

SENSOR FUSION WITH KALMAN FILTER AND SUPPORT VECTOR MACHINE
FOR FAULT DETECTION IN AUTOMATED GUIDED VEHICLE

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SENSOR FUSION WITH KALMAN FILTER AND SUPPORT VECTOR MACHINE
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ABSTRACT

Industries are moving towards automation and the usage of machines such as Automated Guided Vehicle (AGV) is increasing. Thus, demands for the reliability of AGVs are increasing as they have various complex tasks to carry out. Unfortunately, AGVs are still susceptible to faults and breakdown. Therefore, fault detection is important to provide means of self-diagnosis on AGV. However, fault detections are generally threshold based which are unsatisfying in terms of accuracy and are prone to false triggering. Extended Kalman Filter (EKF) has limitations in handling nonlinear models while Unscented Kalman Filter (UKF) seems promising. Support Vector Machine (SVM) was used as a fault detection method. Thus, this research proposes a sensor fusion enhanced with SVM for fault detection on AGV. The first objective of this research is to develop a test AGV. This AGV is a two-wheeled differential driven mobile robot with multiple sensors and able to make various types of movements to emulate an industrial AGV. Next objective is to develop an enhanced sensor fusion method using EKF and UKF for fault detection with SVM on AGV. The last objective is to evaluate the performance of the developed method. Experiments were carried out where the AGV was used as a test bed for sensor fusion and fault detection. The AGV was tested in different experiment setups such as different track layout, different wheel condition, and different castor conditions. Result shows that UKF handles changes and non-linearity better than EKF. The average residual generated during the test for UKF is 0.0083 meter while for EKF is 0.0129 meter. With sensor fusion, deviations in odometry data can be compensated with the usage of a LiDAR sensor as reference. Using UKF parameters to detect fault, the accuracy achieved with SVM is 64.2% compared to 37.9% without SVM. Fault detection accuracy using EKF parameters with SVM is 82.5% while without SVM is 41.0%. As a conclusion, the results show SVM improves fault detection accuracy regardless of using UKF or EKF.

ABSTRAK

Industri sedang menuju ke arah automasi dan penggunaan mesin seperti kenderaan panduan automatik (AGV) semakin meningkat. Oleh itu, permintaan untuk AGV yang boleh diharap semakin meningkat kerana adanya pelbagai tugas kompleks untuk dijalankan. Malangnya, AGV masih tidak bebas daripada masalah dan kerosakan. Oleh itu, AGV harus mempunyai kemampuan untuk menjalankan pemeriksaan sendiri untuk masalah dan kerosakan. Walaubagaimanapun, kaedah pengesanan kerosakan secara amnya adalah berdasarkan nilai ambang yang tidak memuaskan dari segi ketepatan. Penapis Kalman Berlanjutan (EKF) mempunyai cabaran mengendalikan model tidak linear sedangkan Penapis Kalman Tidak Berbau (UKF) menunjukkan potensi. Mesin Sokongan Vektor (SVM) telah digunakan untuk kaedah pengesanan kerosakan. Justeru, kajian ini mencadangkan kaedah pelakuran penderia yang dipertingkatkan dengan SVM untuk pengesanan kerosakan pada AGV. Tujuan pertama kajian ini adalah untuk membangunkan sebuah AGV. AGV ini adalah robot pacuan berbeza dua roda dengan pelbagai penderia yang boleh buat pelbagai gerakan untuk menyerupai AGV industri. Tujuan seterusnya adalah untuk menghasilkan kaedah pelakuran penderia yang diperbaiki dengan EKF dan UKF untuk pengesanan kerosakan dengan SVM pada AGV. Tujuan terakhir adalah menguji prestasi kaedah yang telah dihasilkan. AGV telah digunakan dalam kajian untuk menguji pelakuran penderia dan pengesanan kerosakan. AGV tersebut telah diuji dengan keadaan yang berbeza seperti susunan atur trek, keadaan roda dan keadaan kastor yang berlainan. Hasil kajian menunjukkan bahawa UKF mengendalikan perubahan dan model tidak linear lebih baik daripada EKF. Nilai perbezaan antara anggaran dan sebenar yang dijanakan semasa ujian untuk UKF ialah 0.0083 meter dan untuk EKF ialah 0.0129 meter. Penyelewengan dalam data odometri boleh diperbaiki dengan penggunaan peranti pengesanan cahaya dan penjarakan sebagai rujukan. Ketepatan pengesanan kerosakan dengan penggunaan nilai UKF ialah 64.2% dengan SVM dan 37.9% tanpa SVM. Ketepatan pengesanan kerosakan dengan penggunaan nilai EKF ialah 82.5% dengan SVM dan 41.0% tanpa SVM. Kesimpulannya, hasil kajian menunjukkan bahawa SVM memperbaiki ketepatan pengesanan kerosakan tanpa mengira samada menggunakan UKF atau EKF.

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	iii
	DEDICATION	iv
	ACKNOWLEDGEMENT	v
	ABSTRACT	vi
	ABSTRAK	vii
	TABLE OF CONTENTS	viii
	LIST OF TABLES	x
	LIST OF FIGURES	xi
	LIST OF ABBREVIATIONS	xv
	LIST OF SYMBOLS	xvii
	LIST OF APPENDICES	xx
CHAPTER 1	INTRODUCTION	1
1.1	Introduction	1
1.2	Problem Statement	2
1.3	Objectives of Research	3
1.4	Scope of Research	3
1.5	Report Outline	4
CHAPTER 2	LITERATURE REVIEW	5
2.1	Introduction	5
2.2	Automated Guided Vehicle and Sensors	5
2.3	Sensor Fusion	10
2.4	Fault Detection	18
2.5	Sensor Fusion and Fault Detection on Automated Guided Vehicle	19
2.6	Summary	21

CHAPTER 3	RESEARCH METHODOLOGY	23
3.1	Introduction	23
3.2	Project Planning	23
3.3	Hardware Design	25
3.4	Designing Kalman Filter and SVM Model for Proposed Test AGV	30
3.5	Encoder Test	46
3.6	Current Sensor Test	48
3.7	Experiment Setups	50
3.8	Summary	55
CHAPTER 4	RESULTS AND DISCUSSIONS	57
4.1	Introduction	57
4.2	Trajectory Test	57
4.3	Fault Detection with Kalman Filter and Residual Measurement	59
4.4	EKF and UKF on Track	60
4.5	Fault Detection with SVM	64
4.6	Summary	78
CHAPTER 5	CONCLUSION	79
5.1	Summary	79
5.2	Future works	81
REFERENCES		83
LIST OF PUBLICATIONS		116

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2.1	Guidance system comparison table.	8
Table 2.2	Type of sensors.	9
Table 2.3	Advantages and disadvantages of various fusion methods.	16
Table 2.4	Advantages and disadvantages of sensor fusion for fault detection methods.	22
Table 3.1	Predict class for wheel conditions.	43
Table 3.2	Predict class for castor conditions.	43
Table 3.3	Encoder Test Data.	47
Table 3.1	Output of DMM and Current Sensor.	49
Table G.1	130 samples of sensor fusion algorithm parameter data during a run on a square loop track for experiment which includes estimated odometry values and residual values.	112

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1	Timeline and recent advancement in AGV development.	6
Figure 2.2	Configurations of mobile robots.	6
Figure 2.3	Configuration of a differential two wheeled mobile robot. An AGV with configuration features two drive wheels that can run at different speeds separately. The different turning speeds between these two drive wheels allow the AGV to turn.	7
Figure 2.4	Steps in Kalman filter.	11
Figure 2.5	Odometry plotting of measured and estimated path generated with EKF.	12
Figure 2.6	Actual, linearized (EKF) and unscented transformation.	13
Figure 2.7	Block diagram of UKF sensor fusion algorithm.	13
Figure 2.8	Platform with infrared sensor and ultrasonic sensor.	14
Figure 2.9	(a) Root mean square (RMS) values between consecutive frames exceeding threshold when the space within ultrasonic range is occupied. (b) Image as perceived by infrared sensor showing an activity of a person falling.	15
Figure 2.10	Classification of FDI techniques.	18
Figure 2.11	Residual generation using observer Kalman filter.	19
Figure 2.12	Mobile robot utilizing EKF with multiple positioning module as described.	20
Figure 2.13	Residual value evaluation during encoder fault simulation.	21
Figure 3.1	Flow of research methodology.	24
Figure 3.2	3D CAD model of the AGV's chassis with motors and wheels attached.	26
Figure 3.3	Assembly of AGV chassis.	26

Figure 3.4	Kinetic model of AGV.	27
Figure 3.5	AGV internal where the electronics, motors and wheels are located.	28
Figure 3.6	AGV used with added 9-DOF IMU and LiDAR.	29
Figure 3.7	System architecture of the AGV.	30
Figure 3.8	Flow of UKF algorithm.	37
Figure 3.9	Flow of EKF algorithm.	41
Figure 3.10	Flow of SVM train and predict.	46
Figure 3.11	Setup for encoder test on AGV.	47
Figure 3.12	Setup for current sensor test.	49
Figure 3.13	AGV running on track.	51
Figure 3.14	A square loop track as test track, track A.	51
Figure 3.15	An irregular loop track as test track, track B.	52
Figure 3.16	A figure 8 track as test track, track C.	52
Figure 3.17	Flow of data on AGV.	52
Figure 3.18	a) Good wheel with treads, round and 126mm (5-inch) diameter. b) Damaged wheel, not round, damaged portion less by 4mm. Bumpy. c) Worn-out wheel without tread, round and 122mm diameter. d) Reduced traction. Measured with vernier caliper.	54
Figure 3.19	a) Clean castor with nuts tighten to hold castor at correct height alignment with the other castors. b) Clean castor with nuts loosen causing castor to have uneven height alignment with the other castors and swivelling difficulties. c) PTFE (plumbing) tape wound around axle and foam tape with glue on the wheel of the castor to emulate dirt and problematic wheel turn.	54
Figure 3.20	Block diagram of proposed fault detection for experiment.	55
Figure 4.21	Reference trajectory for experiment.	58
Figure 4.22	Trajectory of the AGV during experiment.	58
Figure 4.23	Current values during normal operation test.	59

Figure 4.4	Current values during fault test.	60
Figure 4.5	AGV estimated trajectory with LiDAR and IMU for track A.	61
Figure 4.6	AGV estimated trajectory with LiDAR and IMU for track B.	61
Figure 4.7	AGV estimated trajectory with LiDAR and IMU for track C.	62
Figure 4.8	Residual of Kalman filter with LiDAR and IMU comparison for track A.	63
Figure 4.9	Residual of Kalman filter with LiDAR and IMU comparison for track B.	63
Figure 4.10	Residual of Kalman filter with LiDAR and IMU comparison for track C.	64
Figure 4.11	Residual and threshold (without SVM).	65
Figure 4.12	Residual generated over three test runs for EKF estimation when the AGV is operating with normal wheel condition.	66
Figure 4.13	Residual generated over three test runs for UKF estimation when the AGV is operating with normal wheel condition.	66
Figure 4.14	Residual generated over three test runs for EKF estimation when the AGV is operating with damaged wheel.	67
Figure 4.15	Residual generated over three test runs for UKF estimation when the AGV is operating with damaged wheel.	67
Figure 4.16	Residual generated over three test runs for EKF estimation when the AGV is operating with worn out wheel.	68
Figure 4.17	Residual generated over three test runs for UKF estimation when the AGV is operating with worn out wheel.	68
Figure 4.18	Mean and standard deviation of generated residual for all six cases based on their Kalman filter type and wheel conditions.	69

Figure 4.19	Residual generated over three test runs for EKF estimation when the AGV is operating with normal castor condition.	70
Figure 4.20	Residual generated over three test runs for UKF estimation when the AGV is operating with normal castor condition.	70
Figure 4.21	Residual generated over three test runs for EKF estimation when the AGV is operating with loose castor condition.	71
Figure 4.22	Residual generated over three test runs for UKF estimation when the AGV is operating with loose castor condition.	71
Figure 4.23	Residual generated over three test runs for EKF estimation when the AGV is operating with dirty castor condition.	72
Figure 4.24	Residual generated over three test runs for UKF estimation when the AGV is operating with dirty castor condition.	72
Figure 4.25	Mean and standard deviation of generated residual for all six cases based on their Kalman filter type and castor faults.	73
Figure 4.26	Learning curve of uneven wheel model (MSE: 0.1905, Accuracy: 0.9167).	74
Figure 4.27	Correlation plot for uneven wheel model.	74
Figure 4.28	Learning curve of uneven castor model (MSE: 0.0765, Accuracy: 0.9388).	75
Figure 4.29	Correlation plot for uneven castor model.	75
Figure 4.30	SVM vs threshold (accuracy).	76
Figure 4.31	SVM model performance (accuracy).	77

LIST OF ABBREVIATIONS

3D CAD	-	3-dimensional computer aided design
4Ds	-	Too Dangerous, too Dull, too Dirty and too Difficult
9-DOF	-	9-degrees of freedom
ADC	-	Analogue to digital conversion
AGV	-	Automated guide vehicle
CCD	-	Charge-coupled device
CMOS	-	Complementary metal-oxide semiconductor
DC	-	Direct current
DMM	-	Digital multimeter
DST	-	Dempster-Shafer theory
EKF	-	Extended Kalman filter
FDI	-	Fault detection and isolation
GPS	-	Global positioning system
IMU	-	Inertial measurement unit
IoT	-	Internet of Things
LiDAR	-	Light detection and ranging
LiPo	-	Lithium polymer
MEMS	-	Microelectromechanical system
MM	-	Multi-model
MSE	-	Mean square error
RFID	-	Radio frequency identification
RMS	-	Root mean square
PC	-	Personal computer
PF	-	Particle filter
SBC	-	Single board computer
SVM	-	Support vector machine
UART	-	Universal asynchronous receiver/transmitter
UAV	-	Unmanned aerial vehicle
UKF	-	Unscented Kalman filter
USB	-	Universal serial bus

QEI - Quadrature encoder interface

LIST OF SYMBOLS

d	-	Axial distance between wheels
k	-	Iteration
n	-	Number of pulses
ϕ	-	Heading angle
π	-	Pi constant (3.142)
r	-	Radius of wheel
t	-	Time
v	-	Velocity of AGV
ω	-	Angular velocity of AGV
N	-	Number of pulses per rotation
T	-	Sampling time
x_k^f	-	State prediction
P_k^f	-	Covariance
K_k	-	Kalman gain
x_k^a	-	Updated state
P_k^a	-	Update covariance
\bar{X}	-	Predicted state
X	-	Updated state
A	-	State transition matrix
B	-	Coefficient matrix
u	-	Input matrix
\bar{P}	-	Predicted state
P	-	Updated state
H	-	Measurement matrix
Q	-	Process noise
R	-	Measurement noise
z	-	Measurement
y	-	Residual
v_e	-	Velocity output based on encoder data

ω_e	-	Steering angle output based on encoder data
r_R	-	Radius of right wheel
r_L	-	Radius of left wheel
ω_R	-	Angular velocity of right wheel
ω_L	-	Angular velocity of left wheel
x_e	-	x-position of AGV based on encoder data
y_e	-	y-position of AGV based on encoder data
ϕ_e	-	Heading angle of AGV based on encoder data
u_e	-	Input matrix based on encoder data
a_x	-	Accelerometer output in x-axis
m_x	-	Magnetometer output in x-axis
m_y	-	Magnetometer output in y-axis
x_i	-	x-position of AGV based on IMU data
y_i	-	y-position of AGV based on IMU data
ϕ_i	-	Heading angle of AGV based on IMU data
u_i	-	Input matrix based on IMU data
v_i	-	Velocity based on IMU output
Δx_l	-	Displacement in x-axis based on LiDAR data
Δx_l	-	Displacement in x-axis based on LiDAR data
$\Delta \phi_l$	-	Heading angle difference based on LiDAR data
x_l	-	x-position of AGV based on LiDAR data
y_l	-	y-position of AGV based on LiDAR data
ϕ_l	-	Heading angle of AGV based on LiDAR data
x	-	x-position of AGV
y	-	y-position of AGV
\dot{x}	-	Sigma points
\dot{y}	-	Transformed sigma points
ω^m	-	Weight of mean
ω^c	-	Weight of covariance
Z	-	Measurement-transformed sigma points
μ_z	-	Mean of measurement space
P_z	-	Covariance of measurement space
Y	-	Residual

- P_{xz} - Cross-covariance between state and measurement
- F - Jacobian of state model
- H - Jacobian of measurement model
- I - Identity matrix

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Reference Specification of Industrial Mobile Robot	91
Appendix B	Datasheet of Cytron LSA08 Line Follower	92
Appendix C	Datasheet of Xsens MTI-670	94
Appendix D	Module Datasheet of Hokuyo URG-04LX-UG01	97
Appendix E	Circuit Design and Schematics	99
Appendix F	Source Code	101
Appendix G	Sample Data Collected	112

CHAPTER 1

INTRODUCTION

1.1 Introduction

In this era of Industry 4.0, more solutions are moving towards automation and such automated solutions are automated guided vehicle (AGV). According to the International Federation of Robotics, the population of service mobile robot were 4 million and is increasing to about 31 million in 2014 till 2017 [1]. AGV is a type of self-propelled, mobile robot and is capable of carrying out task. AGVs are deployed in industrial environment to automate industrial operation and to cut down operation cost [2]. In a warehouse, operation cost can be costly with manual labour due to employee salary. The operation is less efficient due to the limitation of human workers where human workers can feel exhausted and are prone to health problems. AGV as machines, work tirelessly and continuously to ensure high productivity. AGV as robot seems suitable for any task which are too Dangerous, too Dull, too Dirty and too Difficult (4Ds) to be done by humans [3]. Modern AGVs are equipped with more different sensors, allowing them to complete complex tasks. Sensors play a vital role on AGVs to acquire information from the environment so AGVs may operate properly in its working environment [4]. By using sensor fusion, the combination of data from more than one sensor enables better robot perception. Uncertainties in sensors can be reduced and the accuracy and reliability of AGVs can be increased with better perception. However, machines can break down and cause business losses and potential harm to the workers. Thus, there is an increase in demands regarding the reliability and maintenance [5]. With fault detection, anomalies in performance of AGV can be detected which could help improve reliability of AGV. Thus, this research aims to design and develop an enhanced sensor fusion algorithm for fault detection in AGV with better accuracy. Hence,

sensor fusion method with better estimation accuracy could contribute to better fault detection accuracy.

1.2 Problem Statement

Modern AGVs are equipped with more sensors to collect information on the AGV itself and its surrounding. Data generated from sensors enable AGV functions such as detecting obstacles and performance and status monitoring. Information on the AGV can be utilized to optimize maintenance work on AGV. Efficient maintenance can save time and cost which is beneficial.

The weakness of currently utilized AGV systems are the cost for installation, efficiency of the system, flexibility of the system and the safety of the system [5]. The challenges in fault detection includes robustness, multiple fault diagnosis and real time diagnosis [6]. Failure in mobile robot system may cause robot to be off navigation which will be hazardous to human and degrades service performance [7]. Hence, the AGV should be capable of fault detection with multiple sensors for fault diagnosis and the sensors installed should be reliable so the AGV and its fault detection is robust while dealing with uncertainties in practical operation. The importance of fault detection is that it would bring more advantages not only to the mobile robot itself but also to maintenance planning and safety [8].

Residual generation is vital for most case in fault detection. Model based methods are preferred as data driven based methods are computationally costly. Most previous sensor fusion for fault detection work uses extended Kalman filter (EKF) which has limitation in handling nonlinear model [9]. This limitation causes low accuracy of the generated estimated value. Limited accuracy of the generated estimated value using EKF causes the fault detection to be unsatisfying in terms of accuracy. There are other sensor fusion methods claimed to have better estimation accuracy than EKF when used on other applications such as unscented Kalman filter (UKF). As for fault detection algorithm, previous work mostly relies on thresholding

of residual values generated which can be falsely triggered due to inaccuracies of EKF. Classification methods such as support vector machine (SVM) can be used to identify abnormalities in AGV performances.

1.3 Objective of Research

The purpose of this research is to design and develop enhanced sensor fusion for fault detection on AGV. The objectives of this research are:

- i. To design and develop an AGV as a test bed for fault detection. Sensors such as current sensor and encoder will be implemented on the test AGV.
- ii. To design an enhanced sensor fusion and fault detection method on AGV. Multiple sensor data generated on test AGV will be fused using EKF and UKF. SVM will be used for fault detection.
- iii. To evaluate the performance of methods on AGV and compare performance for fault detection on AGV. The performance of methods is measured in terms of estimation accuracy of sensor fusion method and the fault detection accuracy.

1.4 Scope of Research

A prototype AGV will be designed and developed as a test bed to experiment sensor fusion methods and fault detection. A two wheeled differential drive mobile robot will be used as the test AGV. Sensors are to be applied to the AGV. These sensors are vital for an AGV operations as the data outputs from these sensors can be used to measure the performance of the AGV and its fault detection capabilities.

Next, the test AGV uses Arduino Mega microcontroller as controller to govern the operation of the test AGV. Some C programming as prerequisite for coding the program to drive the actuators of the test AGV and to control the sensors. The Raspberry Pi 4 is to collect and analyse data, computing the sensor fusion algorithm. The programming environment to run sensor fusion and fault detection algorithm is mostly in Python programming language.

Lastly, the performance of the fault detection will be evaluated using residual calculation and error evaluation. The generated residual will be evaluated using SVM for fault detection. Based on the residual values calculated, the accuracy of estimation of each sensor fusion method can be measured and abnormality on AGV can be detected using fault detection method.

1.5 Thesis Outline

This report is divided into five chapters with Chapter 1 being the introduction of this report where problem statement, objective and scope of research are discussed. Chapter 2 is the literature review where research and review of AGV, sensor fusion and fault detection are discussed and summarized. Chapter 3 is where the project methodology is explained in detail. Experiment setup and execution to test the AGV test bed, sensor fusion and fault detection methods are mentioned in Chapter 3. Next, Chapter 4 is the result and outcome of the experiment mentioned in Chapter 3. Finally, Chapter 5 is the conclusion and suggestion for future work of this project. This final chapter is to summarize the research based on the findings in previous chapters and to proposed possible improvements for future research work.

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LIST OF PUBLICATIONS

Indexed Conference Proceedings

1. **Dares, M.,** Goh, K. W., Koh, Y. S., Yeong, C. F., Su, E., and Tan., P. H. (2020). Development of AGV as Test Bed for Fault Detection. In *2020 6th International Conference on Control, Automation and Robotics (ICCAR)* (pp. 379-383). IEEE. doi: 10.1109/ICCAR49639.2020.9107977. **(Indexed by SCOPUS)**
2. **Dares, M.,** Goh, K. W., Koh, Y. S., Yeong, C. F., Su, E., and Tan., P. H. (2021). Automated Guided Vehicle Robot Localization with Sensor Fusion. In *2021 International Conference on Computational Intelligence in Machine Learning (ICCIML)* (pp. 135-143). Springer Nature Singapore. doi: https://doi.org/10.1007/978-981-16-8484-5_11. **(Indexed by SCOPUS)**