

DEEP LEARNING-BASED WATERLINE DETECTION
FOR AUTONOMOUS SURFACE VESSEL
NAVIGATION

BY

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the degree of Master of Science (Mechatronics Engineering)

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ABSTRACT

Visual-based obstacle detection from an autonomous surface vessel (ASV) is a complex task due to high variance of scene properties such as different illumination and presence of reflections. One approach in implementing the task is through extracting waterlines to enable inferring of vessel orientation and obstacles presence. Classical computer vision algorithms for detection holds limitation in robustness and scalability. With recent breakthroughs in deep neural network architectures, vision-based object detection is seen to obtain high performance. In this work, the Deep Learning models based on Convolutional Neural Network (CNN) to implement binary semantic segmentation is studied. This architecture identifies each pixel to water and non-water classes. In purpose of benchmarking models, Fully Convolutional Network (FCN), SegNet and U-Net are trained on a publicly available dataset, IntCatch Vision Data Set (ICVDS), to evaluate the performance. From the experiments carried out, quantitative results show effectiveness of the models with accuracy all above 95.55% and lowest average speed of 11 frames per second. To improve, pre-trained networks (VGG 16, Resnet-50 and MobileNet) are used as a backbone, obtaining an improved accuracy above 98.14% with lowest inferring speed of 10 frame per second. Using the developed ASV, new dataset of 143 images called Malaysia ASV Dataset (MASVD) is collected, labelled and made publicly available. The trained models are tested with the newly collected dataset obtaining accuracy of 75%. The high accuracy performance results at near real-time speed using standard PC running on Nvidia GTX1080 shows potential for the models to be employed for collision avoidance algorithm in ASV navigation.

خلاصة البحث

يعد اكتشاف العوائق المرتكزة على المرئيات من سفينة سطحية مستقلة (ASV) مهمة معقدة بسبب التباين العالي لخصائص المشهد مثل الإضاءة المختلفة ووجود انعكاسات. يتمثل أحد الأساليب في تنفيذ المهمة في استخراج خطوط المياه لتمكين استنتاج اتجاه السفينة ووجود العقبات. خوارزميات رؤية الكمبيوتر الكلاسيكية للكشف تحمل قيودًا على المتانة وقابلية التوسع. مع التطور الكبير حديثًا في تصاميم الشبكات العصبية العميقة ، فإن اكتشاف الكائنات المبنية على الرؤية يحقق أداءً عاليًا. في هذا العمل ، تم دراسة نماذج التعلم العميق القائمة على الشبكة العصبية التلافيفية (CNN) لتنفيذ تجزئة الدلالي الثنائي. تحدد هذه البنية كل بيكسل للفئات المائية وغير المائية. لأغراض التقييم ، يتم تدريب الشبكة التوافقية الكاملة (FCN) و SegNet و U-Net على مجموعة بيانات متاحة للجمهور المسمى باختصار IntCatch Vision Data Set (ICVDS) ، لتقييم الأداء. من التجارب التي أجريت في هذا العمل ، أظهرت النتائج الكمية فعالية النماذج بدقة تزيد عن 95.55٪ بسرعة لا تقل عن 11 إطارات في الثانية. للتحسين ، يتم استخدام الشبكات المدربة مسبقًا (VGG 16 و Resnet-50 و MobileNet) كعمود أساسي ، حيث تحصل على دقة محسنة تفوق 98.14٪ بأقل سرعة استدلالية تبلغ 10 إطارًا في الثانية. باستخدام ASV المطور ، يتم تجميع مجموعة بيانات جديدة من 143 صورة تدعى Malaysia ASV Dataset (MASVD) وتصنيفها وإتاحتها للجمهور. يتم اختبار النماذج المدربة باستخدام مجموعة البيانات التي تم جمعها حديثًا والحصول على دقة بنسبة 75٪. يؤدي الأداء العالي الدقة إلى السرعة في قرب الوقت الفعلي باستخدام أجهزة الكمبيوتر القياسية التي تعمل على Nvidia GTX1080 ، مما يدل على إمكانية استخدام الطرز في خوارزمية تجنب الاصطدام في التنقل ASV.

APPROVAL PAGE

I certify that I have supervised and read this study and that in my opinion, it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Master of Science (Mechatronics Engineering)

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DECLARATION

I hereby declare that this dissertation is the result of my own investigations, except where otherwise stated. I also declare that it has not been previously or concurrently submitted as a whole for any other degrees at IIUM or other institutions.

Muhammad Ammar bin Mohd Adam

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LIST OF ABBREVIATIONS

ASV	Autonomous Surface Vessel
CAD	Computer Aided Design
CPU	Central Processing Unit
DC	Direct-current
DCNN	Deep Convolutional Neural Network
DNN	Deep Neural Network
EKF	Extended Kalman Filter
FCN	Fully Convolutional Network
GCS	Ground Control Station
GPS	Global Positioning System
GPU	Graphics Processing Unit
LIDAR	Light Detection and Ranging
NB	Naïve Bayes
PC	Personal Computer
RADAR	Radio Detection and Ranging
RAM	Random Access Memory
RANSA	Random Sample Consensus
SONAR	Sound Navigation Ranging
SRAM	Static Random-Access Memory
SVM	Support Vector Machine

LIST OF SYMBOLS

A	Accuracy
β	Weight of recall to precision in F-score
F_1	Specific metric of F-score ($\beta = 1$)
F_β	Generic metric F-score
P	Precision
R	Recall

CHAPTER ONE

INTRODUCTION

1.1 OVERVIEW

Autonomous surface vessels (ASV) are marine crafts that operates missions on the surface of water with minimal human intervention (Yan et al., 2010). With recent advances in marine technology, ASVs are developed to work autonomously with a reliable navigation system to reduce maritime operation hazard while improving work efficiency (Romano, 2012). In order to deploy fully autonomous, collision avoidance is a critical issue to address to ensure safety in complex marine environments (Cheng et al., 2018). Recent breakthroughs in Deep Neural Networks (DNN) has demonstrated capability of obtaining high accuracy for object detection and classification especially in computer vision which can be taken advantage to enhance safety and reliability of autonomous navigation (Thapa, 2018). At this time, obstacle avoidance systems for marine vehicles are mostly developed using Radio Detection and Ranging (RADAR) as main sensor and supported by additional position and orientation sensing devices (Haltermann et al., 2010). Through implementing vision-based detection using DNN, a cheaper yet accurate and effective solution is made possible, contributing to improved situational awareness for ASVs (Wang et al., 2011). In image-based applications, the common particular DNN implemented is the Deep Convolutional Neural Network (DCNN).

1.2 PROBLEM STATEMENT

Visual-based recognition of water and non-water region from watercraft view is a relatively new approach for ASV navigation. Traditionally, waterline detection from a

constantly moving camera onboard the vessel requires a complex computation and training models in order to obtain high accuracy results. Moreover, as for any mobile autonomous robot, accurate and fast processing of obstacle detection is an essential criterion to enable real-time navigation (Xu et al., 2017). Due to recent advances in maritime technology, development of unmanned vessels has become a cheaper and simpler solution for numerous marine operations. Consequently, this enables easier collection process of image data with different spatial, spectral and temporal information (Patel et al., 2019). Taking advantage on the possibility, effective learning algorithm as the classification tool is required, generating high accuracy segmentation with real-time performance.

While there are many detection applications showing high accuracy performance, the scene variance for water environment is very high. It is critical to ensure robustness of the implemented model and understanding its limitations. In addition, a balanced trade-off between accuracy and inferencing speed is important to ensure the performance is efficient and optimised. In application of ASV, water region recognition enables extraction of waterline features which can be extended for obstacle detection and tilt measurement. There are few existing works implementing Deep Learning for waterline detection, however performance benchmarking of models and datasets are yet to be conducted.

1.3 RESEARCH OBJECTIVES

The general aim of the presented work is to evaluate performances of different methods and datasets in water segmentation using Deep Learning algorithm approach. In particular, the objectives are as follows:

- 1) To design and develop an ASV prototype for collecting new dataset in waterline detection
- 2) To compare and analyse the performance of Deep Learning semantic segmentation models on existing waterline detection dataset
- 3) To improve the visual segmentation capabilities with pre-trained network
- 4) To evaluate the performance of trained Deep Learning algorithm on new dataset collected

1.4 RESEARCH METHODOLOGY

In order to achieve the objectives of the project, following methodology is implemented:

1. *Extensive literature review on ASV and DCNN approaches.* Research is done by gathering information from available resources including online journals and conference papers.
2. *Design and development of ASV.* Based on other development works of ASV, the prototype in this study is designed and developed as a platform for data collection.
3. *Data collection and annotation of new dataset.* Self-collected visual images are labelled to be used for DCNN model evaluation.
4. *Testing and validation of different models on existing and new datasets.* Evaluation of selected models for benchmarking is conducted to compare performance of available popular models
5. *Optimisation of performance using pre-trained network.* Modification of architecture are introduced to improve performance of detection models.

6. *Evaluation of performance on existing and new datasets.* Validation of performance of the optimised models is implemented to compare performance with basic models.

The flowchart of the research methodology adopted in this work is illustrated in Figure 1.1.

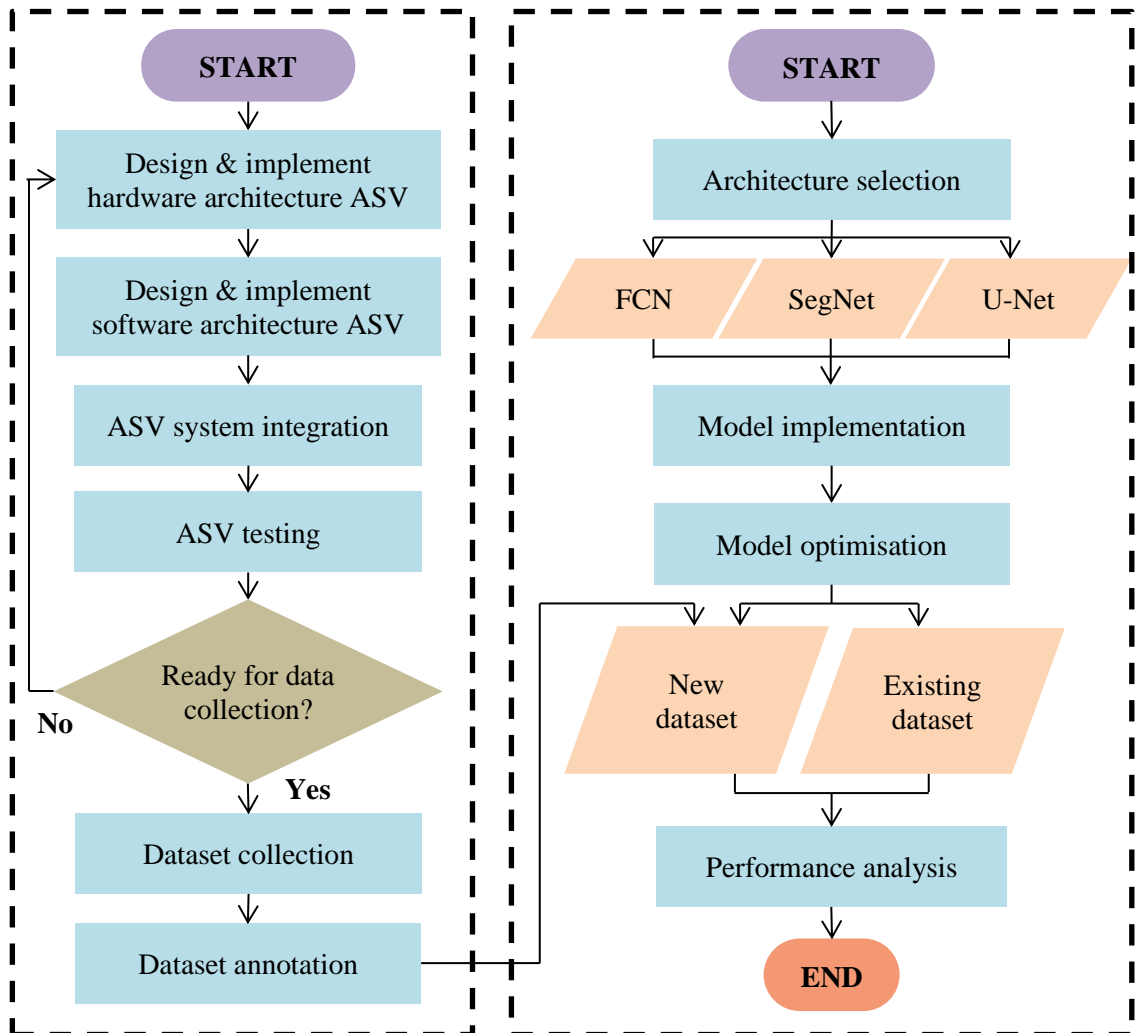


Figure 1.1 Flowchart of Research Methodology

1.5 RESEARCH SCOPE

This research work is limited to the application of ASV specifically for hydrographic survey in calm water environment. In order to collect the new dataset, Maryam Lake in

International Islamic University Malaysia, a closed lake in Malaysia is selected and data collection is conducted on a clear and bright day.

1.6 PUBLICATION

Part of this research work is presented in the following publication:

Mohd Adam, MA, Zainal Abidin, Z, Ibrahim, AI, Mohd Ghani, AS and Anchumukkil, AJ (2019). Design and Development of Mini Autonomous Surface Vessel for Bathymetric Survey, The 11th National Technical Seminar on Unmanned System Technology 2019, UMP Gambang, Pahang, 2nd – 3rd December 2019. Place of publication: Springer LNEE (Lecture Notes in Electrical Engineering) – (PUBLISHED)

1.7 THESIS STRUCTURE

The research works are organised in this thesis into five chapters. The structure is as follows:

Chapter 1: Introduction

This chapter presents an overview of the project including problem statement, research objectives, research scope and contributions.

Chapter 2: Literature Review

This chapter discusses the literature survey conducted in the field of waterline detection using Deep Learning for ASV navigation. ASV development, waterline detection methods, DNN segmentation models and evaluation metrics are covered in detail.

Chapter 3: Research Methodology

This chapter discusses the experiment design to conduct benchmarking of different DNN models and datasets for water segmentation and waterline detection. In addition, this chapter includes the selected performance metrics for evaluation.

Chapter 4: Results & Analysis

This chapter presents and discusses the resulting performance from implementing water segmentation and waterline detection using different DNN models and datasets in comparison.

Chapter 5: Conclusion

This chapter summarises the findings and analysis achieved in this project. Additionally, this chapter presents the limitation and recommendations for this work.

CHAPTER TWO

LITERATURE REVIEW

2.1 INTRODUCTION

With the growing demand for employing autonomous surface vessels in different applications, a reliable autonomous navigation system is the main concern among the ASV developers to avoid maritime accidents while improving efficiency in marine operations. Currently, marine ecosystems are administered by defined set of rules to avoid collisions in navigations. International Maritime Organization (IMO) established International Regulations for Preventing Collisions at Sea 1972 (COLREGs) which governs ships and vessels with standard navigation rules globally depending on their different classes (Thapa, 2018). Depending on regions, specific regulations are also introduced in specific oceans such as in the Europe continent. European Code for Navigation and International Sailing Federation is implemented to ensure safety in maritime navigation (Thapa, 2018). These safety navigation standards must be abided by any boat captains in steering vessels within the water regions. Similarly, introducing self-driving watercrafts also requires following the same defined laws to avoid any collisions. In replacement of onboard vessel operators, the decision-making is to be implemented by the developed autonomous system which is solely based on processing input from sensors onboard the ship. Therefore, it is crucial in selecting a reliable and robust solution for both hardware and software components.

In this chapter, survey on previous works is presented under the scope of autonomous surface vessel developments, popular Deep Learning frameworks for semantic segmentation as well as range of metric evaluations for benchmarking

performance of different models. For ASV development, previous approaches on obstacle avoidance and waterline detection are studied. On the other hand, for Deep Learning frameworks, FCN, SegNet and U-Net are selected and further explored as these networks are the state-of-the-art architectures in segmentation application. For performance evaluation, common segmentation measurement metrics are surveyed.

2.2 AUTONOMOUS SURFACE VESSEL

Over recent years, several commercial unmanned surface vehicles of small-sized class are available for hydrographic survey in inland waters such as Inception MK1 (Unmanned Survey Solutions), Z-Boat 1250 (Teledyne Marine) and SL20 (OceanAlpha). All the boats are designed with the ability to navigate remotely and autonomously, except for Z-Boat which lacks autonomous navigation. However, these products are expensive and designed for service works rather than for research and development works. On the other hand, HydroDron (Marine Technology Ltd), is introduced for research work and have been developed in hydrographic survey applications with capability of integrating variant sensors or components such as done in Stateczny (2018). The dimensions, however, are considered oversize for the application of this research which are 4.23 m in length and 2.08 m in width. Another developed ASV is the Sonobot (EvoLogics GmbH), a low-cost solution for hydrographic survey in shallow waters. This vessel is designed as a platform for further development in autonomous bathymetric works. Sonobot is 1.2 m long, 0.92 m wide and 0.5 m high, with twin-hull design (Kebkal et al., 2014). Due to success of the small-sized boat being used as a mobile robot to implement hydrographic survey, the system architecture is used as a baseline, with improvements and modification extended from

this work. One major difference in the ASV of this work is in the hull design, where mono-hull structure is employed.

2.2.1 Obstacle Avoidance

The recent main challenges in ASV development is in the autonomous system, especially in path planning and obstacle avoidance algorithms (Liu et al., 2015; Ma et al., 2019) . There have been many works being done using different approaches and sensors. For obstacle detection, common sensors utilised in applications includes passive-ranging (monocular and stereo-vision) and active-ranging cameras (SONAR, RADAR and LIDAR) (Halterman et al., 2010). Passive-ranging has the advantage of better lateral and temporal resolution but relatively low depth resolution and accuracy. On the other hand, active-ranging provides higher resolution and accuracy in depth dimension but relies on combination of multiple factors including beam width, scan rates, pulse rates and effective ranges (Halterman et al., 2010). As a result, the complexity as well as operation cost in implementing active-ranging type of sensors is higher than passive-ranging sensing devices. In this work, passive-ranging sensors possess an extra advantage due to lower cost requirement in ASV development.

With the advancements in image processing algorithms and artificial intelligence techniques, vision-based approach is becoming more popular and reliable. Among the approach to implement visual-based obstacle avoidance in maritime applications is through detecting waterlines, or also commonly known as horizon line (Fefilatyev et al., 2006). There are several techniques in identifying the boundary line between water and non-water regions, which is presented in the following section.

2.3 WATERLINE DETECTION

Waterline detection is essential to identify water region in obstacle avoidance as well as to rectify boat tilt measurement from inertial sensors (Steccanella et al., 2019). This particular application for ASV is relatively new and only few works are known to been done in this area.

FefilatyeV et al. (2006) detected horizon through visual images using machine learning methods including Support Vector Machine (SVM), J48 and Naïve Bayes (NB) classifiers. The study defines multiple attributes for feature extraction and works well but rigidly for images similar to the pre-trained dataset. The pre-defined attributes limit the capability to predict accurately for new environments and requires experts to decide the particular features for extraction. For a robust system, it is more efficient and preferable to implement a self-learning pattern recogniser which is capable to decide distinctive features on its own from multiple trainings such as the neural networks algorithm.

In another work by Wang et al. (2011), pixel characteristic analysis is conducted on grayscale image to accomplish accurate water-sky boundary detection by calculating gradient estimations for each pixel in vertical lines. As a result, the maximum or minimum contrast image change is considered as boundary points on horizon line which is followed by Random Sample Consensus (RANSAC) method for line-fitting. The waterline extraction is shown to be robust and fast. However, this work is based on the general assumption that water-sky brightness shows apparent contrast in brightness, which environment with variant illuminance level is yet to be tested.

On the other hand, Lipschutz et al. (2013) implemented waterline detection using image processing-based algorithms such as edge detection, Hough transform,

covariance and histogram, relying solely on luminance values. This approach allows direct detection of horizon with accurate results and fast processing speed despite presence of obstacles. However, study is limited to obtain waterline detection, where different processing is required for obstacle detection. The error is measured from detected horizon angle relative to horizontal line and the height of the detected line from centre of image. The metrics implemented in evaluating performance is applicable as a baseline scoring method in the experiment.

As improvement from previously stated works, Steccanella et al. (2019) takes advantage of Deep Learning algorithm in segmenting water and non-water, obtaining high accuracy results. Also, RANSAC is utilised to fit horizon line from boundary points extracted from the binary segmentation. To evaluate, error from predicted horizon angle is compared to ground truth angle. However, while there are range of architectures available for segmentation using DCNN, only U-Net is experimented.

Benchmarking different pixel-wise classification models in this application is yet to be presented. The following section details the common and well-known architectures in segmentation problems.

2.4 DEEP LEARNING FRAMEWORKS FOR SEGMENTATION

Deep Learning is a representation learning through a multi-layer network, where each level of learning is transformed to a higher-level representation using non-linear elements. These layers extract important features without the need of specific human definition (Lecun et al., 2015). The significant achievements of Deep Learning in addressing cross-field problems, including image classification, object detection and object segmentation, have attracted interest among most computer vision researchers. One of the interesting applications utilising this approach is in self-driving cars by