.12	42 number of inliers points between resulting map (without ANN) and ground truth map	135
Figure 4.13	77 number of inliers points between resulting map (with ANN) and ground truth map	135
Figure 4.14	CPU consumption in one minute of the RBPF using 30 particles	138
Figure 4.15	CPU consumption in one minute of the RBPF using 400 particles	138
Figure 4.16	(a) Map robot 2 (b) Map robot 1	139
Figure 4.17	731 features matching point using ORB algorithm	140
Figure 4.18	36 pairs of inliers point using RANSAC algorithm	141
Figure 4.19	Everage number of inliers in map matching score of cooperative robot based on number of particles	143
Figure 4.20	Number of inliers score of each resulting maps based on number of particles	144

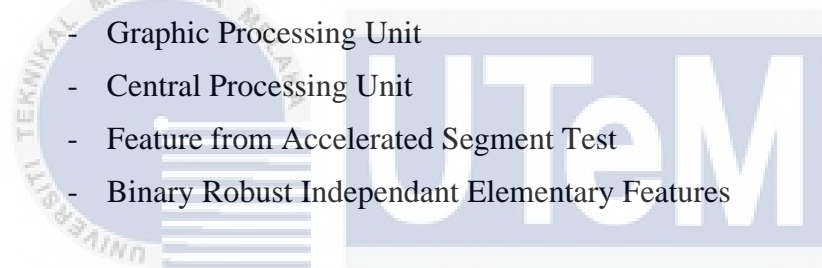
Figure 4.21	Standard deviation of map matching score based on number of particles	144
Figure 4.22	(a) Map merging (without ANN) by using 30 particles (b) Map merging (with ANN) by using 30 particles	147
Figure 4.23	55 pairs of inliers point using RANSAC algorithm	148
Figure 4.24	Map merging constructed by RANSAC algorithm (with ANN) by using 600 particles	149



LIST OF ABBREVIATIONS

SLAM	- Simultaneous Localization and Mapping
CSLAM	- Cooperative SLAM
MRSLAM	- Multi-Robot SLAM
MRS	- Multi-Robot System
SaR	- Search and Rescue
RBPF	- Rao-Blackwellized Particle Filter
OGM	- Occupancy Grid Map
GPS	- Global Positioning System
LiDAR	- Light Detection and Ranging
LDS	- Laser Distance Sensor
AGV	- Automated Guided Vehicle
ANN	- Artificial Neural Network
LM	- Levenberg Marquardt
PF	- Particle Filter
EIF	- Extended Information Filter
SEIF	- Sparse Extended Information Filter
KF	- Kalman Filter
EKF	- Extended Kalman filter
VSF	- Variable Structure Filter
SVSF	- Smooth Variable Structure Filter
HMM	- Hidden Markov model
RFS	- Random Finite Set
FBM	- Feature Based Mapping
SIFT	- Scale Invariant Feature Transform
SURF	- Speeded Up Robust Features
MP-CSLAM	- Median Of Local Posterior Probability CSLAM
TMP-CSLAM	- Time-MP-CSLAM
RANSAC	- Random Sample Consensus
MTM	- Map Transformation Matrix
PGVD	- Probabilistic Generalized Voronoi Diagram

ROS	- Robot Operating System
WFD	- Wave-front Frontier Detector
CTS	- Cellular Transport System
Radish	- Data Set Repository
MSE	- Mean Squared Error
RMSE	- Root Mean Squared Error
CHOPIN	- Human and Robotoc Teams in Catastrophic Incidents
LRS	- Laser Range Scanner
LRF	- Laser Range Finder
ICC	- Instantaneous Center of Curvature
SIR	- Sampling Importance Filter
ORB	- Oriented FAST and Rotated BRIEF
Rviz	- ROS Visualizer
URDF	- Unified Robot Description Format
GPU	- Graphic Processing Unit
CPU	- Central Processing Unit
FAST	- Feature from Accelerated Segment Test
BRIEF	- Binary Robust Independant Elementary Features



اونيورسيتي تيكنيكل مليسيا ملاك

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

LIST OF PUBLICATIONS

The followings are the list of publications related to the work on this thesis:

Jamaludin, A., Mohamad Yatim, N., Mohd Noh, Z., Buniyamin, N., 2023. Rao-Blackwellized Particle Filter Algorithm Integrated with Neural Network Sensor Model Using Laser Distance Sensor. *Micromachines*, 14(3), 560. Available at: <https://doi.org/10.3390/mi14030560>.

Jamaludin, A., Mohamad Yatim, N., Mohd Noh, 2023. The Effect of Artificial Neural Network Towards the Number of Particles of Rao-Blackwellized Particle Filter using Laser Distance Sensor. *International Journal of Advanced Computer Science and Applications(IJACSA)*, 14(1). Available at: <http://doi.org/10.14569/IJACSA.2023.0140176>.



LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Weight And Bias For Real-World Ann Model	171
Appendix B	Maps For 30 To 400 Particles (Single Robot)	172
Appendix C	Maps For 30 To 600 Particles (Cooperative Robot)	174



CHAPTER 1

INTRODUCTION

1.1 Background

These days the necessity to respond successfully to catastrophic and unanticipated incidents has increased, which include natural and civil crises, industrial accidents and acts of terrorism and crime. Present defense agencies face a lack of specialist dedicated resources, leading to the vulnerability of search and rescue (SaR) teams to the risk of human lives and less than ideal successful casualty aid within the civilian community (Couceiro, Portugal and Rocha, 2013). From this cause, robotics are designed and developed to enhance the safety of human rescue workers and potential victims, and to achieve faster, more accurate, and cost-effective responses in SaR applications in cooperation with human rescue teams (Kruijff et al., 2012). By taking advantage of the expendability of robotics, a team of mobile robots operating cooperatively will reduce human capital and increase productivity from human exhaustion during crisis operations. To survive and operate within its environments, an autonomous robot has to solve two crucial problems: mapping an unknown environment and locating its relative position within the map. These two common problems in robotics are known as simultaneous localization and mapping (SLAM).

SLAM plays an important role in robotics, and particularly in mobile robot systems. SLAM's primary objective is to jointly measure the robot's position as well as the surrounding map model (Alexandre, 2013; Saeedi et al., 2016; Wen et al., 2019; Ullah et al., 2020). For this purpose, Rao-Blackwellized particle filter (RBPF) algorithm and

occupancy grid map (OGM) algorithm are proposed in this study for individual robot framework. However, in this study, the main purpose is to design and develop cooperative simultaneous localization and mapping (CSLAM) for mobile robot. While it is difficult enough to build single SLAM robot, moving to multiple robots adds another layer of difficulty. For CSLAM, the crucial part is the ability to collaborate in order to merge the maps produced by individual robots and it is the benchmark of the performance of the CSLAM. Robots must include all of the data available to build a coherent world map in a multiple robot environment while locating themselves within the global map. CSLAM has many advantages, including the ability to complete missions quicker and being resilient to the malfunction of any one of the robots. However, these advantages come at the expense of a complex system that necessarily involves robot teamwork and cooperation. Hence, the methods and algorithms to solve the cooperative robot's problem which is merging the map is studied and included in this work. Random Sample Consensus (RANSAC) algorithm for map merging is employed in this study to solve the crucial part of the CSLAM problem. This is due to the algorithm can be implemented in real-time applications and suitable for SaR applications since SaR need to achieve faster and real-time responses.

To achieve high accuracy of the mapping, many researchers chose to go for high-cost sensors to solve CSLAM (Bautin et al., 2013; Andre, Neuhold and Bettstetter, 2014; Li et al., 2014; Saeedi et al., 2014b; B et al., 2017; Demim, Nemra, et al., 2017; Seong, Lee and Kim, 2019; Martins, Portugal and Rocha, 2021). High-cost sensors typically require a greater financial investment as they possess advanced features, higher precision, and enhanced capabilities, but they also come with a higher price tag. Hence, this will cause staggering cost for multiple robot system. Thus, the alternative is to implement low-cost sensors with limited sensing to perform CSLAM. Low-cost sensors refer to sensors that are

economically affordable and suitable for applications where cost is a significant consideration. These sensors are characterized by their relatively lower price point compared to high-end alternatives. However, this approach introduces challenges such as low accuracy of the sensors measurements and unstable cooperative mapping were reported (Waniek, Ieee and Biedermann, 2015). In addition, although RANSAC algorithm is reported to have fast computation time but the accuracy is lower than other method like Hough Transform and direct optimization method (Nasir, Hille and Roth, 2012; Iv, 2014; Bultmann et al., 2017). However, the other methods are not as fast as RANSAC to have real-time application, hence, RANSAC is chosen.

In this research, a CSLAM algorithm integrated with artificial neural network (ANN) is proposed and evaluated using both simulation and real robots. Within this framework, a sensor model is developed to interpret measurements and generate corrected readings using ANN. The aim is to improve sensor measurements, enhance map estimation accuracy and optimize the RANSAC algorithm for the map merging process. This finding will be beneficial in overcoming low-cost sensors limitation in order to enhance the capability of multi-robots' system with low-cost sensors.

1.2 Motivation

Robotics can contribute to enhance the safety of human rescue workers and potential victims, by achieving achieve faster, more accurate, and cost-effective responses in SaR applications. It is achieved through the use of mobile robotic agent teams in cooperation with human rescue teams (Kruijff et al., 2012). Through taking advantage of the expendability of robotics, a team of mobile robots operating cooperatively will reduce