

AUTOMATIC DETECTION, SEGMENTATION AND CLASSIFICATION OF
ABDOMINAL AORTIC ANEURYSM USING DEEP LEARNING

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A project report submitted in partial fulfilment of the
requirements for the award of the degree of
Master of Engineering (Electrical – Computer and Microelectronic System)

Faculty of Electrical Engineering
Universiti Teknologi Malaysia

JUNE 2015

*Specially dedicated to my beloved family, lecturers and friends
For the guidance, encouragement and inspiration
Throughout my journey of education.*

ACKNOWLEDGEMENT

Firstly I would like to take this opportunity to express my sincere appreciation to my project supervisor, Dr. Usman Ullah Sheikh for his encouragement, teaching and guidance. He has been providing helpful advice and support needed for me to move towards the right path. Besides, I am also very thankful to the post doctorate, Dr. Sajad Farokhi who was assigned to provide me guidance and advices on the technical problems that I encountered. I have gained much knowledge which has contributed towards my understanding and thoughts regarding my project.

Furthermore, I would also like to thank my colleagues and friends who have provided assistance and support at various occasions. Their views and tips have indirectly helped me to complete this research project successfully. Last but not least, I am also thankful to my family members for their support and understanding throughout the course of my study.

ABSTRACT

This study is focused on developing an automated algorithm for the detection and segmentation of Abdominal Aortic Aneurysm (AAA) region in CT Angiography images. The outcome of this research will offer great assistance for radiologists to detect the AAA region and estimate its volume in CT datasets efficiently. In addition, suitable treatment strategies can also be suggested based on the classification of the AAA severity and measurement of the aorta diameter. This research takes the initiative by exploring and applying deep learning architecture in the study of AAA detection and segmentation, which has never been done by other researchers before in AAA problems. The findings from this study will also act as a reference for other similar future works. Deep Belief Network (DBN) is applied for the purpose of AAA detection and severity classification in this study. Optimum parameters for training the DBN are determined for the training data from the selected dataset. AAA region can be successfully segmented from the CT images and the result is comparable to the existing method with advantage over the existing method that the proposed method is fully automatic and added with auto detection and classification features. The limitation of the trained DBN in AAA detection accuracy can be improved by incorporating and adjusting the detection probability threshold and shape constraints. In future, the DBN can be further enhanced by adding and training it with more data which covers a wider variety of features, as well as extending its capability to perform detailed segmentation on AAA region.

ABSTRAK

Kajian ini memberi tumpuan kepada membangunkan algoritma automatik untuk mengesan dan segmentasi kawasan Aneurisme Aorta Abdomen (AAA) dalam imej-imej angiografi tomografi berkomputer (CT). Hasil daripada kajian ini akan memberi sumbangan dan membantu ahli-ahli radiologi untuk mengesan kawasan dan menganggar luas AAA dalam dataset CT secara berkesan. Selain itu, strategi rawatan yang sesuai juga boleh dicadangkan berdasarkan klasifikasi tahap penyakit AAA dan ukuran diameter aorta. Kajian ini mengambil inisiatif dengan menerokai dan menggunakan struktur 'deep learning' untuk membantu dalam pengesanan dan segmentasi AAA. Cara ini belum pernah dilaksanakan oleh ahli-ahli kajian yang lain dalam masalah segmentasi AAA. Penemuan dan hasil daripada kajian ini juga boleh digunakan sebagai rujukan untuk kajian-kajian yang sama pada masa akan datang. Dalam kajian ini, Deep Belief Network (DBN) digunakan untuk tujuan pengesanan AAA dan klasifikasi tahap penyakit AAA. Nilai optima untuk parameter-parameter bagi melatih DBN ditentukan daripada data latihan dataset seorang pesakit. Kawasan AAA berjaya disegmentasikan daripada imej-imej CT dan hasil segmentasi yang diperoleh adalah sebaik dengan hasil segmentasi daripada kaedah yang sedia ada, dengan kelebihan di mana kaedah yang dicadangkan ini adalah automatik sepenuhnya dan ditambah dengan ciri-ciri pengesanan dan klasifikasi secara automatik. Had ketepatan DBN yang dilatih untuk pengesanan AAA boleh diperbaiki dengan membuat penyesuaian ke atas ambang kebarangkalian pengesanan dan mengenakan kekangan bentuk. Pada masa hadapan, prestasi DBN boleh dipertingkatkan lagi dengan menambah dan melatihnya dengan lebih banyak data yang merangkumi lebih banyak variasi ciri-ciri, selain memperluaskan keupayaannya untuk melaksanakan segmentasi terperinci ke atas kawasan AAA.

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LIST OF ABBREVIATIONS

AAA	-	Abdominal Aortic Aneurysm
ANN	-	Artificial Neural Network
CAD	-	Computer-Aided Detection
CTA	-	Computerized Tomography Angiography
DBM	-	Deep Boltzmann Machine
DBN	-	Deep Belief Network
DICOM	-	Digital Imaging and Communications in Medicine
DNN	-	Deep Neural Network
EM	-	Electron Microscopy
EVAR	-	Endovascular Aneurysm Repair
FCM	-	Fuzzy C-Means
HU	-	Hounsfield Unit
LSE	-	Level Set Evolution
MPR	-	Multi Planar Reconstruction
MRF	-	Markov Random Field
MRI	-	Magnetic Resonance Imaging
MVE	-	Maximum Volume Ellipsoid
OAR	-	Open Aneurysm Repair
RBM	-	Restricted Boltzmann Machine
ROI	-	Region of Interest
SBM	-	Shape Boltzmann Machine
SSAE	-	Stacked Sparse Auto-Encoder
SVM	-	Support Vector Machine

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CHAPTER 1

INTRODUCTION

1.1 Introduction

An aneurysm is an area of a localized widening of a blood vessel. Abdominal aortic aneurysm (AAA) is known as a cardiovascular disease which involves localized dilation (swelling or enlargement) of an aorta that occurs between the renal and iliac arteries [1]. Generally, abdominal aortic aneurysms are categorized according to the aorta's infra-renal region diameter by either absolute or relative measurements. While the normal diameter of an aorta is around 20mm, commonly an aneurysm is considered to be present if the absolute size of the infra-renal aorta reaches 30mm [1, 2]. It is then recommended by the Society for Vascular Surgery and the North American Chapter of the International Society for Cardiovascular Surgery that an AAA be defined as a permanent localized dilation of an artery with a 50 percent increase in diameter compared to the expected normal diameter, in order to account for age related factor of increases in aortic diameter, and also not to ignore the gender related differences such as larger aortic diameter in men compared to women [2].

An AAA is known to have two sections which is the lumen (inner part) and the thrombus (outer fatty part) [3]. The abnormal weakening of the aortic wall will lead to its deformation and thus generation of a thrombus by coagulation between lumen and thrombus during blood flow between the aorta layers [1, 2, 4]. If not diagnosed or treated, rupture may happen due to the progressive growth of an aneurysm. This condition could be fatal as the rupture would cause serious internal bleeding and subsequent hypovolemic shock [3].

AAA is nowadays a relatively common vascular disorder, and its rupture is one of the commonest causes of death in the society [2, 4, 5]. Despite the seriousness of the disease, the AAAs' health impact is not readily obvious due to the fact that majority of the aortic aneurysms are asymptomatic and without complications. On the other hand, aneurysms that show symptoms pose a higher risk of rupture. Two main clinical features which are suggestive of either the recent expansion or leakage are abdominal pain or back pain. Indication of AAA rupture involves the presence of the triad of abdominal pain, shock and a pulsatile abdominal mass. These kind of complications are often life threatening and can happen within short span of time. Hence, these have triggered some in the medical community to propose screening of populations at high risk for AAA. It is a challenging task of diagnosing and enabling early detection of AAA before the onset of symptoms [2, 6].

From various studies, the prevalence of AAA depends on quite a variety of risk factors including aging, heredity, gender (male), and tobacco use [6]. Biomechanically, a number of factors are said to be responsible for AAA complications such as variations in collagen and elastin levels, influence of reflected pressure wave, and diffusion of nutrients across mural thrombus. The loss of elastin will cause the aorta to be enlarged, whereas the loss of collagen volume can lead to rupture in the aorta wall. As the mechanical stress increases over the strength of the degenerated aortic tissues, rupture happens due to the high pressure on the aneurysm inner wall [7-9].

Over the years since 1950s, there are two approaches devised for the treatment of AAA, which are Open Aneurysm Repair (OAR) and Endovascular Aneurysm Repair (EVAR). An open repair is a major surgical procedure which involves the resection of the abnormal artery and replacement with a graft. It is an extensive procedure requiring cross clamping of the aorta, and has high mortality rate up to more than 40%. This method has some major drawbacks where the quality of life is compromised post-surgery because of postoperative pain, prolonged recovery period and the high costs associated with both surgery and recovery [7, 10]. On the other hand EVAR appears as an alternative approach that avoids the extensive tissue dissection compared to open repair, where this method is a minimally invasive

endovascular repair procedure. By using this method, a stent is placed within the lumen of the aorta which covers the entire lumen and thus can decrease the blood pressure acting on the aortic wall. However, the EVAR treatment approach is also subject to post-procedural complications such as endoleaks (graft leak), shrinkage or the mechanical failure of the device, which can occur in 15% to 52% of the cases. Therefore, Computerized Tomography Angiography (CTA) is performed to obtain accurate information about the pre- and post-operative treatment, as well as to evaluate the patient health status during the period of disease [4, 7].

CTA imaging is employed to segment AAA in order to diagnose the severity of disease, in addition to get accurate measurement of aorta diameter, assessing the AAA shape and status of graft within aorta [4]. It is the preferred imaging method as it has a nearly 100% sensitivity for aneurysm, and more importantly, it allows minimum invasive visualization of the aorta's lumen thrombus and calcifications [6]. Typically, CTA is carried out by injecting patients with a contrast agent to enhance the visibility of blood flow in the CT images. Then the enlarged portions of the aorta are manually identified on a number of cross-sectional images in order to obtain a full volume measure [3]. However, the whole process is very tedious and time consuming where it may take up to 30 minutes to complete the work for each patient and it causes inconvenience for radiologists and physicians. Besides, the 3D visualization of AAA performed by radiologist in a slice to slice fashion becomes impractical as the amount of datasets produced increase. Such manual method is subjective, prone to error and non-reproducible. In fact, the validity and consistency of the method is also questionable as different measurements can be obtained for the same aneurysm region when it is performed by different radiologists or by the same radiologist at different times [3, 4]. Figure 1.1 shows a typical appearance of AAA in CT angiography images.

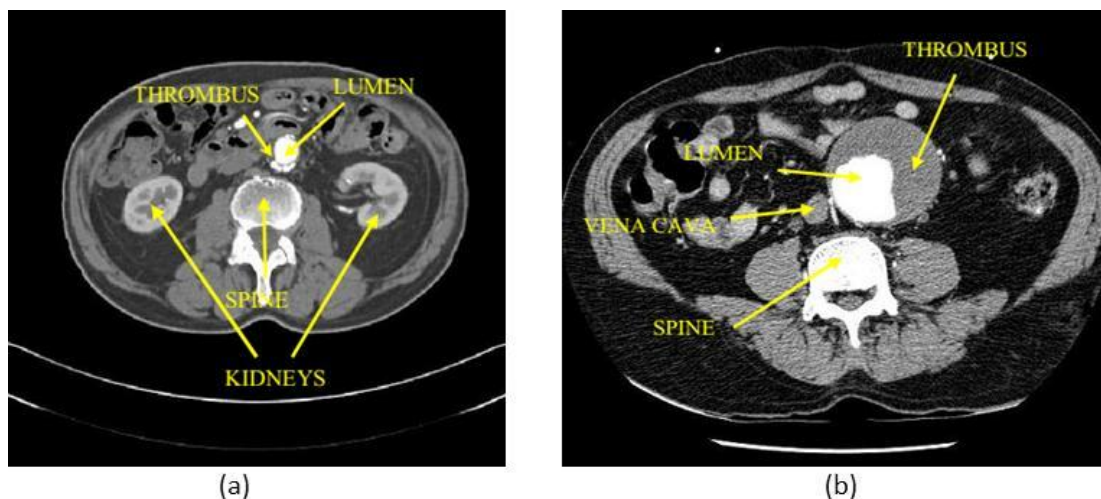


Figure 1.1 Appearance of AAA in CT angiography slices. (a) Small volume of AAA, (b) large volume of AAA.

1.2 Problem Background

Diagnostic imaging is of crucial importance in medical field today, where it provides an effective means for noninvasively mapping the anatomy of a subject. The development of these technologies has significantly increased knowledge of normal and diseased anatomy for medical research, as well as act as a critical component in diagnosis and treatment planning. As the number and size of medical images increases, the usage of computers and developing computerized techniques to facilitate medical images processing and analysis has become necessary. The potential usage and applications in biomedical field and clinical assessments such as quantification of tissue volumes, treatment planning, study of anatomical structure and diagnosis has motivated researchers and numerous effort have been put in to develop image segmentation algorithms. Over recent years, different segmentation algorithms have been proposed based on the particular application, imaging modality, and application requirements [11].

In the case of clinical planning and treatment on AAA, it remains a challenging task to handle the accurate detection of AAA via CTA image segmentation to assist radiologists and physicians in the work of images processing and AAA diagnosis. Although there are several image segmentation approaches for

vascular structures have been developed, the process is still difficult, though not impossible, in identifying and differentiating between the boundaries of an AAA thrombus and the surrounding muscles or other vascular structures. The restricting factors involved are such as the presence of severe calcifications in the aorta tissue, similarity in intensity values of thrombus and surrounding tissues, and irregular structure of aorta [1, 3, 4]. Figure 1.2 shows an example of this complication.

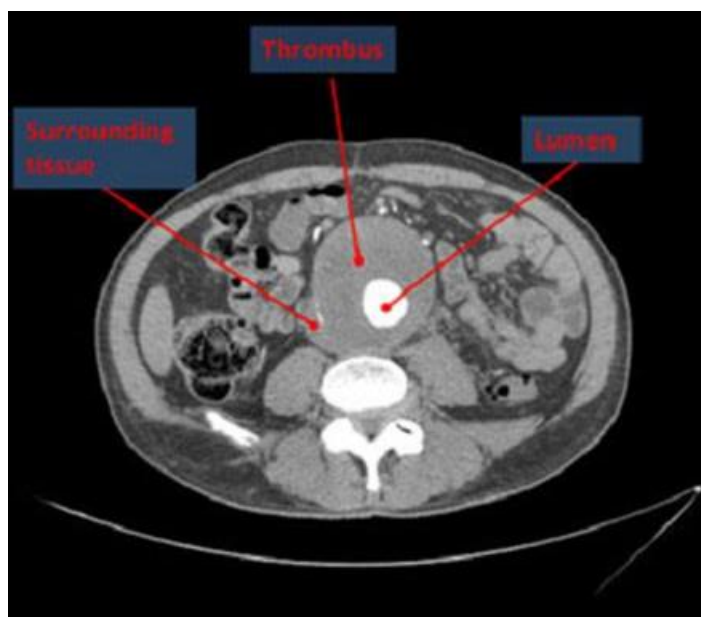


Figure 1.2 Axial view of lumen and thrombus in a CT slice using the contrast agent, blood in lumen is highlighted but thrombus intensity levels are similar to other surrounding tissues [1].

In order to cope for the abovementioned difficulties, there are quite a number of computerized AAA segmentation techniques and algorithms proposed and published by researchers in the field recently. The proposed techniques usually fall into two categories which are semi-automatic, where majority of it involves human intervention in the procedure of initialization of seed points, and fully automatic techniques. However, so far the majority of the computerized algorithms proposed suffer from inefficiency and poor performance in detection and segmentation of AAA.

In this research, a fully automatic approach for accurately detecting and segmenting the AAA thrombus is explored and proposed. Its performance and accuracy is measured and compared with the current existing semi-automatic methods.

1.3 Objectives

The main objective of this research is to develop an efficient framework for fully automatic detection and segmentation of AAA region in CT Angiography images. This research will facilitate the clinical decision making in the case of AAA. Specifically, the proposed computerized (via deep learning) method can help to reduce the time of segmentation process compared to conventional manual method, and it will be of comparable or equivalent in terms of performance and accuracy. The few objectives can be summarized and listed as below:

- a) To develop an automatic method for the detection and identification of AAA region from CTA images using Deep Learning methodology.
- b) To provide an approach for the measurement of abdominal aorta diameter, then classify the disease severity based on aorta quantification results for the sake of suitable surgical treatment choice for the patient.
- c) To compare the performance and result obtained from the proposed method with an existing method.

1.4 Scope of Research

The research is focused on developing a fully automatic method for segmentation of AAA in CT angiography images to assist in making therapeutic decisions for treatment of patient in an efficient way.

The proposed method or algorithm in this research will be applicable only for segmentation of the AAA CT angiography images. The types and classes of deep learning architectures will be studied and a suitable deep learning architecture will be proposed for the automatic detection of AAA region, followed by segmentation of AAA.

MATLAB software is used for developing the algorithm for the detection, segmentation of the aortic lumen and thrombus and classification of AAA severity. During the research half of the CT images in DICOM format from one dataset will be sampled and used for the development of the deep learning network, while the other half of the CT images from the same dataset will be used to test and validate the developed algorithm for the segmentation of AAA.

The complete segmentation of AAA is divided into two stages. Firstly the CT image is scanned through with an image window and classified using the developed deep learning network. Then the patches detected to contain AAA region is segmented to be further analysed. The AAA region is then segmented using the level set algorithm, followed by some post processing to further improve feasibility of the method. The segmented AAA region is sent to another deep learning network for disease severity classification. The diameter of the AAA is also measured based on the information embedded in the DICOM header of dataset.

1.5 Significance of Research

The advancement of technology in clinical imaging modalities have helped to improve the process and effectiveness of diseases diagnosis. However, this at the same time also means there is significant increment in the amount of data or medical images to be analysed and evaluated by radiologists and doctors. Hence, there are many researches which are focused on the development of automatic or semi-automatic algorithm in order to effectively reduce the diagnosis processing time.

This research which is aimed at developing an automated algorithm for the detection and segmentation of AAA in CT angiography images will offer great assistance for radiologists to detect the AAA region and estimate its volume in CT datasets efficiently. In addition, suitable treatment strategies can also be suggested based on the classification of the AAA severity and measurement of the aorta diameter.

On the other hand, this research also takes the initiative by exploring and applying deep learning architecture in the study of AAA detection and segmentation, which has never been done by other researchers before in AAA problems. The findings from this study will also acts as a reference for other similar future works.

1.6 Thesis Organization

This thesis is organized as follow:

- a) Chapter 2: Introduces the problems and challenges of medical image segmentation. Then the chapter discusses on different existing methods of AAA segmentation in CT images, as well as application of deep learning in image segmentation problems, reviewing literatures in the related research area.
- b) Chapter 3: Provides some background and basic theory necessary to understand the concepts introduced in the proposed method.
- c) Chapter 4: Discusses on the proposed method for the detection and segmentation of AAA region in CT angiography images. Besides, the classification of AAA severity and the AAA diameter measurement technique is also explained.
- d) Chapter 5: Demonstrates the experimental result of the proposed method, functionality, and feasibility and discussion on the challenges and limitation of the method used.
- e) Chapter 6: Conclusion and recommendation for future possible developments which can further enhance the segmentation of AAA.

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