FUZZY C-MEANS CLUSTERING ALGORITHM WITH LEVEL SET FOR MRI CEREBRAL TISSUE SEGMENTATION

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I cordially dedicate this thesis to the biggest treasures of my life, my parents, my brothers and my sisters who gave me their love and also for their endless support and encouragement.

Dad and wife,
I love you for every second of my life

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ABSTRACT

The brain is the most complex organ in the human body, and it consists of four regions namely, gray matter, white matter, cerebrospinal fluid and background. It is widely accepted as an imaging modality for detecting a variety of conditions of the brain such as tumours, bleeding, swelling, infections, or problems associated with blood vessels. Brain images mostly contain noise, inhomogeneity and sometimes deviation. Therefore, accurate segmentation of brain images is a very difficult task. This thesis presents a new approach of Magnetic Resonance Imaging (MRI) brain tissue segmentation, which consists of three main phases: (1) Noise removal using median filter, (2) Tissue clustering based on the fuzzy c-means, and (3) Tissue segmentation using the fuzzy level set method, which finally separates white matter from gray matter. The results show that the segmentation's accuracy rates of 98% is achieved when tested on 100 samples of MRI brain images atlas dataset.

ABSTRAK

Otak adalah organ yang paling kompleks dalam badan manusia, dan ia terdiri daripada empat kawasan iaitu bahan kelabu, bahan putih, cecair serebrospina dan latar belakang. Ianya diterima secara meluas sebagai modaliti pengimejan untuk mengesan pelbagai keadaan otak seperti tumor, pendarahan, bengkak, jangkitan, atau masalah yang berkaitan dengan saluran darah. Imej otak kebanyakannya mengandungi hingar, ketidakseragaman dan kadang-kadang pemesongan. Oleh itu, tugas mensegmentasikan imej otak dengan tepat adalah amat sukar. Tesis ini membentangkan satu pendekatan baru bagi segmentasi tisu otak MRI yang terdiri daripada tiga fasa utama: (1) Penyingkiran hingar menggunakan penapis median, (2) Pengkelompokan tisu berasaskan *fuzzy c-means*, dan (3) segmentasi tisu menggunakan *fuzzy level set*, yang akhirnya memisahkan bahan putih daripada bahan kelabu. Hasil kajian menunjukkan bahawa kadar ketepatan segmentasi sebanyak 98% dicapai apabila diuji ke atas 100 sampel daripada dataset imej otak MRI.

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The discovery of X-rays by Roentgen in 1895 signaled the birth of Medical Imaging. This was a great invention in the advanced area of non-invasive medical diagnosis and Roentgen was awarded the Nobel Prize in the year 1901 for this work. Many discoveries have emerged in the medical imaging field such as the utilization of x-ray in the field of medicine, making effective and accurate diagnosis possible. It would be tedious to list all the inventions and discoveries. The same difficulties arise in attempts to describe all the various types of medical images (Walczak, 2008). In this regard, only the very significant discoveries, such as image characterization, which are products obtained from these technologies, will be discussed.

A crucial feature of medical imaging is segmentation, which makes it possible to visually diagnosis all types of diseases. Image segmentation plays a vital role in image analysis and computer vision. Image segmentation is used to divide an image into several non-overlapping sectors with homogeneous and uniform characteristics such as intensity and color. The approaches in image segmentation can be sectioned into three four major categories namely, thresholds, edge detection, and clustering region extraction. In the process of capturing color images, boundaries between objects are blurred and distorted In addition; object definition is unclear, resulting in a degree of uncertainty in terms of the knowledge gathered about an object in the scene (Aishwarya and Nagaraju, 2012).

Data clustering is a statistical analysis tool used as a methodology for data analysis in a number of fields such as machine learning, image analysis, data mining, pattern recognition and bioinformatics. The categorization of like objects into a number of groups is known as clustering. More precisely, clustering can be defined as the partition of data into subsets (clusters) in such a way that each bit of data in the subset (ideally) shares some common characteristics which are normally proximate in relation to some definite distance measure (Beevi *et al*., 2010). Fuzzy techniques are usually used as complementary techniques that already exist and which can facilitate more robust and better method development as has been demonstrated in a number of scientific branches. Fuzzy techniques have proven very successful in image processing (Pal and Pal, 1993). Image segmentation makes a significant contribution in relation to medical images applications.

The last decade has seen growing research interest in the development of an efficient and robust algorithm for utilization in the area of medical image segmentation. Fuzzy C-Means (FCM) algorithm, which happens to be the unsupervised renowned clustering method in medical image segmentation is extensively used (Beevi *et al*., 2010).

Fuzzy c-means has many advantages such as delivering the best results for overlapped data set and it is comparatively better than k-means algorithm. Unlike k-means, where data point must belong exclusively to one cluster center, here data point is assigned membership to each cluster center as a result of which data points may belong to more than one cluster center. Fuzzy c-means has been a very important tool for image processing in clustering objects in an image. Mathematicians introduced the spatial term into the FCM algorithm to improve the clustering accuracy under noise (Liu, Zhang and Liu, 2008) .

1.2 Problem background

Computer vision and image analysis is the most important task of image segmentation. Several proposals to divide object feature extractions have been put forward (Krinidis and Chatzis, 2010). However, research challenges in the design of efficient and robust segmentation algorithms, owing to the complexity and variety of the images, remain (Yang and Tianzi, 2009). The aim of image segmentation is the division of the image into sectors which overlap with each other and are inconsistent in relation to definite properties like density, tone, color, and defined texture homogeneity. Four categories of image segmentation can be identified: groups, expos, threshold levels and extractions on the edge of the area. Each has their own strengths and weaknesses.

Benign diseases and malignant tumors cannot always be distinguished by Magnetic resonance imaging (MRI). This will prevent the observation of defects in the brain due to the brains complex nature in terms of the shape size, location, tissues and the fact that it also contains 100 billion nerves. The problem is that brain tumors exist within a very complex human brain system (Balafar *et al*., 2008).

From the experience of a number of researchers, the manual segmentation approach is difficult to perform and requires a comparatively longer time period. The desired approach is automated brain tumor segmentation. The ability to visualize brain extracts and to distinguish other parts of the brain tumor in the diagnostic process will lead to an improved diagnosis and accuracy and at the same time reduce the patient's pain level. Some current approaches are acceptable for medical images with less noise. That means the brain area is clear and the brain tissues are simply formed. However, this does not apply to images that have noise and asymmetric forms of brain tissue which show diffused edges of the brain tissue.

The noise problem was solved by (Uoyu and Hyo) in 2010 by modifying FCM making use of filter Sigma theory to account for the divided brain images of the neighboring pixels, leading to an improvement in the quality of the image during segmentation. One noise which is embedded in medical images is Gaussian noise which is a set of values taken from a zero mean Gaussian distribution which are added to each pixel value. Impulsive noise involves changing a part of the pixel values with random ones. Clustering can be defined as a classification process in which patterns or objects are sectored in such a way that samples of the same cluster have a greater degree of similarity with each other than they do with samples which belong to a different cluster (Krinidis and Chatzis, 2010). Fuzzy clustering scheme and hard clustering scheme are the two major clustering strategies.

An evolutionary method was described by Amiya et al in 2011 for unsupervised grayscale image segmentation in which images are automatically segmented into their constituent components. FCM clustering was employed in their proposed method to generate the Genetic algorithm population which segments the images automatically.

The level set method was first proposed by Osher and Sethian(1988) as a way of using numerical methods to track contour evolution. A fresh volume of data input is generated by this technique in solving partial differential equations (PDE) with a function term extraction. Segmentation accuracy has been shown to be improved by the application of this technique. (Tsai and Oshe, 2011) developed numerical approximations for the level set method, regularizing solutions, representing object boundaries with curvature based velocities, regarding an image as a set of continuous functions etc. Considerable advancement has been made owing to the methods specified level concept in improving the evolution and implementation of the algorithms.

A modified new algorithm known as partial FCM was produced by (Shamsi and Seyedarabi, 2012). Two factors were employed in this algorithm. The first measures the distance between neighbor pixels and the central pixel and the second is the difference between the value of neighboring pixels and the central pixel. In comparison to conventional FCM images, the proposed algorithm has a considerable effect on segmentation noise, producing less noise on the image. The complexity of the brain makes imprecise the results from the above previous methods.

1.3 Problem statement

There are some issues with medical images that are of concern such as:

1. How to remove the image noise while retaining the edges and other detailed features as much as possible.
2. FCM is sensitive to the selection of initial cluster centers and an incorrect choice of the centers can result in the algorithm getting stuck at suboptimal solutions. FCM operates in the search space by constantly moving from one single-point to another until a peak reached (Nath and Talukdar, 2012).
3. A number of methods have been proposed for medical segmentation. However, these methods are still unable to handle the brains complex structure. Also, when it comes to dealing with segmentation of MRI cerebral tissues, they're a major drawback and challenge (Li, Chui et al. 2011).

This research work presents the segmentation of MRI cerebral tissues, disregarding other parts of the brain, using Fuzzy C-means (FCM) clustering with the level set algorithm.

1.4 Research Questions

There are some major issues to contend with:

1. How can noise in medical images be removed?
2. How can cerebral tissue be clustered?
3. How can MRI cerebral tissues be segmented?

1.5 Dissertation Aim

The main aim of this dissertation is to implement fuzzy C-means algorithm to segment the brain MRI cerebral tissues using level set to obtain the best results, which implies pictures clear of noise and spots, until we can derive obvious images that doctors can easily recognize.

1.6 Objective

This dissertation intends to complete these objectives:

1. To study and apply an appropriate technique to remove Gaussian noise in medical images.
2. To cluster MRI cerebral tissue before segmentation takes place.
3. To segment clusters of MRI cerebral tissue by using level set algorithm.

1.7 Research Scope

The scope of this thesis is described as follows:

Medical images for the human brain from MRI database the input data are from.

- This project is focused on MRI cerebral tissue images.
- This project is benefit the brain Atlas for MRI dataset where downloaded from http://www.med.harvard.edu/AANLIB/home.html.
- The implementation phase is done by using MATLAB.

1.8 Research Framework

In this work, we focused on MRI cerebral tissue segmentation. Figure 1.1 shows the total MRI image segmentation system consisting of the most fundamental elements.

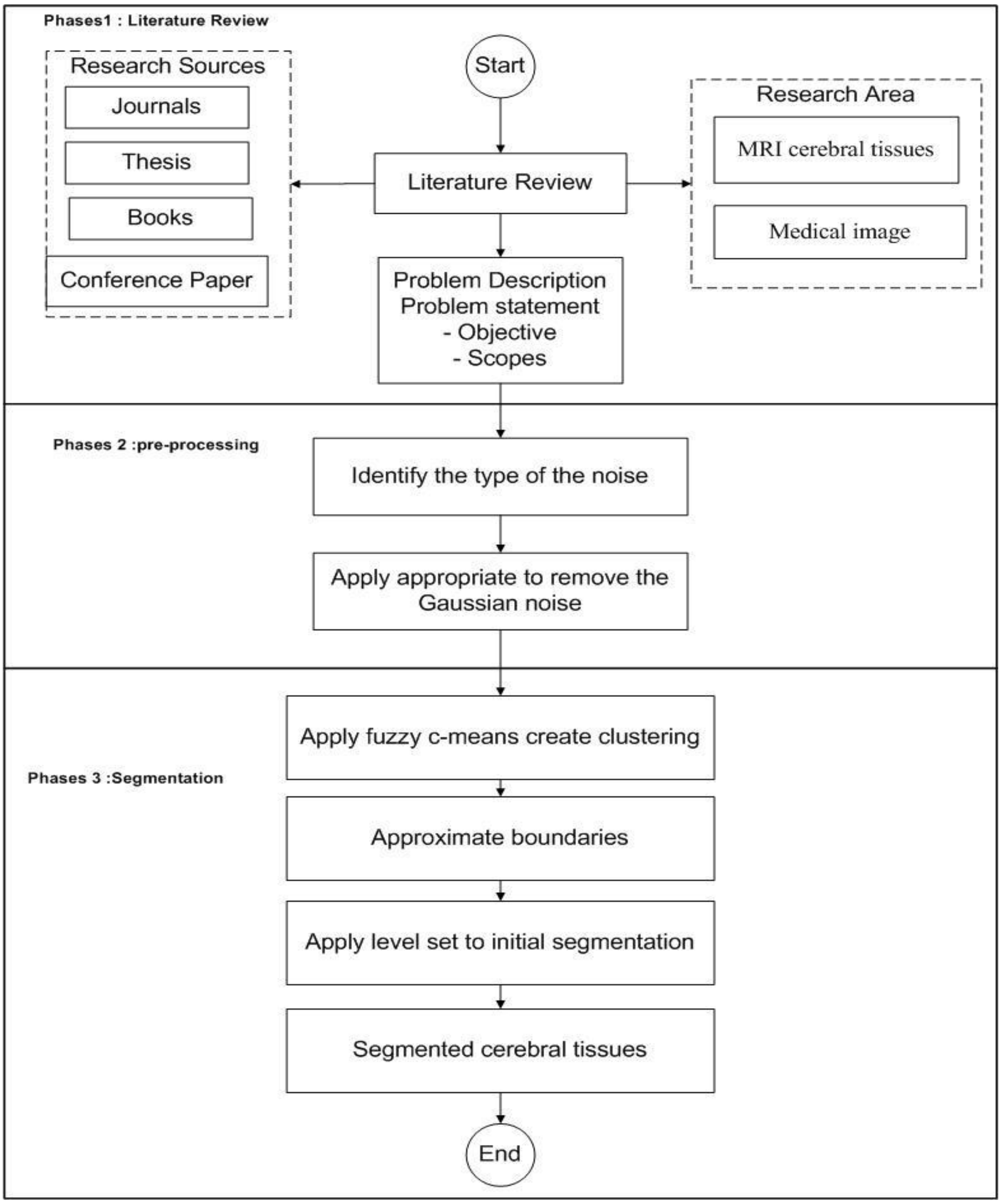

Figure 1.1 Research framework of MRI cerebral tissue segmentation.

1.9 Thesis organization

The remainder of this research is organized as follows:

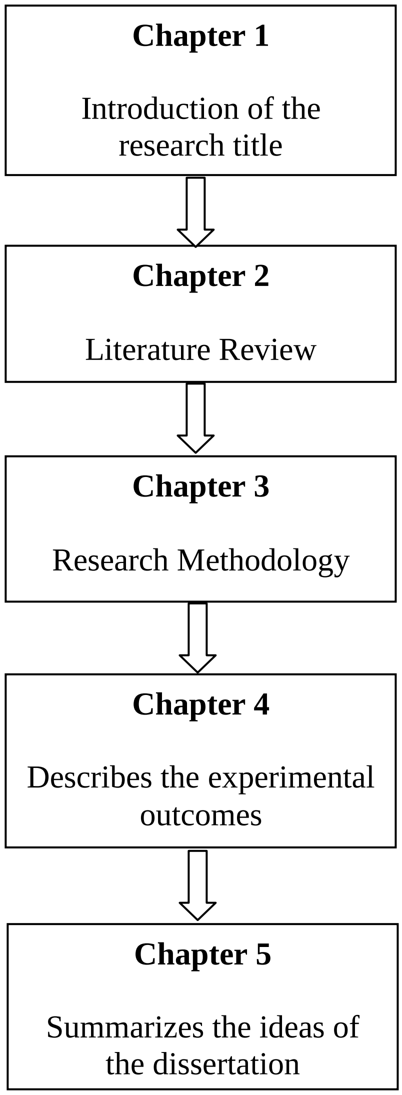

Figure 1.2 Organization of Dissertation.

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