ADVANCED DRIVER ASSISTANCE SYSTEM BASED ON THERMAL IMAGING AND MACHINE LEARNING

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DEDICATION

This thesis is dedicated to my lovely family members, helpful lecturers and supportive friends

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ABSTRACT

Based on a research conducted by Malaysian Institute Road Safety Research (MIROS), it is found that human error contributes up to 80% of road accidents. The answer to this issue would be through the implementation of autonomous car equipped with Advanced Driver Assistance System (ADAS) replacing manual human control. ADAS utilizes the concept of sensor fusion which data from multiple sensors such as camera, radar and LIDAR are collected and processed to handle different traffic situations. This is due to the fact that each sensor has their own strength and weakness. The current SAE J3016 automation level 2 and level 3 vehicles defined by Society of Automotive Engineers (SAE) does not include thermal imaging and it is expected that thermal sensor will be widely adopted in the future. Thermal sensor senses heat instead of light which would allow ADAS system to operate normally even when in low light environment, cluttered environment and inclement weather such as rain, fog and snow compared to visible cameras. With the rise of computer vision and deep learning, ADAS can be equipped with thermal sensor and Convolutional Neural Network to detect vehicles and pedestrian on the road. YOLOv3 is used in this research due to the lower computing power needed allowing easy deployment on compact low power embedded platform. In addition, a light weight YOLOv3 model called YOLOv3 Tiny is also used to achieve a faster inference speed. Thermal dataset provided by FLIR is used to train both models in PC and Nvidia Jetson TX2 is selected to be end target deployment platform. Performance evaluation is conducted with different network size and colour channels for benchmarking the detection speed and accuracy. The YOLOv3 model in this work has a mAP of 52.09% and on the embedded platform single channel YOLOv3 Tiny is able to achieve performance up to 27 frames per second.

ABSTRAK

Berdasarkan kajian yang dilakukan oleh Institut Penyelidikan Keselamatan Jalan Raya Malaysia (MIROS), didapati bahawa kesalahan manusia menyumbang kepada 80% kemalangan jalan raya. Jawapan untuk masalah ini adalah melalui pelaksanaan kereta autonomi yang dilengkapi dengan Sistem Bantuan Pemandu Termaju (ADAS) menggantikan kawalan manual manusia. ADAS menggunakan konsep sensor lakur yang mana data dari pelbagai sensor seperti kamera, radar dan LIDAR dikumpulkan dan diproses untuk menangani situasi lalu lintas yang berbeza. Ini disebabkan kerana setiap sensor mempunyai kekuatan dan kelemahan masing-masing. Kenderaan automatik SAE J3016 tahap 2 dan tahap 3 yang ditakrifkan oleh Persatuan Jurutera Automotif (SAE) tidak termasuk pengimejan termal dan diharapkan sensor termal akan digunakan secara meluas di masa depan. Sensor termal merasakan haba dan bukannya cahaya yang akan membolehkan sistem ADAS beroperasi secara normal walaupun dalam keadaan pencahayaan rendah, persekitaran yang berselerakan dan cuaca buruk seperti hujan, kabut dan salji berbanding dengan kamera yang dapat dilihat. Dengan peningkatan penglihatan komputer dan pembelajaran mendalam, ADAS dapat dilengkapi dengan Rangkaian Neural Konvolusional untuk mengesan kenderaan dan pejalan kaki di jalan raya. YOLOv3 digunakan dalam penyelidikan ini kerana kuasa pengkomputeran yang lebih rendah yang diperlukan yang membolehkan penggunaan mudah pada platform terbenam kuasa rendah padat. Set data termal yang disediakan oleh FLIR akan digunakan untuk melatih model dan Nvidia Jetson TX2 dipilih untuk menjadi platform sasaran akhir. Penilaian prestasi dilakukan untuk menanda aras kelajuan dan ketepatan pengesanan. Model YOLOv3 dalam kajian ini mempunyai mAP 52.09% dan YOLOv3 Tiny mampu mencapai prestasi sehingga 27 kerangka per saat apabila digunakan dalam sistem terbenam.

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LIST OF ABBREVIATIONS

ADAS	-	Advanced Driver Assistance System
APU	-	AMD Accelerated Processing Unit
CNN	-	Convolutional Neural Network
CPU	-	Central processing Unit
CUDA	-	Compute Unified Device Architecture
FPGA	-	Field Programmable Gate Arrays
GPU	-	Graphics Processing Unit
SAE	-	Society of Automotive Engineers
VPU	-	Vision Processing Unit
VRAM	-	Video Random Access Memory
YOLO	-	You Only Look Once object detection system

CHAPTER 1

INTRODUCTION

1.1 Overview

Most of the people have seen autonomous vehicle in science fiction movies. Today, autonomous vehicle is no longer a fantasy and is going to become a reality. Autonomous vehicle promises a safer journey where majority of the accidents that is caused by human error (1) can be fully eradicated. Driver fatigue, disobeying traffic rules, distraction, failure to check for blind spot and even driver under the influence of drug or alcohol will no longer be an issue. Since the vehicle is fully autonomous, the driver can eventually sit back and relax and uses the commutation time effectively. Elder and disabled can be benefited from autonomous vehicle as well since everything is handled by the computer in the vehicle.

The Society of Automotive Engineers (SAE) defines six level of driving automation in J3016 standard. SAE Level 0 indicates no automation and required manual control while the highest SAE Level 5 indicates a fully autonomous vehicle. As in year 2020, no commercially SAE Level 4 vehicle exists in the market yet. In order to reach a higher autonomation level, the vehicle must be able to understand its surrounding environment and make critical decision to prevent accidents. That is where ADAS comes into play in autonomous vehicle. Multiple sensors such as camera are deployed in the vehicle granting visual capability to ADAS.

When driving on the road, there will be pedestrian, cars, trucks and many more other objects. By integrating deep learning models such as Convolutional Neural Networks (CNN) into ADAS, objects on the road can be recognized and detected to avoid collision. Since there is size and power constraint on vehicle, a compact embedded system is much preferred than a full-size computer. Hence, a single shot detector-based CNN is suitable for in this scenario due to the lower computation requirements.

Thermal cameras are mostly used in military or search and rescue operation and they are rarely utilized in standard vehicle due to the higher price. The self-driving Uber car accident in 2018 (2) highlighted that the current sensor topologies of using radar, LiDAR and visible camera is insufficient and thermal camera is required to improve the robustness of the system. Hence FLIR cooperates with Veoneer, a global automaker to introduce thermal sensing in the next generation of vehicles (3).

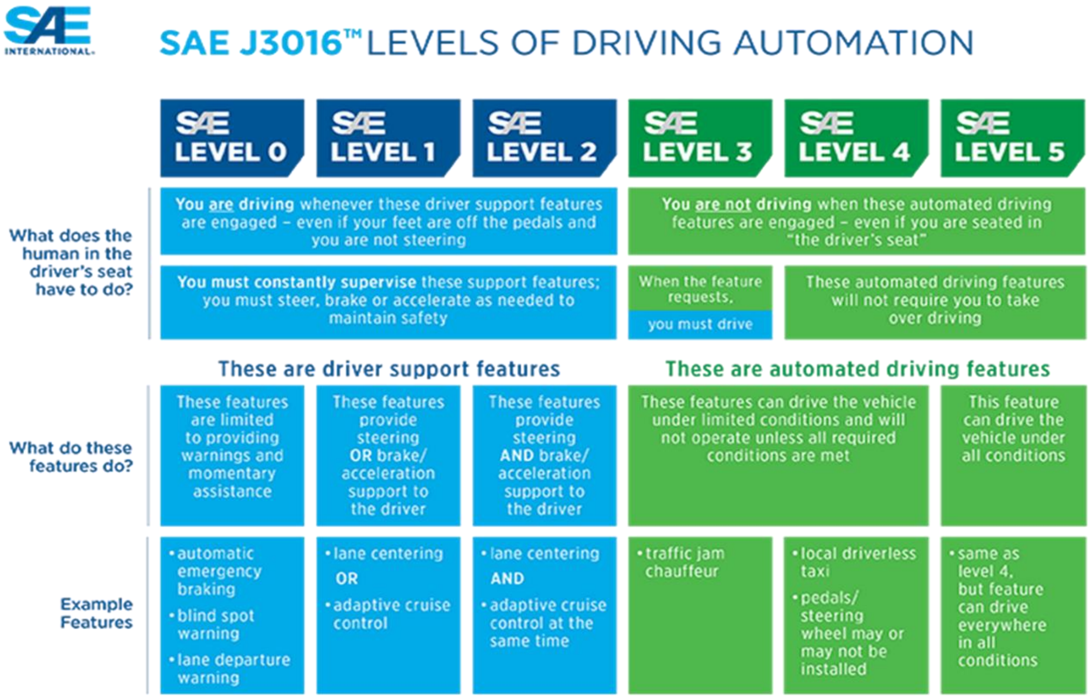

Figure 1.1 Driving Automation levels defined by SAE (4).

1.2 Problem Statement

Usage of CNN detection network can be seen everywhere. However, majority of the CNN networks are trained on RGB images. CNN networks trained on RGB images will not work well on thermal images as the network learns the colour of an object during the training process (5). Besides that, training grayscale thermal images on CNN networks allows more features to be extracted and yielding a higher accuracy results (6).

In addition, region proposal-based CNN network is heavy and requires a long processing time for object detection and classification. ADAS system typically requires fast processing time to handle various driving situations. Furthermore, existing ADAS without thermal sensor has poor detection at night and causes fatal accident as in (2). Existing work based on thermal camera are also limited and can be seen in Chapter 2.3.

1.3 Objectives

The objectives of the research are :

(a) To train a CNN model with thermal images for usage in ADAS

(b) To deploy the trained CNN model onto hardware embedded system

(c) To conduct performance evaluation of the CNN model in terms of speed and accuracy

1.4 Scope

The project focuses only on the part where the ADAS system performs object detection, classification and localization. Hence there will be no other fancy features in ADAS such as object distance and path estimation, cruise control, etc. The final system will then be deployed in Nvidia Jetson TX2 platform for testing and evaluation.

As the title of the thesis suggest, the system will be trained and tested on thermal image only. Due to usage of provided thermal dataset by FLIR, there will be limited class selected for classification which are :

(a) Vehicles

(b) Pedestrian

(c) Bicycles

(d) Dogs

1.5 Thesis Outline

The thesis comprises five chapters which they are Introduction, Literature Review, Research methodology, Results and Discussion, and Conclusion. Chapter 1 Introduction discusses about the problem, motivation, objectives and set the scope for the project. In Chapter 2, study of related works will be documented and listing down the research gaps. Chapter 3 describes the methodology taken for this project in details. The results obtained from the project will be placed and discussed in Chapter 4. Chapter 5 consists of the overall sum up for the whole project as well as recommendations for future works.

REFERENCES

1. David S. "Accident/Crash Causation and Analysis" In *Traffic Safety and Human Behavior*. Emerald Gr Publ Ltd. 2007;695–726.

2. BBC. *Uber halts self-driving car tests after death*. Available from: http://www.bbc.co.uk/news/business-43459156. [Accessed 27th January 2020]

3. FLIR. *FLIR Systems Partners with Veoneer for First Thermal Sensor-Equipped Production Self-Driving Car with a Leading Global Automaker | FLIR Systems*. Available from: https://www.flir.com/news-center/press-releases/flir-systems-partners-with-veoneer-for-first-thermal-sensor-equipped-production-self-driving-car-with-a-leading-global-automaker/. [Accessed 16th December 2019]

4. SAE. *SAE International Releases Updated Visual Chart for Its "Levels of Driving Automation" Standard for Self-Driving Vehicles*. Available from: https://www.sae.org/news/press-room/2018/12/sae-international-releases-updated-visual-chart-for-its-"levels-of-driving-automation"-standard-for-self-driving-vehicles. [Accessed 18th November 2019]

5. Olah C, Cammarata N, Schubert L, Goh G, Petrov M, Carter S. Zoom In: An Introduction to Circuits. *Distill*. 2020 Mar 10;5(3):e00024.001.

6. Bui HM, Lech M, Cheng E, Neville K, Burnett IS. Using grayscale images for object recognition with convolutional-recursive neural network. In: *2016 IEEE 6th International Conference on Communications and Electronics, IEEE ICCE 2016*. July 27-29, 2016. Ha Long Bay, Vietnam. Institute of Electrical and Electronics Engineers Inc.; 2016. 321–325.

7. HONDA. *Driver Attention Monitor | 2017 Honda CR-V | Honda Owners Site*. Available from: https://owners.honda.com/vehicles/information/2017/CR-V/features/Driver-Attention-Monitor/1/driver-attention-monitor-pdf. [Accessed 2nd July 2020]

8. BWM. *BMW Parking Assistant – The Complete Guide*. Available from: https://www.bmwux.com/bmw-performance-technology/bmw-technology/bmw-parking-assistant-complete-guide/. [Accessed 2nd July 2020]

9. Fred Lambert. *Tesla self-driving traffic light and stop-sign interaction*

explained in leaked manual - Electrek. Available from: https://electrek.co/2020/03/30/tesla-self-driving-traffic-light-stop-sign-explained-leaked-manual/. [Accessed 13rd June 2020]

10. EURO NCAP. *EURO NCAP | Driver Assistance System*. Available from: https://www.euroncap.com/en/ratings-rewards/driver-assistance-systems/ [Accessed 8th July 2020]

11. M. Boban, A. Kousaridas, K. Manolakis, J. Eichinger and W. Xu. Connected Roads of the Future: Use Cases, Requirements, and Design Considerations for 5G V2X. *IEEE Vehicular Technology Magazine*. 2018. 13(3) : 110-213.

12. TI. *ADAS domain controller integrated circuits and reference designs | TI.com*. Available from: https://www.ti.com/solution/adas-domain-controller. [Accessed 13rd June 2020].

13. Paul A, Chauhan R, Srivastava R, Baruah M. Advanced Driver Assistance Systems. In: *SAE Technical Papers*. SAE International; 2016.

14. Shakshuki EM, Alghamdi W, Sheltami T. Integrated context-aware driver assistance system architecture. *Mobile Information System*. 2013;9:225–40.

15. Karim nice, Tracy V.Wilson, and Gerald Guverich. *CCD and CMOS: Filmless Cameras | HowStuffWorks*. Available from: https://electronics.howstuffworks.com/cameras-photography/digital/digital-camera2.htm. [Accessed 2nd July 2020]

16. LYNRED-USA. VISIBLE vs. THERMAL DETECTION: Advantages and Disadvantages. Available from: https://www.lynred-usa.com/homepage/about-us/blog/visible-vs-thermal-detection-advantages-and-disadvantages.html. [Accessed 16th December 2019]

17. Jim Lucas. *What Is Infrared? | Live Science*. Available from: https://www.livescience.com/50260-infrared-radiation.html. [Accessed 16th December 2019]

18. Michaela Jackson. *Night Vision vs. Thermal Imaging Explained - speedir*. Available from: https://speedir.com/blog/night-vision-vs-thermal-imaging-explained/. [Accessed 3rd July 2020]

19. FLIR. *Thermal Imaging vs. Night Vision | FLIR Systems*. Available from: https://www.flir.com/discover/ots/thermal-vs-night-vision/. [Accessed 19th November 2019]

20. Luke Hunt. *Southeast Asia's Deadly Annual Haze is Back – The Diplomat*. Available from: https://thediplomat.com/2019/09/southeast-asias-deadly-annual-haze-is-back/. [Accessed 8th July 2020]

21. FLIR. *Can Thermal Imaging See Through Walls? And Other Common Questions | FLIR Systems*. Available from: https://www.flir.com/discover/cores-components/can-thermal-imaging-see-through-walls/. [Accessed 16th December 2019]

22. Ed Edwards. *How Radar Detectors Work*. Available from: https://www.thomasnet.com/articles/instruments-controls/how-radar-detectors-work/. [Accessed 3rd July 2020]

23. Akshay Srinivasa. *Understanding Radar for automotive (ADAS) solutions - PathPartnerTech*. Available from: https://www.pathpartnertech.com/understanding-radar-for-automotive-adas-solutions/. [Accessed 8th July 2020]

24. Archer Software. *Lidar vs Radar: pros and cons for autonomous driving | Vehicles tracking, Self-driving cars, RADAR, LIDAR | Archer Software*. Available from: https://archer-soft.com/blog/lidar-vs-radar-pros-and-cons-autonomous-driving. [Accessed 8th July 2020]

25. AutoPilot Review. *LiDAR vs. Cameras for Self Driving Cars - What's Best? - AutoPilot Review*. Available from: https://www.autopilotreview.com/lidar-vs-cameras-self-driving-cars/. [Accessed 3rd July 2020]

26. FLIR. Why Adas and Autonomous Vehicles Need Thermal Infrared Cameras.

27. Fei-Fei L, Deng J, Li K. ImageNet: A large-scale hierarchical image database. *2009 IEEE Conference on Computer Vision and Pattern Recognition*. June 20-25 2009. Miami, Florida: IEEE. 2009. 248-255.

28. Lecun Y, Eon Bottou L, Bengio Y, Abstract| PH. Gradient-Based Learning Applied to Document Recognition. *Proc IEEE*. 1998;86(11):2278–2324.

29. CS231n. *CS231n Convolutional Neural Networks for Visual Recognition*. Available from: https://cs231n.github.io/convolutional-networks/. [Accessed 29th June 2020]

30. Liu S, Deng W. Very deep convolutional neural network based image classification using small training sample size. In: *Proceedings - 3rd IAPR Asian Conference on Pattern Recognition, ACPR 2015*. Institute of Electrical

and Electronics Engineers Inc.; 2016. 730–734.

31. Boureau Y-L, Ponce J, Fr JP, Lecun Y. A Theoretical Analysis of Feature Pooling in Visual Recognition. In: *Proceedings of the 27th International Conference on Machine Learning*. Haifa, Israel, 2010. 931-938.

32. Wang Y, Li Y, Song Y, Rong X. The influence of the activation function in a convolution neural network model of facial expression recognition. *Applied Sciences*. 2020. 10(5): 1897.

33. *Reducing Loss: Gradient Descent | Machine Learning Crash Course*. Available from: https://developers.google.com/machine-learning/crash-course/reducing-loss/gradient-descent. [Accessed 29th Jume 2020]

34. Hu W, Zhang Y, Li L. Study of the application of deep convolutional neural networks (CNNs) in processing sensor data and biomedical images. *Sensors*. 2019. 19(16): 3584.

35. Chang FA, Tsai CC, Tseng CK, Guo JI. Embedded multiple object detection based on deep learning technique for advanced driver assistance system. *2017 IEEE 60th International Midwest Symposium on Circuits and Systems (MWSCAS)*. August 6-9, 2017. Boston, MA. IEEE. 2017. 172-175.

36. Ren S, He K, Girshick R, Sun J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2017. 39(6): 1137–1149.

37. John V, Mita S, Liu Z, Qi B. Pedestrian detection in thermal images using adaptive fuzzy C-means clustering and convolutional neural networks. *2015 14th IAPR International Conference on Machine Vision Applications (MVA)*. May 18-22, 2015. Tokyo, Japan. 246–249.

38. Wei J, He J, Zhou Y, Chen K, Tang Z, Xiong Z. Enhanced Object Detection With Deep Convolutional Neural Networks for Advanced Driving Assistance. *IEEE Transactions on Intelligent Transportation Systems*, 2019. 21(4): 1572-1583.

39. Cai Z, Fan Q, Feris RS, Vasconcelos N. A Unified Multi-scale Deep Convolutional Neural Network for Fast Object Detection. 14th European Conference on Computer Vision. October 11-14, 2016. Amsterdam, Netherlands. Springer. 2016. 354-380.

40. Kim B, Jeon Y, Park H, Han D, Baek Y. Design and implementation of the

vehicular camera system using deep neural network compression. In *Proceedings of the 1st International Workshop on Deep Learning for Mobile Systems and Applications (EMDL '17)*. June 19-23, 2017. New York, USA. Association for Computing Machinery. 2017. 25–30.

41. Du X, El-Khamy M, Lee J, Davis L. Fused DNN: A deep neural network fusion approach to fast and robust pedestrian detection. *2017 IEEE Winter Conference on Applications of Computer Vision (WACV)*. March 24-31, 2017. Santa Rosa, USA. IEEE. 2017. 953–961.

42. Mittal U, Srivastava S, Chawla P. Object Detection and Classification from Thermal Images Using Region based Convolutional Neural Network. *Journal of Computer Science*, 2019. 15(7): 961–971.

43. Yasrab R, Gu N, Zhang X. An encoder-decoder based Convolution Neural Network (CNN) for future Advanced Driver Assistance System (ADAS). *Applied Science*. 2017. 7(4): 312.

44. Redmon J, Divvala S, Girshick R, Farhadi A. You only look once: Unified, real-time object detection. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. June 27-30, 2016. Las Vegas, USA. IEEE. 2016. 779–788.

45. Girshick R, Donahue J, Darrell T, Malik J. Rich feature hierarchies for accurate object detection and semantic segmentation. *2014 IEEE Conference on Computer Vision and Pattern Recognition*. June 23-28, 2014. Columbus, USA. IEEE. 2014. 580-587

46. Redmon J, Farhadi A. YOLO9000: Better, Faster, Stronger. 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). July 21-26, 2017. Honolulu, USA. IEEE. 2017. 651-6525.

47. *Anchor Boxes for Object Detection - MATLAB & Simulink*. Available from: https://www.mathworks.com/help/vision/ug/anchor-boxes-for-object-detection.html. [Accessed 13rd June 2020]

48. Redmon J, Farhadi A. YOLOv3: An Incremental Improvement. 2018 Apr 8;

49. *Classification: Precision and Recall | Machine Learning Crash Course*. Available from: https://developers.google.com/machine-learning/crash-course/classification/precision-and-recall. [Accessed 29th June 2020]

50. Goutte C, Gaussier E. A Probabilistic Interpretation of Precision, Recall and

F-Score, with Implication for Evaluation. *27th European Conference on Information Retrieval Research*. March 21-23, 2005. Santiago de Comppostela, Spain. 2005. Springer. 2005. 345-359.

51. Everingham M, Van Gool L, I Williams CK, Winn J, Zisserman A, Everingham M, et al. The PASCAL Visual Object Classes (VOC) Challenge. *International Journal of Computer Vision*, 2010. 88(2): 303–338.

52. *COCO - Common Objects in Context*. Available from: https://cocodataset.org/#detection-eval. [Accessed 8th July 2020]

53. ACPO Code of Practice for Operational Use of Road Policing Enforcement Technology. 2002.

54. Vehicle Stopping Distance and Time.

55. Siu Han, Jessie Shen. *NAND flash contract prices to rise 15% in 2Q20*. Available from: https://www.digitimes.com/news/a20200313PD202.html. [Accessed 8th July 2020]