ENHANCED LEVEL SET SEGMENTATION METHOD FOR DENTAL CARIES DETECTION

ABDOLVAHAB EHSANI RAD

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Computer Science)

Faculty of Computing
Universiti Teknologi Malaysia

JUNE 2015

Dedicated to my beloved parents and family, whom without their love and support this research would have never been completed.

ACKNOWLEDGEMENT

First of all, I would like to take this opportunity to gratefully acknowledge the wholehearted supervision of Assoc. Professor Dr. Mohd Shafry Mohd Rahim during this work. His dedication, skillful guidance, helpful suggestions and constant encouragement made it possible for me to deliver a dissertation of appreciable quality and standard.

I would also like to say special thanks my co-supervisors Dr. Ismail Bin Mat Amin and Dr. Nor Ashikin Bte Sharif, whose precious guidance, support and encouragement were pivotal in establishing my self-confidence in this endeavor.

I would like to thank the staff of Universiti Teknologi Malaysia, and especially the Faculty of Computing, for their kind cooperation.

I am forever indebted to my parents for their patience and understanding, alleviating my family responsibilities and encouraging me to concentrate on my study.

ABSTRACT

Caries detection system is important for dental disease diagnosis and treatment. It can be identified using X-ray imaging. The X-ray image contains interest point of dental to get the teeth information according to specific diagnostic intention. The Region of Interest (ROI) includes the caries area on tooth surface. The imaging challenges like noise, intensity inhomogeneities and low contrast causes the difficulty for identifying correctly the ROI in dental images. According to the recent studies, among all medical image segmentation methods, level set has the best segmentation accuracy. However, there are several components in the level set that need to be enhanced to determine the exact boundary to separate the ROI. The signed force function to control the direction of level set evaluation process, speed function to control the speed of movement and Initial Contour (IC) generation to obtain a more accurate ROI require an enhancement for the better accuracy. In this research, a new enhancement of segmentation method has been proposed based on finding an accurate outcome. The method includes two phases: IC generation and intelligent level set segmentation. In addition, caries detection process is performed with new detection method. To generate the IC for dental X- ray images, a new local IC selection for level set method is proposed. Statistical and morphological information of image is extracted to establish a technique that is able to find a suitable IC. In the second phase, statistical information of the pixels inside and outside the generated contour and linear motion filtering is used to construct the region-based signed force function to provide more stabilisation to proposed method. Furthermore, 31 features of image are extracted to train the neural network and to generate proper speed function parameter. The results of proposed method provide the high accuracy and efficiency in the process of getting teeth boarder. The next process is to detect from the segmented images. The research also proposed a new method using integral projection and feature map for every single tooth to obtain the information of caries area. The achieved overall performance of proposed segmentation method is evaluated at 120 periapical dental radiograph (X-ray), with 90% accuracy rate. In addition, the caries detection accuracy rate on 155 segmented images is 98%.

ABSTRAK

Sistem pengecaman karies adalah penting bagi proses dianogsis dan rawatan penyakit pergigian. Ini boleh dikenalpasti melalui imej X-ray. Imej X-ray mengandungi maklumat penting untuk mendapatkan informasi berkaitan gigi bagi tujuan diagnostik secara khusus. Kawasan Kepentingan (ROI) mengandungi maklumat kawasan permukaan gigi tersebut. Cabaran yang perlu ditangani adalah kekotoran imej, kedalaman cahaya dan rendah kontras menyebabkan ROI bagi imej X-ray gigi tidak dapat dikenal pasti dengan tepat. Berdasarkan kepada kajian semasa terhadap semua kaedah segmentasi imej perubatan, kaedah set tahap adalah kaedah yang memberi nilai ketepatan yang baik. Walaupun begitu, masih terdapat komponen dalam kaedah segmantasi set tahap memerlukan peningkatan kaedah segmentasi dengan menentukan sempadan yang tepat untuk memisahkan ROI. Fungsi daya adalah untuk mengawal arah proses pengujian set tahap, fungsi kelajuan adalah untuk mengawal kadar kecepatan pengembangan dan penjanaan sempadan asas untuk mendapatkan ROI yang lebih tepat memerlukan penambahbaikan untuk mendapatkan ketepatan segmentasi yang lebih tepat. Dalam kajian ini, kaedah segmentasi yang baru telah dicadangkan berdasarkan kaedah set tahap untuk mendapatkan hasil yang lebih tepat. Kaedah tersebut mempunyai dua fasa: iaitu penghasilan Kontur Awalan (IC) dan kepintaran segmentasi imej berlandaskan kaedah set tahap. Di samping itu, proses pengesanan karies akan dilaksanakan dengan kaedah pengesanan yang baru. Bagi menjana IC pada imej, satu kaedah IC yang baru untuk kaedah set tahap telah dicadangkan. Maklumat statistik dan morfologi imej diekstrak untuk menghasilkan satu teknik yang boleh mencari IC yang sesuai. Pada fasa kedua, maklumat statistik untuk nilai piksel dalam dan luar kontur yang terhasil dan penggunaan penapisan gerakan linear digunakan untuk menjana fungsi daya berdasarkan kawasan bagi mengawal dan menyediakan lebih kestabilan terhadap kaedah yang dicadangkan. Selain itu, 31 ciri-ciri imej yang telah diekstrak untuk melatih rangkaian neural dan menjana parameter fungsi kelajuan yang bersesuaian. Hasil kajian menunjukkan kaedah yang telah dicadangkan memberi nilai ketepatan yang tinggi dan efisien dalam proses mendapatkan sempadan gigi. Proses seterusnya adalah untuk mengesan karies daripada imej yang telah disegmentasi. Kajian ini turut mencadangkan kaedah baru menggunakan kaedah unjuran integral dan peta sifat yang telah dibangunkan untuk setiap gigi bagi mendapatkan maklumat kawasan karies. Prestasi keseluruhan yang dicapai daripada kaedah segmentasi yang dicadangkan dinilai dengan 120 radiograf gigi periapical (X-ray), nilai ketepatan 90%. Di samping itu, pengesanan karies untuk 155 imej yang disegmentasi adalah pada nilai ketepatan 98%.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

A	–	Area
ANN	–	Artificial Neural Network
AR	–	Abnormal Region
BR	–	Background Region
BPNN	–	BackPropagation Neural Networks
C	–	Constant
CAD	–	Computer-Aided Design
CT	–	Computed Tomography
E	–	Energy
ESF	–	Edge Stopping Function
FP	–	False Positives
GLCM	–	Grey Level Co-occurrence Matrix
HOG	–	Histogram of Oriented Gradient
IC	–	Initial Contour
ILS	–	Intelligent Level Set
IP	–	Integral Projection
LS	–	Level Set
LT	–	Local Threshold
MRI	–	Magnetic Resonance Imaging
MRIBC	–	Morphological Region-Based Initial Contour
NR	–	Normal Region
PAR	–	Potentially Abnormal Region
PPV	–	Predefined Pixels Value
R	–	Region
ROI	–	Region of Interest
SDF	–	Signed Distance Function
SFF	–	Signed Force Function

SFP	–	Speed Function Parameter
SUSAN	–	Smallest Univalue Segment Assimilating Nucleus
SVM	–	Support Vector Machine
T	–	Threshold
UTM	–	Universiti Teknologi Malaysia
WHO	–	World Health Organization
	–	

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Introduction

Medical imaging concludes various imaging techniques and processes to take image of human body (or parts and function thereof) for the purposes of diagnostic, treatment, examine the diseases or study of normal anatomy and physiology. Therefore, it has an important functionality in the improvement of human health (Bennett and Hauser, 2013). The field of medical imaging has complexity and it's depended on a context, which requires extra activities of medical experts, medical physicists, biomedical engineers as well as technicians. Hence, using image for diagnostic needs electronic technology and also medical equipment to capture pictures that exhibit inside of human body. Most common types of medical imaging tests include X-rays, Computed Tomography (CT) scans, digital mammography, Magnetic Resonance Imaging (MRI) and ultrasounds.

Dental radiograph imaging provides the information of teeth which is the normal process in dentistry area. There are many advantages and application to analyse this data in medical purposes such as: dental treatment and dental diagnosis. Dental disease is one of the most epidemic and common disease in human (Krol, 2003). To evaluate the condition of teeth and early dental disease detection it is essential to regularly checkup by dentist (Selwitz *et al.*, 2007). Early diagnosis in caries detection is important for treatment planning of the dental disease, which is affecting a majority

of population.

However, there are some important processes to achieve the information of teeth and analysis these images using computer. Image segmentation is the most known challenging process in medical image processing and even in dental image analysis (Li *et al.*, 2006). In previous years the image segmentation methods have been developed and improved to overcome the difficulties of images. However this process still remains challenging and difficult. Segmentation of dental images refers to identify and extract each individual tooth or any part of teeth in image from other parts like gum and pulp.

This thesis proposes an accurate segmentation method and feature extraction technique to extract the individual tooth from dental radiograph images and analyse segmented images to detect the caries.

1.2 Problem Background

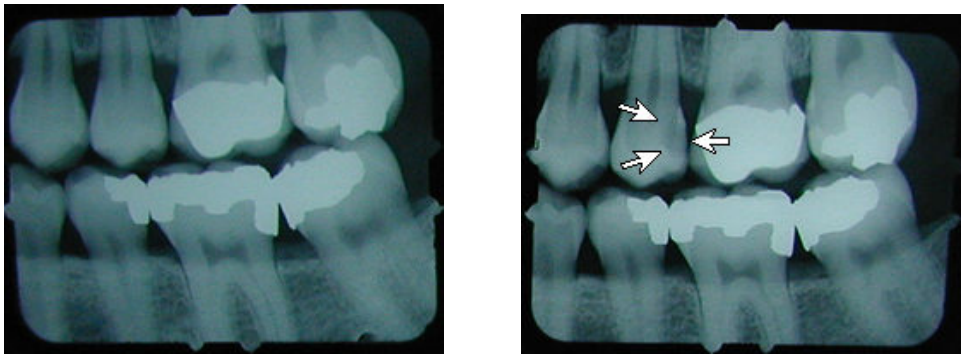
Dental X-ray images are an important imaging examination, which can provide the detail of teeth and gums to dentist for early diagnosis and treatment purposes. It is considerable that failure in disease diagnosis by dentist or any specialist will cause damage to the patient health. However, it is normal that human makes mistakes in disease diagnosis even dentists or specialist, but what is the solution to reduce these mistakes to minimum or even zero? To overcome these problems, development of computer-aided diagnosis and caries detection algorithm has turn into a priority to help the dentists and specialists to make a better and faster decision on diagnosis and furthermore treatment.

In dental imaging and diagnosis applications, X-ray are recommended because

it shows the size, location and condition of teeth. In addition, they are able to detect the presence of cavities before they appear on the tooth's surface. The X-rays are cheaper than other imaging techniques and easy to access.

The teeth have many structures which can be distinguished by the features and textures appeared on the images. Structures which are dense (such as metal restoration or silver fillings) will appear white on film because of blocking the most of photons. The structures of empty area which contains just air, will appear by black on a film, and the other portions that will appear as shades of gray, which contain tissue, teeth and fluid. Dentists are now able to perform early diagnosis and treatment by observing the non-intrusive estimates such as the roughness and tooth surface which shows the texture and moreover, opacification and changes in tooth surface color (Roberson *et al.*, 2006). Furthermore, investigation or examination using human eye which has low sensitivity rate has less accuracy and the chance of missing some caries or miss treatment will occur (Olsen *et al.*, 2009). Moreover, detecting of some cavities in early stages cannot be seen by visual examination and even difficult to detect by human vision system in X-ray images.

The location, affection of hard tissues, etiology and rate of caries progress are the factors for dental caries classification (Sonis, 2003). Mostly the caries regions on tooth surface is not visible to human eyes and it is difficult to recognise it. Figure 1.1 shows barely visible caries on tooth over time.



(a) (b)

Figure 1.1: Caries area on dental X-ray image (a) the X-ray without caries. (b) the X-ray image which has been taken some months later, and can detect the cavities between the teeth, which is not visible by visual examination.

Recently, developing an algorithm for caries detection and tooth damage measurement has been majority of studies (Kutsch, 2011). These systems can show the demineralization, which cannot be observe visually. It has recommended that such systems must be used to enhance the visual or visual-tactile examination, which has done by a dentist. The process of analysis of such dental images is important in order to help dentist with their work. This process comprises many different steps of image processing such as: image enhancement, segmentation, feature extraction, detection and classification.

Segmentation of dental images refers to recognition and extraction of each individual tooth or any regions of tooth like pulp and crown (Smith and Docef, 1997). Extracted regions or each individual tooth from each image represents the ROI, which contains the data to use in further steps. ROI can be define as a distinct portion of the image which identifies the one or any particular objects extracted form image (Metzler *et al.*, 2001; Michael and Nelson, 1989). Figure 1.2 demonstrates the example of extracted ROI from a bitewing dental X-ray image and each object inside the rectangle shows the ROI.

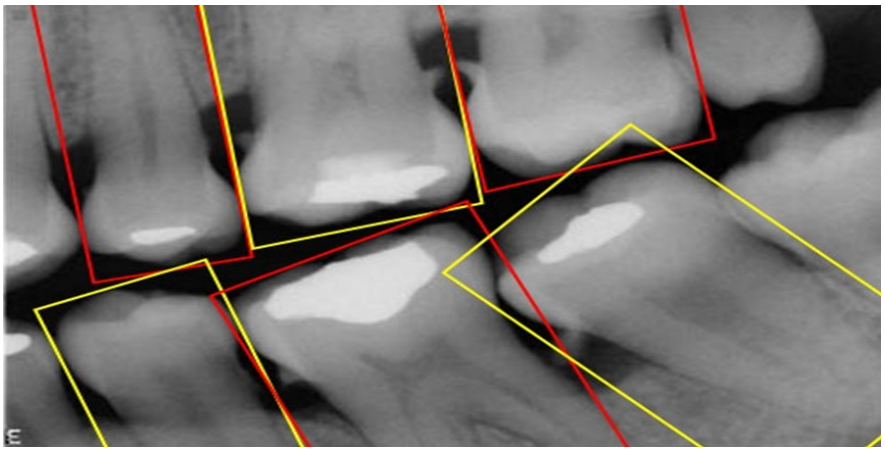


Figure 1.2: Segmentation of bitewing X-ray image and extracted ROI of each tooth with rectangle boundary around it.

Segmentation process is required the extraction of teeth surface features. Feature extracted from dental X-ray images are used to identify the area of teeth that contains the caries. There are several features that can be extracted from the image properties. This features can be classified in five groups: features based on the image characteristics, features based on statistical calculation, features based on the region of pixels, features based on the boundary of segmented region and features based on the textures on image.

Most researches on segmentation have been done within the past ten years as the computational ability of computers has increased. There is no uniquely superior technique, as each application presents its own specific challenges. It would be foolish at best to expect one algorithm alone to be successful at segmentation in any affected problem areas. This is especially true when the objects under consideration are natural (biological), rather than man-made, since: 1) biological objects exist in many shapes, sizes, colors and textures even within a single species, and 2) many different species resemble one another. Segmentation of medical images is more challenging problem due to some facts such as large variety in topologies, the complexity of structures and imaging problems like poor image qualities, low contrast, noise, several types of

artifacts and limitation of scanning methods.

Image segmentation is important and challenging process in most of the medical applications to obtain the accurate and reliable results. Notice to diagnosis and treatments, boundaries of each organ become important in medical images (Clarke *et al.*, 1995). According to X-ray image properties and image segmentation and computer vision, researchers work on this problem to propose automatic or semi-automatic image segmentation methods.

However, working with X-ray images has some difficulties like noise, intensity in homogeneities and low contrast between certain tissues. The visible tissue around the teeth is gum which has similar intensity that caused more difficulties on segmentation process. Also this type of image is gray level, thus using the color feature in not possible in processing task. Noise in medical X-ray images has a number of origins, but the most fundamental is from the X-ray source itself. This type of noise is called ”Quantum noise”, in reference to the discrete nature of the X-ray photons producing it (Sprawls, 1995). That is why segmentation on some teeth boundary has some complexity. There are many different factors that causes the intensity inhomogeneity in each images which one of the most common problem is the source of image producing device which depends on the variations of imaging situation (Chunming *et al.*, 2008).

Segmentation of dental X-ray images are more difficult due to intensity inhomogeneity which the most of regions has same range of intensity. This issue makes more challenging process in order to recognize the segmentation regions based on the pixels intensity. Most of the researchers (Nomir and Abdel-Mottaleb, 2007; Shah *et al.*, 2006; Huang *et al.*, 2012; Al-sherif *et al.*, 2012) used the intensity homogeneity technique for image segmentation which is not suitable for this kind of images. Generally, using intensity inhomogeneity feature is not appropriate for segmentation of dental images.

Recent work on dental image segmentation is (Lin *et al.*, 2014) which has been performed based on local singularity analysis. They used connected component analysis and Otsus thresholding to recognize each tooth. Moreover, they utilized snake boundary tracking for tooth delineation and morphological operation. The experimental result on 28 periapical dental X-ray images which consist of 75 useful teeth shows the accuracy of True Positive (TP) by 0.8959 and False Positive (FP) by 0.0093.

Level-set methods (Osher and Sethian, 1988) have been more interesting to researchers from different areas (Deng and Tsui, 2002; Nilsson and Heyden, 2003; Jeon *et al.*, 2005). The advantage of this method is that the all level-sets represent a nice extraction of regions and boundaries without uses of complex data structures. However, level-set function is limited to separation of two regions. And if it is more than two regions, the level-set method loses the parts of its capability. Moreover, the result depends on initial contour placement (Shrimali *et al.*, 2009). The researchers (Shuo *et al.*, 2006, 2007) used variational level-set method through the use of SVM to train and find the initial contour point. However, their work is not accurate and it is not an automatic method, and needs human involvement and more over it is time consuming process.

Likewise, Gao and Chae (2010) focused on segmentation of individual tooth from CT images proposing coupled variational level set method. However, due to dental image difficulties the proposed method still have some problem with identifying the metal artifacts and accuracy in teeth segmentation. Lin P *et al.* (2010) used level-set methods for teeth alignment algorithm and segmentation of teeth. Their result shows it is a promising method but still has problem in segmentation such as time consuming and misclassifying teeth in segmentation. Originally, the level-set method uses a numerical technique for tracing interfaces and shapes (Udupa and Samarasekera, 1996), and it has been even more applied to image segmentation and especially medical images in the previous years (Shuo *et al.*, 2007; Gao and Chae, 2010). The term of level set function refers to contours of surfaces which are represents the zero level set in higher dimensional function.

Recently many studies have been done to improve the image segmentation using level set method. Taheri *et al.* (2010) used intensity thresholding to define the speed function in level set for 3D tumor image segmentation. Proposed level set based segmentation method is efficient while the image is clear enough and boundaries of tumor and non-tumor regions is visible. In case, the method is not suitable for noisy images such as dental X-ray images. Zhang *et al.* (2010) proposed a region based active contours method. They utilized the gussian filtering for regularizing the level set segmentation method and reduced re-initialization of traditional level set method. However, method still depends on selection of initial contour and poor selection of initial contour will cause the result of segmentation.

Therefore, the accuracy of every process in such a dental image analysis are important for clinical diagnosis applications to reduce the risk of wrong diagnosis and speed up the treatment process. In this research the X-ray images are analyzed in order to detect the caries which are not visible by human visual inspection. The segmentation is challenging process in this research which requires improvement to obtain the high accuracy in result of caries detection.

1.3 Problem Statement

Among well-known contributions on this problem, level set based method has shown effective performance on medical and dental images segmentation. However, the accuracy of the image segmentation process need to be improve for dental X-ray images. It is because the images contain noises from imaging equipment and reflection of dental works and moreover the poor boundaries between tissues. Therefore the manual process of initial contour selection in level set method need to intelligently automate to obtain the most suitable initial contour points for getting the accurate segmentation results. Beside that, the speed function and signed force function

parameters need to be intelligently identify to avoid inappropriate selection which causes unsatisfactory segmentation result. The accurate segmentation result will provide better features for caries detection process.

In most of the image segmentations using level set function, the contour level zero or initial contour has been chosen manually for all images (Gao and Chae, 2010; Shuo *et al.*, 2006, 2007), and segmentation process is done without selecting the proper initial contour which affect the result of segmentation. Selection of proper initial contours manually for each image is also a time consuming process. Images that contain noise or images that need to segment the local regions will fail in segmentation process by using this method.

One of the most important and yet largely unsolved issues in level set segmentation framework is parameter selection for speed function and signed force function (Taheri *et al.*, 2010). Usually, parameter of speed function fixed beforehand by the developer of algorithm and that will result in the best possible segmentation for images (Li *et al.*, 2011; Chunming *et al.*, 2011; Shuo *et al.*, 2007). Inappropriate choice of parameters may result in unsatisfactory segmentation and user may have to spend a significant amount of time correcting the segmentation. Furthermore, the proper signed force function will speed up the method and increase the accuracy of segmentation of images with poor boundaries.

Detection of caries in each segmented tooth requires to extract the new features of each tooth surface and identify the caries and non caries area. Develop a feature map of each tooth surface will speed up the detection process

1.4 Research Goal

The goal of this research is to increase the accuracy of segmentation process by enhancement of the level set segmentation method for extracting the individual tooth and moreover obtain the features for accurate caries detection.

1.5 Research Objectives

The main objectives of research include:

- To propose a new scheme to generate the appropriate initial contour for each images which causes more accurate result in dental image segmentation.
- To enhance the level set method by using morphological concept and artificial neural network for define the speed function parameter selection with new signed force function parameter to increase the segmentation performance.
- To develop caries detection method with the proposed segmentation method to improve the caries detection performance.

1.6 Research Scope

The research objectives are achieved by identifying the problem scope which covers the following aspects:

- Propose a novel morphological region-based initial contour generation method

and level set based method by utilizing motion filtering for signed force function and moreover neural network and feature extraction methods to generate the speed function parameter for dental X-ray image segmentation.

- Analysis on dental X-ray images which is collect from Universiti Teknologi Malaysia (UTM) Health Center, and used as dataset for this study. The images are periapical dental X-rays which is common for dental disease detection and diagnosis in clinics.
- Evaluation of segmentation performance in compare with other recent dental segmentation methods.
- Develop appropriate feature extraction technique to achieve the features map of caries area and non caries area. Furthermore, identify the tooth which has problem and achieve the area of caries.

1.7 Significance of Study

Dental diseases has high risk of affection in the globe and mostly in adult population. Worldwide WHO (World Health Organization) studies reports that the main purpose of tooth loss and most of dental disease causes by dental caries which is involving large population in world. Dental caries is one of the main concerns in dental diagnosis and treatment community which more than 90% of all the adults have dental caries (WHO, 2012). In Malaysia also more than 80% of adults have dental disease and suffering from it.

The study shall contribute to four area of digital image processing; the image enhancement, the image segmentation, feature extraction and finally classification process. Segmentation of such a dental X-ray images compare to other medical images due to its difficulties is more challenging procedure. The segmentation must be able to eliminate the background of X-ray image of teeth and achieve the individual tooth. It

is necessary to propose an accurate and robust segmentation method to use in medical images field to analysis and process of huge volumes datasets. A proper segmentation method can save long time and help doctors in order to achieve fixed results to guide them in their diagnosis and treatment (Jurgen et al., 2007). Most of the segmentation algorithms are semi-automatic. They need some human interactions to initialize and start the process and the results depend on the initial values and human experience. Moreover, necessity of such a system in dental education to assist dental students in developing the analytical and psychomotor skills is also considerable. This work will be possible to the scientific community to be a basis for other methods or to the improvement of our method which method concerns the detection of dental caries in the X-ray images.

1.8 Organization of The Thesis

This dissertation is organized as follows.

This chapter presents on overview of the dental radiograph image segmentation, background of research and problems involved in this process. It also discusses some recent research contributions in this area specifically focusing on dental X-ray image segmentation methods and highlight the problems in existing methods.

Chapter 2 presents an overview of significant contributions and literature review in the area of medical image analysis methods. It also demonstrates advantages and drawbacks of each medical image segmentation method. Furthermore, neural network and feature extraction methods are explained

Chapter 3 presents the research methodology of the proposed techniques and discusses step-by-step processes and proposed algorithms used in image segmentation

method. This chapter also discusses all the proposed techniques involved in implementation of proposed methodology on dental X-ray image segmentation and caries detection approach.

Chapter 4 presents the dataset development of this study and describes pre-processing process for obtained images. This chapter discusses the specification of dataset used in this study and how to make a better quality out of reduced image quality to achieve reliable results.

Chapter 5 elaborates on the realisation of all the two main objectives of this research. It presents the proposed method to generate initial contour for level set segmentation. Furthermore, the proposed method to produce the parameter and improve the parametric level set based segmentation is explained.

Chapter 6 presents detection process which includes extraction of each individual tooth and produce feature map of tooth surface to classification of caries and non caries area. According to the expertise guide the detection process will be done.

Chapter 7 demonstrates the experimental results for current dental X-ray image dataset. The results of each periapical radiograph image segmentation are presented with explanation. Furthermore, the popular and recent research in dental image segmentation implemented and compared with this work to evaluate the performance and accuracy of this research. This chapter also provides comparison between proposed method with other famous methods in dental X-ray image segmentation with current dataset.

Finally, chapter 8 concludes the major achievements drawn from this research and future directions are recommended.

REFERENCES

Abdulsalam (2010). *Tooth Decay, http://toothdecaybyam.blogspot.com/p/classification.html*.

Adams, R. and Bischof, L. (1994). Seeded region growing. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*. 16(6), 641–647.

Al-sherif, N., Guo, G. and Ammar, H. H. (2012). A New Approach to Teeth Segmentation. In *Multimedia (ISM), 2012 IEEE International Symposium on*. IEEE, 145–148.

Aly, A. A., Deris, S. B. and Zaki, N. (2011). Research review for digital image segmentation techniques. *International Journal of Computer Science & Information Technology*. 3(5), 99–106.

Azarbad, M., Ebrahimzadeh, A. and Babajani-Feremi, A. (2010). Brain tissue segmentation using an unsupervised clustering technique based on PSO algorithm. In *Biomedical Engineering (ICBME), 2010 17th Iranian Conference of*. IEEE, 1–6.

Bajcsy, R. and Lieberman, L. (1976). Texture gradient as a depth cue. *Computer Graphics and Image Processing*. 5(1), 52–67.

Baraldi, A. and Parmiggiani, F. (1995). An investigation of the textural characteristics associated with gray level cooccurrence matrix statistical parameters. *Geoscience and Remote Sensing, IEEE Transactions on*. 33(2), 293–304.

Bennett, C. C. and Hauser, K. (2013). Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach. *Artificial intelligence in medicine*. 57(1), 9–19.

Caselles, V., Kimmel, R. and Sapiro, G. (1997). Geodesic active contours. *International journal of computer vision*. 22(1), 61–79.

Chan, R. H., Ho, C.-W. and Nikolova, M. (2005). Salt-and-pepper noise removal by median-type noise detectors and detail-preserving regularization. *Image Processing, IEEE Transactions on*. 14(10), 1479–1485.

Chan, T. F. and Vese, L. A. (2001). Active contours without edges. *Image processing, IEEE transactions on*. 10(2), 266–277.

Chen, Y., Thiruvenkadam, S., Tagare, H. D., Huang, F., Wilson, D. and Geiser, E. A. (2001). On the incorporation of shape priors into geometric active contours. In *Variational and Level Set Methods in Computer Vision, 2001. Proceedings. IEEE Workshop on*. IEEE, 145–152.

Choras, R. S. (2007). Image feature extraction techniques and their applications for CBIR and biometrics systems. *International journal of biology and biomedical engineering*. 1(1), 6–16.

Chunming, L., Huang, R., Ding, Z., Gatenby, C., Metaxas, D. and Gore, J. (2008). A variational level set approach to segmentation and bias correction of images with intensity inhomogeneity. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2008*. (pp. 1083–1091). Springer.

Chunming, L., Huang, R., Ding, Z., Gatenby, J., Metaxas, D. N. and Gore, J. C. (2011). A level set method for image segmentation in the presence of intensity inhomogeneities with application to MRI. *Image Processing, IEEE Transactions on*. 20(7), 2007–2016.

Ciofolo, C. (2004). Atlas-based segmentation using level sets and fuzzy labels. In *Medical Image Computing and Computer-Assisted Intervention–MICCAI 2004*. (pp. 310–317). Springer.

Clarke, L., Velthuizen, R., Camacho, M., Heine, J., Vaidyanathan, M., Hall, L., Thatcher, R. and Silbiger, M. (1995). MRI segmentation: methods and applications. *Magnetic resonance imaging*. 13(3), 343–368.

Dalal, N. and Triggs, B. (2005). Histograms of oriented gradients for human detection. In *Computer Vision and Pattern Recognition, 2005. CVPR 2005. IEEE Computer Society Conference on*, vol. 1. IEEE, 886–893.

Deng, J. and Tsui, H.-T. (2002). A fast level set method for segmentation of low contrast noisy biomedical images. *Pattern Recognition Letters*. 23(1), 161–169.

Dougherty, G. (2009). *Digital image processing for medical applications*. Cambridge University Press.

Ehsanirad, A. (2010). Plant classification based on leaf recognition. *International Journal of Computer Science and Information Security*. 8(4), 78–81.

Elyasi, A., Ganjdanesh, Y., Kangarloo, K. and Hossini, M. (2011). Level set segmentation method in cancer's cells images. *Journal of American Science*. 7(2), 196–204.

Eyad Haj, S., Nassar, D. E. M. and Ammar, H. H. (2006). Image segmentation for automated dental identification. In *Electronic Imaging 2006*. International Society

for Optics and Photonics, 60640X–60640X.

Fedkiw, S. O. R. (2003). Level set methods and dynamic implicit surfaces.

Gao, H. and Chae, O. (2010). Individual tooth segmentation from CT images using level set method with shape and intensity prior. *Pattern Recognition*. 43(7), 2406–2417.

Gibbs, P., Buckley, D., Blackband, S. and Horsman, A. (1996). Tumour volume determination from MR images by morphological segmentation. *Physics in medicine and biology*. 41(11), 2437.

Gonzalez, R. C. and Woods, R. E. (2002). *Digital image processing*.

Gove, P. B. (2002). *Webster's third new international dictionary of the English language, unabridged*. Merriam-Webster.

Haralick, R. M., Shanmugam, K. and Dinstein, I. H. (1973). Textural features for image classification. *Systems, Man and Cybernetics, IEEE Transactions on*. (6), 610–621.

Haring, J. I. and Jansen, L. (2000). *Dental radiography: principles and techniques*. WB Saunders.

Hojjatoleslami, S. and Kittler, J. (1998). Region growing: a new approach. *IEEE Transactions on Image processing*. 7(7), 1079–1084.

Horowitz, S. L. and Pavlidis, T. (1976). Picture segmentation by a tree traversal algorithm. *Journal of the ACM (JACM)*. 23(2), 368–388.

Hu, M.-K. (1962). Visual pattern recognition by moment invariants. *Information Theory, IRE Transactions on*. 8(2), 179–187.

Hu, Y., Grossberg, M. and Mageras, G. (2009). Survey of recent volumetric medical image segmentation techniques. *Biomedical Engineering*, 321–346.

Hua, L., Elmoataz, A., Fadili, J. M. and Ruan, S. (2003). An improved image segmentation approach based on level set and mathematical morphology. In *Third International Symposium on Multispectral Image Processing and Pattern Recognition*. International Society for Optics and Photonics, 851–854.

Huang, P.-W., Lin, P.-L., Kuo, C.-H. and Cho, Y. (2012). An effective tooth isolation method for bitewing dental X-ray images. In *Machine Learning and Cybernetics (ICMLC), 2012 International Conference on*, vol. 5. IEEE, 1814–1820.

Jain, A. K. and Chen, H. (2004). Matching of dental X-ray images for human identification. *Pattern recognition*. 37(7), 1519–1532.

Jeon, M., Alexander, M., Pedrycz, W. and Pizzi, N. (2005). Unsupervised

hierarchical image segmentation with level set and additive operator splitting. *Pattern Recognition Letters*. 26(10), 1461–1469.

Kass, M., Witkin, A. and Terzopoulos, D. (1988). Snakes: Active contour models. *International journal of computer vision*. 1(4), 321–331.

Keyes, L. and Winstanley, A. (2001). Using moment invariants for classifying shapes on large-scale maps. *Computers, Environment and Urban Systems*. 25(1), 119–130.

Kimmel, R. and Bruckstein, A. M. (2003). Regularized Laplacian zero crossings as optimal edge integrators. *International Journal of Computer Vision*. 53(3), 225–243.

Krol, D. M. (2003). Dental caries, oral health, and pediatricians. *Current Problems in Pediatric and Adolescent Health Care*. 33(8), 253 – 270. ISSN 1538-5442.

Kronfeld, T., Brunner, D. and Brunnett, G. (2010). Snake-based segmentation of teeth from virtual dental casts. *Computer-Aided Design and Applications*. 7(2), 221–233.

Kutsch, V. K. (2011). *Caries Detection, Inside Dentistry*. AEGIS Communications.

Lai, Y. and Lin, P. (2008). Effective segmentation for dental X-ray images using texture-based fuzzy inference system. In *Advanced Concepts for Intelligent Vision Systems*. Springer, 936–947.

Leventon, M. E., Grimson, W. E. L. and Faugeras, O. (2000). Statistical shape influence in geodesic active contours. In *Computer Vision and Pattern Recognition, 2000. Proceedings. IEEE Conference on*, vol. 1. IEEE, 316–323.

Li, B. N., Chui, C. K., Chang, S. and Ong, S. H. (2011). Integrating spatial fuzzy clustering with level set methods for automated medical image segmentation. *Computers in Biology and Medicine*. 41(1), 1–10.

Li, S., Fevens, T., Krzyzak, A. and Li, S. (2006). Automatic clinical image segmentation using pathological modeling, PCA and SVM. *Engineering Applications of Artificial Intelligence*. 19(4), 403–410.

Lin, P., Huang, P., Huang, P., Hsu, H. and Chen, C. (2014). Teeth segmentation of dental periapical radiographs based on local singularity analysis. *Computer Methods and Programs in Biomedicine*. 113(2), 433 – 445. ISSN 0169-2607.

Lin P, L., Lai, Y. and Huang, P. (2010). An effective classification and numbering system for dental bitewing radiographs using teeth region and contour information. *Pattern Recognition*. 43(4), 1380–1392.

Linda, G. S. and George, C. S. (2001). *Computer Vision*. PrenticeHall.

Lloyd, S. (1982). Least squares quantization in PCM. *Information Theory, IEEE Transactions on*. 28(2), 129–137.

Ma, W.-Y. and Manjunath, B. (1997). Edge flow: a framework of boundary detection and image segmentation. In *Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on*. IEEE, 744–749.

Mahoor, M. H. and Abdel-Mottaleb, M. (2005). Classification and numbering of teeth in dental bitewing images. *Pattern Recognition*. 38(4), 577–586.

Malladi, R., Sethian, J. A. and Vemuri, B. C. (1995). Shape modeling with front propagation: A level set approach. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*. 17(2), 158–175.

Mangin, J.-F., Frouin, V., Bloch, I., Regis, J. and Lopez-Krahe, J. (1995). From 3D magnetic resonance images to structural representations of the cortex topography using topology preserving deformations. *Journal of Mathematical Imaging and Vision*. 5(4), 297–318.

Manousakas, I., Undrill, P., Cameron, G. and Redpath, T. (1998). Split-and-merge segmentation of magnetic resonance medical images: performance evaluation and extension to three dimensions. *Computers and Biomedical Research*. 31(6), 393–412.

Metzler, V. H., Thies, C. and Lehmann, T. M. (2001). Segmentation of medical images by feature tracing in a self-dual morphological scale-space. In *Medical Imaging 2001*. International Society for Optics and Photonics, 139–150.

Michael, D. J. and Nelson, A. C. (1989). HANDX: a model-based system for automatic segmentation of bones from digital hand radiographs. *Medical Imaging, IEEE Transactions on*. 8(1), 64–69.

Mumford, D. and Shah, J. (1989). Optimal approximations by piecewise smooth functions and associated variational problems. *Communications on pure and applied mathematics*. 42(5), 577–685.

Nagel, R. (2011). *Cure Tooth Decay*.

Nassar, D. E. M., Chaudhry, F. U. and Ammar, H. (2004). On Performance Evaluation of Image Segmentation Algorithms: Success is Not All or None. In *In Proceeding, 1st International Computer Engineering Conference (ICENCO 2004), Egypt*. Dec. 354–359.

Nilsson, B. and Heyden, A. (2003). A fast algorithm for level set-like active contours. *Pattern Recognition Letters*. 24(9), 1331–1337.

Nomir, O. and Abdel-Mottaleb, M. (2005). A system for human identification from X-ray dental radiographs. *Pattern Recognition*. 38(8), 1295–1305.

Nomir, O. and Abdel-Mottaleb, M. (2007). Human identification from dental X-ray

images based on the shape and appearance of the teeth. *Information Forensics and Security, IEEE Transactions on*. 2(2), 188–197.

Nunes, J. C., Guyot, S. and Delechelle, E. (2005). Texture analysis based on local analysis of the bidimensional empirical mode decomposition. *Machine Vision and applications*. 16(3), 177–188.

Oliveira, J. and Proena, H. (2011). Caries Detection in Panoramic Dental X-ray Images. In *Computational Vision and Medical Image Processing*. (pp. 175–190). *Computational Methods in Applied Sciences*, vol. 19. Springer Netherlands.

Olsen, G. F., Brilliant, S. S., Primeaux, D. and van Najarian, K. (2009). An image-processing enabled dental caries detection system. In *Complex Medical Engineering, 2009. CME. ICME International Conference on*. IEEE, 1–8.

Osher, S. and Sethian, J. A. (1988). Fronts propagating with curvature-dependent speed: algorithms based on Hamilton-Jacobi formulations. *Journal of computational physics*. 79(1), 12–49.

Otsu, N. (1975). A threshold selection method from gray-level histograms. *Automatica*. 11(285-296), 23–27.

Paragios, N. and Deriche, R. (2000). Geodesic active contours and level sets for the detection and tracking of moving objects. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*. 22(3), 266–280.

Patel, B. C. and Sinha, D. G. (2010). An adaptive K-means clustering algorithm for breast image segmentation. *International Journal of Computer Applications*. 10(4), 35–38.

Peng, D., Merriman, B., Osher, S., Zhao, H. and Kang, M. (1999). A PDE-based fast local level set method. *Journal of Computational Physics*. 155(2), 410–438.

Perez, A. and Gonzalez, R. C. (1987). An iterative thresholding algorithm for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*. 9(6), 742–751.

Pham, D. L., Xu, C. and Prince, J. L. (2000). Current methods in medical image segmentation 1. *Annual review of biomedical engineering*. 2(1), 315–337.

Phen-Lan, L., Lai, Y.-H. and Huang, P.-W. (2012). Dental biometrics: Human identification based on teeth and dental works in bitewing radiographs. *Pattern Recognition*. 45(3), 934–946.

PhongDinh, V. and Le, B. (2008). Dental Radiographs Segmentation Based on Tooth Anatomy. IEEE, International Conference on Research, Innovation and Vision for the Future in Computing & Communication Technologies.

Pohlman, S., Powell, K. A., Obuchowski, N. A., Chilcote, W. A. and Grundfest-Broniatowski, S. (1996). Quantitative classification of breast tumors in digitized mammograms. *Medical Physics*. 23(8), 1337–1345.

Qin, X., Liu, S., Zhengqiang, W. and Han, J. (2008). Medical image enhancement method based on 2D empirical mode decomposition. In *Bioinformatics and Biomedical Engineering, 2008. ICBBE 2008. The 2nd International Conference on*. IEEE, 2533–2536.

Ray, A. and Sasmal, K. (2010). A New Approach for Clustering of x-ray Images. *IJCSI International Journal of Computer Scienc*.

Ridler, T. and Calvard, S. (1978). Picture thresholding using an iterative selection method. *IEEE transactions on Systems, Man and Cybernetics*. 8(8), 630–632.

Rink, K. and Tonnies, K. (2006). A modification of the level set speed function to bridge gaps in data. In *Pattern Recognition*. (pp. 152–161). Springer.

Roberson, T., Heymann, H. O. and Swift Jr, E. J. (2006). *Sturdevant's art and science of operative dentistry*. Elsevier Health Sciences.

Russakoff, D. B., Rohlfing, T. and Maurer Jr, C. R. (2002). Fuzzy segmentation of X-ray fluoroscopy images. In *Proc. SPIE*, vol. 4684. 147.

Sahoo, P. K., Soltani, S. and Wong, A. K. (1988). A survey of thresholding techniques. *Computer vision, graphics, and image processing*. 41(2), 233–260.

Said, E. H., Nassar, D. E. M., Fahmy, G. and Ammar, H. H. (2006). Teeth segmentation in digitized dental X-ray films using mathematical morphology. *Information Forensics and Security, IEEE Transactions on*. 1(2), 178–189.

Selwitz, R. H., Ismail, A. I. and Pitts, N. B. (2007). Dental caries. *The Lancet*. 369(9555), 51 – 59. ISSN 0140-6736.

Serra, J. (1986). Introduction to mathematical morphology. *Computer vision, graphics, and image processing*. 35(3), 283–305.

Sezgin, M. *et al.* (2004). Survey over image thresholding techniques and quantitative performance evaluation. *Journal of Electronic imaging*. 13(1), 146–168.

Shah, S., Abaza, A., Ross, A. and Ammar, H. (2006). Automatic tooth segmentation using active contour without edges. In *Biometric Consortium Conference, 2006 Biometrics Symposium: Special Session on Research at the*. IEEE, 1–6.

Shrimali, V., Anand, R., Kumar, V. *et al.* (2009). Current trends in segmentation of medical ultrasound b-mode images: a review. *IETE technical review*. 26(1), 8.

Shuo, L., Fevens, T., Krzyzak, A., Jin, C. and Li, S. (2007). Semi-automatic

computer aided lesion detection in dental X-rays using variational level set. *Pattern Recognition*. 40(10), 2861–2873.

Shuo, L., Fevens, T., Krzyzak, A. and Li, S. (2006). An automatic variational level set segmentation framework for computer aided dental X-rays analysis in clinical environments. *Computerized Medical Imaging and Graphics*. 30(2), 65–74.

Sirona (2008). *SIDEXIS XG*. The Dental Company. Retrievable at `http://manuals.sirona.com/en/imaging-systems/software/sidexis-xg.html`.

Smith, M. J. and Docef, A. (1997). *A study guide for Digital Image Processing*. vol. 1. Scientific Publishers, Incorporated.

Smith, S. M. and Brady, J. M. (1997). SUSANa new approach to low level image processing. *International journal of computer vision*. 23(1), 45–78.

Sonis, S. T. (2003). *Dental Secrets*. Hanley & Belfus.

Sprawls, P. (1995). *Physical principles of medical imaging*. Medical Physics Pub.

Taheri, S., Ong, S. H. and Chong, V. (2010). Level-set segmentation of brain tumors using a threshold-based speed function. *Image and Vision Computing*. 28(1), 26–37.

Udupa, J. K. and Samarasekera, S. (1996). Fuzzy connectedness and object definition: theory, algorithms, and applications in image segmentation. *Graphical models and image processing*. 58(3), 246–261.

van Bemmel, C. M., Spreeuwers, L. J., Viergever, M. A. and Niessen, W. J. (2003). Level-set-based artery-vein separation in blood pool agent CE-MR angiograms. *Medical Imaging, IEEE Transactions on*. 22(10), 1224–1234.

Wan, S.-Y. and Higgins, W. E. (2003). Symmetric region growing. *Image Processing, IEEE Transactions on*. 12(9), 1007–1015.

WHO, W. H. O. (2012). *Oral health*. Retrievable at `http://www.who.int/mediacentre/factsheets/fs318/en/`.

Xie, X. (2010). Active contouring based on gradient vector interaction and constrained level set diffusion. *Image Processing, IEEE Transactions on*. 19(1), 154–164.

Xie, X. and Mirmehdi, M. (2008). MAC: Magnetostatic active contour model. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*. 30(4), 632–646.

Xingfang, Y., Yumei, H. and Yan, L. (2010). An improved SUSAN corner detection algorithm based on adaptive threshold. In *Signal Processing Systems (ICSPS), 2010 2nd International Conference on*, vol. 2. IEEE, V2–613.

Xu, C., Yezzi Jr, A. and Prince, J. L. (2000). On the relationship between

parametric and geometric active contours. In *Signals, Systems and Computers, 2000. Conference Record of the Thirty-Fourth Asilomar Conference on*, vol. 1. IEEE, 483–489.

Yezzi Jr, A., Kichenassamy, S., Kumar, A., Olver, P. and Tannenbaum, A. (1997). A geometric snake model for segmentation of medical imagery. *Medical Imaging, IEEE Transactions on*. 16(2), 199–209.

Yoon, O.-K., Kwak, D.-M., Kim, D.-W. and Park, K.-H. (1999). MR brain image segmentation using fuzzy clustering. In *Fuzzy Systems Conference Proceedings, 1999. FUZZ-IEEE'99. 1999 IEEE International*, vol. 2. IEEE, 853–857.

Zhang, K., Zhang, L., Song, H. and Zhou, W. (2010). Active contours with selective local or global segmentation: a new formulation and level set method. *Image and Vision computing*. 28(4), 668–676.

Zhou, J. and Abdel-Mottaleb, M. (2005). A content-based system for human identification based on bitewing dental X-ray images. *Pattern Recognition*. 38(11), 2132–2142.

Zhu, F. and Tian, J. (2003). Modified fast marching and level set method for medical image segmentation. *journal of X-Ray Science and Technology*. 11(4), 193–204.