論文 / 著書情報
Article / Book Information

題目(和文)	
Title(English)	Fuzzy Guided Segmentation and Labeling for Dental Based Personal Identification System
著者(和文)	TANGELMARTIN L
Author(English)	Martin Tangel
出典(和文)	学位:博士(学術), 学位授与機関:東京工業大学, 報告番号:甲第9345号, 授与年月日:2013年9月25日, 学位の種別:課程博士, 審査員:廣田 薫,新田 克己,室伏 俊明,小野 功,宮下 英三
Citation(English)	Degree:Doctor (Academic), Conferring organization: Tokyo Institute of Technology, Report number:甲第9345号, Conferred date:2013/9/25, Degree Type:Course doctor, Examiner:,,,,
学位種別(和文)	博士論文
Type(English)	Doctoral Thesis

Fuzzy Guided Segmentation and Labeling for Dental Based Personal Identification System

Martin Leonard Tangel

11D35055

Supervisor: Prof. Kaoru HIROTA

Doctoral Thesis

Tokyo Institute of Technology
Interdisciplinary Graduate School of Science and Engineering
Department of Computational Intelligence and Systems Science

September 2013

Fuzzy Guided Segmentation and Labeling for Dental Based Personal Identification System

Martin Leonard Tangel
マルティン　レオナルド　タンゲル
11D35055

Supervisor: Prof. Kaoru HIROTA

Doctoral Thesis

Tokyo Institute of Technology
東京工業大学
Interdisciplinary Graduate School of Science and Engineering
大学院総合理工学研究科
Department of Computational Intelligence and Systems Science
知能システム科学専攻

September 2013

Abstract

The integrated concept of Multiscale Image Aggregation and Multiple Fuzzy Attribute for Dental-based Personal Identification System is proposed.

The average segmentation result from the proposed method is more accurate than Otsu method and robust against inconsistent contrast, uneven exposure, and pixel's noise of the radiograph. An experiment using 122 dental radiographs covering periapical and bitewing radiographs from Faculty of Dentistry University of Indonesia, which represent the real situation where radiographs are used in dentistry and forensics, and 77.7% average segmentation accuracy is obtained by comparing each automatic segmentation result with the corresponding manual segmentation result as a reference. This proposal is a crucial part in our automatic dental-based identification system that is underdevelopment. Since manual dental-based identification is widely used for personal identification, an accurate automatic dental-based identification system is helpful to assist forensic experts in identifying large number of victims. Thus, it makes numerous works manageable such as those in the Indian Ocean tsunami and Tohoku Earthquake.

As for the classification process, a classification on special type of dental image called periapical radiograph is studied and classification is done without speculative classification (in case of ambiguous object), therefore an accurate and assistive result can be obtained due to its capability to handle ambiguous tooth. Experiment result on 78 periapical dental radiographs from University of Indonesia indicates 82.51% total classification accuracy and 84.29% average classification rate per input radiograph. The proposed classification method is planned to be implemented as a submodule for an under developing dental based personal identification in the University of Indonesia. To demonstrate feasibility, an identification process in the simulated retrieval scenario is performed. Based on the demonstrated automatic computer-aided identification, the proposed techniques perfectly identified eight queries out of 10 queries within quadratic complexity.

Acknowledgements

First, I would like to express my sincere gratitude to my supervisor, Professor Kaoru Hirota, for accepting me in his lab and willing to supervise my master and doctoral studies. His encouragement, guidance, and inspiration were invaluable these last three and four years. I would like to express my sincere gratitude to Professor Shigeaki Sakurai, Professor Toshiaki Murofushi, Professor Katsumi Nitta, Professor Isao Ono, and Professor Eizo Miyashita for their precious time, valuable comments that have guided me on my master and doctoral thesis.

I would like to thank Dr. Fang-Yan Dong, assistant professor at Hirota Lab, and Dr. Kazushi Okamoto for the time and advice they gave me. Additionally, my sincere gratitude goes to Ms. Harumi Hoshino for all the irreplaceable help that she gave to me. Dr. M. Rahmat Widyanto, my caring supervisor when I was the 4th year bachelor student in the Faculty of Computer Science, University of Indonesia, who recommended me to pursue master & Ph.D. degree in Tokyo Institute of Technology. Dr. Nurtami, from the faculty of dentistry University of Indonesia, who provided the dental radiographs and consultation.

I am also grateful to my friends at the Hirota lab. I am thankful to Prof. Hatakeyama, Dr. P. Q. Le, Dr. A. M. Iliyasu, Dr. Liu and Dr. C. N. Nyirenda for patiently answering my questions about research.

I would also like to thank Dr. H. Markovic, Dr. Chastine Fatichah, Y. Tang, F. Yan, J. Pomares, A. Garcia, J. Lu, M. Matsushita, T. Akamatsu, A. Shibata, and K. Ohnishi for their very insightful discussions. I would also like to thank all Hirota Lab members for their continuing support and never ending patience with my constant requests for assistance.

Finally, I would like to thank my parents for their constant support and encouragement, thank to my mom, dad (Iwan Tangel & Mei Hoa), grandpa-grandma (Jayadi & Indrawati Kurniawan), uncle (Yustinus, Julius, Dhanny, Arief Kurniawan), & sister-brothers (Monika, Alex, Harry) for their dedication, patience, and prayer to support me to in spirit to finish the thesis – an invaluable present I receive in the fourth year of Master-Doctoral IGP A program. Thank you all for your never-ending love for me.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

Identifying a physically unrecognizable deceased is a demanding task, especially when the problem is scaled up into identifying victims of massive disasters such as those victims of March 11th tsunami in Great-Tohoku Earthquake 2011 or Indian Ocean Tsunami 2004. Until now, several identification methods exist such as face, DNA, Iris, fingerprint, and dental based identification. Among them, it is shown that dental based identification has high identification with low cost to detect the victims with massive physical destruction [1, 2, 3]. In addition to that, tooth is also one of the most resistant against heat and time; in other words, dental based identification can be applied for the burned or decayed deceased which is commonly found in the post disaster area [4].

1.1 Background Problems in Identifying Huge Victims

In identification of deceased bodies, dental features play a crucial role due to their high survivability compared to other biometric features. The importance of dental features has been indicated in [1], where 46.2% victims from 2004 Indian Ocean tsunami were identified using dental records. However, since the number of victims is huge, an identification process should be assisted by an automatic dental-based personal identification system. According to the data from New Scientists, it is shown that in 2011, it takes 40 months in order to identify 2,749 victims of World Trade Center. Meanwhile, three years after there is improvement in the identification rate. It is shown in the identification time needed during the Indian Ocean Tsunami 2004. 2,200 victims out of 190,000 victims are identified in 9 months. In spite of the progress, however, experts mention that the efficiency rate of identification is low. They demand the existence or improvement of the current identification tools, especially the automatic identification system.

Figure 1.1 shows the massive effects caused by disasters happened from 2001 to 2010, which is marked by the World Trade Center 2001 tragedy, followed by several major disasters such as 2002 Bali bombing, 2004 Indian Ocean Earthquake (which triggered author's motivation to start research on dental based identification system), 2008 Sichuan earthquake, and 2010 Haiti earthquake. The number of victims are huge, varies from thousands to hundred thousand victims. Moreover, if we include the recent tragedies after 2010, such as Great Tohoku earthquake March 11th 2011 , Christchurch earthquake, and there are still many more to mention.

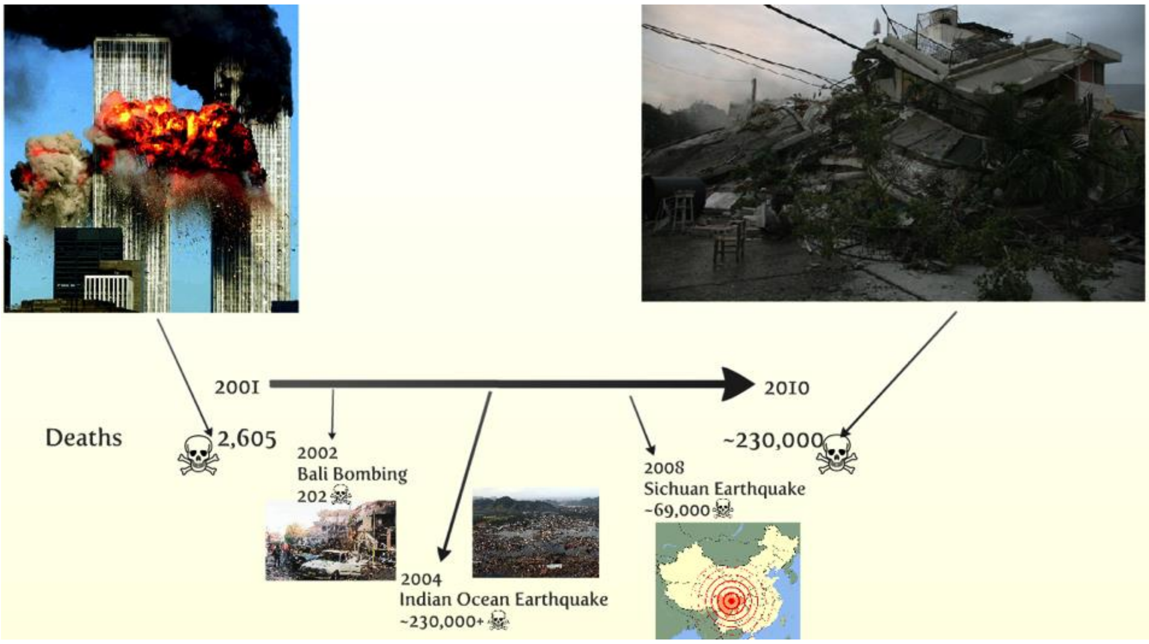


Fig. 1.1. Natural, man-made disasters and number of victims from 2001 to 2010

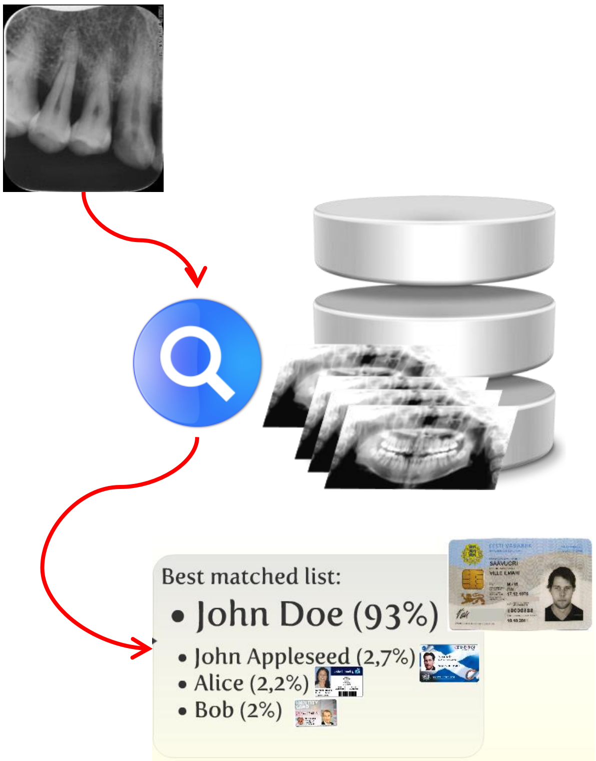


Fig. 1.2. Graphical description of proposed dental-based personal identification system

Evidence type	Circumstantial	Physical			
		External	Internal	Genetic	Dental
Accuracy	Med.	High	Low	High	High
Time for Identification	Short	Short	Long	Long	Short
Antemortem Record Availability	High	Med.	Low	High	Med.
Robustness to Decomposition	Med.	Low	Low	Med.	High
Instrument Requirement	Low	Med.	High	High	Med.

Fig. 1.3. The comparison among dental based identification method with others [14].

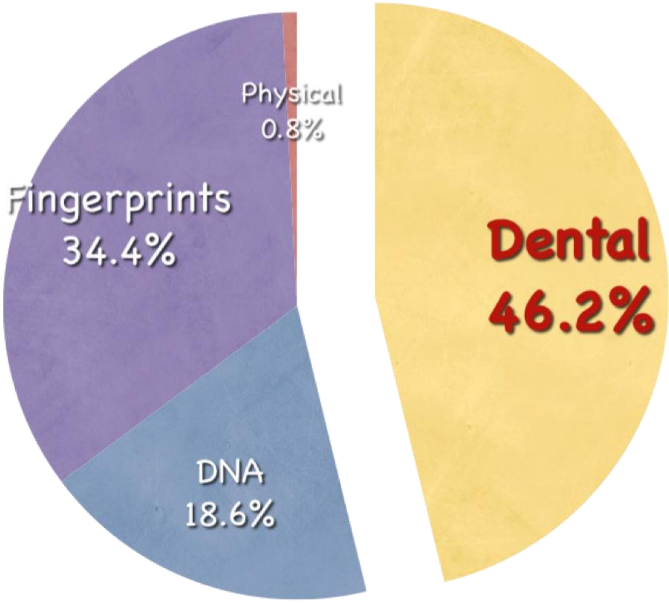


Fig. 1.4. The main identifiers from Indian Ocean Tsunami [1].

1.2 Identification Process

Post–Mortem (PM) identification, i.e. identification after death, includes comparisons with Ante-Mortem (AM) data. There are two methods of PM identification, positive and presumptive identification methods. Positive identification methods compare AM and PM data that are unique to each individual. These methods include dental, fingerprints, palm prints, footprints comparisons, DNA identification, and radiographic superimposition. Presumptive identification methods have a purpose to exclude potential mismatches based on race, gender, age, and blood type. These methods include the use of visual recognition, serology, anthropometric data, and medical history.

The work in this research focuses on the positive identification of dental comparisons. In PM identification, forensic odontologists utilize mainly dental radiographs to compare the dental morphology (including fillings and crowns) of unidentifiable victim to the available teeth data. While Fig. 1.2 describes the scheme of the identification system, Fig. 1.3 provides the superiority of the dental based identification system from several aspects. Moreover, based on the identification result of the Indian Ocean tsunami 2004, Fig. 1.4 proves the feasible contribution of the dental based identification system.

During the identification process, however, manual radiograph comparison is a laborious and time-consuming process that requires thorough work and skill. Given the huge amount volumes of dental records and victims, the task to match PM to AM records becomes tedious. Therefore a computer-aided dental based identification system can shortlist the candidate of the victims and make this process feasible for use by forensics. Meanwhile, for the sake of accuracy, the forensics just needs to crosscheck and do the proper manual dental comparison to the shortlist. Dental works information as shown in Fig. 1.5 may also help the identification process.

• Missing tooth	• Unerupted tooth	• Cavity on tooth
• Anomalous condition	• Mesial restoration	• Occlusal restoration
• Porcelain jacket crown	• Facial restoration	• Lingual restoration
• Full coverage crown	• Amalgam restoration	• Stainless steel crown
• Non-metallic restoration ceramic or acrylic/metal	• Distal restoration	• Gold/cast metal restoration
• Temporary restoration, ¾ crown	• Pointic root canal	• Treated tooth
• Removable partial denture	• Deciduous tooth	• Virgin tooth

Fig. 1.5. Dental works that may help the identification process

Dental work is useful. Since dental work is done by a dentist, it can be a unique identifier that can be used further during the identification process if we take into account the dentists-patients relationship. In this research, however, the scope is limited only to the teeth without dental work due to the limitation of the provided radiograph.

1.3 Dental Radiograph Types

The general categorization of dental radiograph is classified into intraoral or extraoral x-ray image. Both types of images are taken using X-ray radiation. The produced dental radiograph consists of teeth, bones, and surrounding soft tissues. There are two types of radiographs, intraoral and extraoral as shown in Fig. 1.6.

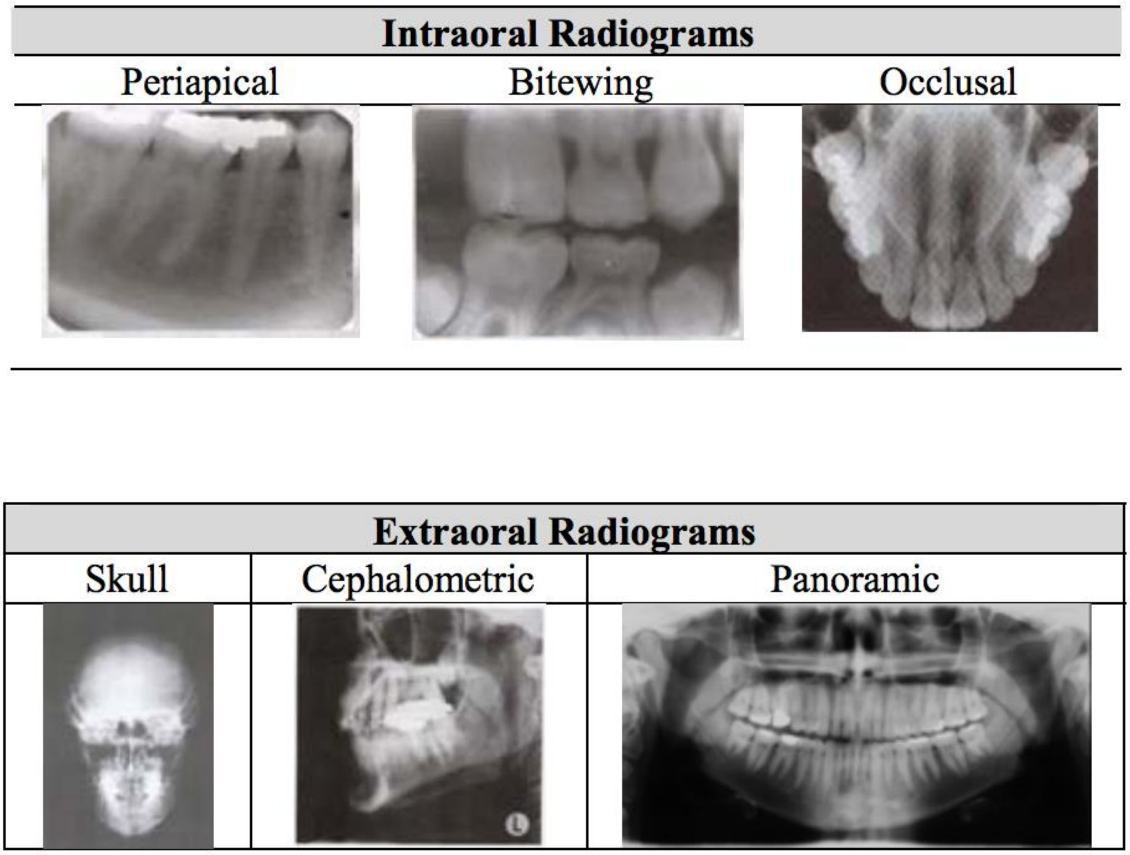


Fig. 1.6. Universal numbering system [72].

In terms of the use of radiograph in dentistry, there are three popular types of dental radiograph that are commonly used, they are periapical, bitewing, and panoramic (shown in Fig. 1.7). Referring to this fact, this research also focus on these three types of images since the high availability of the mentioned types implies their usability by the forensics, and mainly on periapical since the existing research on periapical type is still lacking.

Aside from the different uses of radiograph types, radiograph can also be differentiated by the way the radiograph is taken. Periapical radiograph is useful to show the whole tooth from crown to beyond the end of the root. This can be used to detect abnormalities of the root surrounding bone structure. Bitewing radiograph shows detail of upper and lower part of teeth in certain area of the mouth. This radiograph can be used to detect decay between teeth and bone density changes caused by disease. Panoramic radiograph shows the entire mouth area, both upper and lower jaws, and it is useful in localizing fractures or pathologic entities. This type is commonly employed in the U.S. military for enabling the fast recording of soldiers's x-ray dental images.

Fig. 1.7. Categories of dental radiograph, top-left: periapical, top-right: bitewing, bottom: panoramic.

Since periapical radiograph consists only either upper or lower series of tooth, this type of radiograph is more representative to postdisaster conditions as described in Fig. 1.8. For the example in the real world, the upper and lower jaws of a victim are disintegrated in the flight accident in Gunung Salak, Indonesia 2012. Moreover, it is more practical for the forensics to reconstruct periapical radiograph during the postmortem examination. In order to confirm the performance, experiments on 78 periapical radiographs, which consist of lower and upper jaw, are conducted. The radiographs dominantly consist of molar and premolar teeth. The classification accuracy of each individual tooth is assessed. In addition to that, the classification accuracy over input radiograph is also evaluated statistically. Dental classification refers to the process of classifying each tooth into general four types (incisor, canine, premolar, and molar). For the complete reference of the universal dental numbering system, refer to Fig. 1.9.

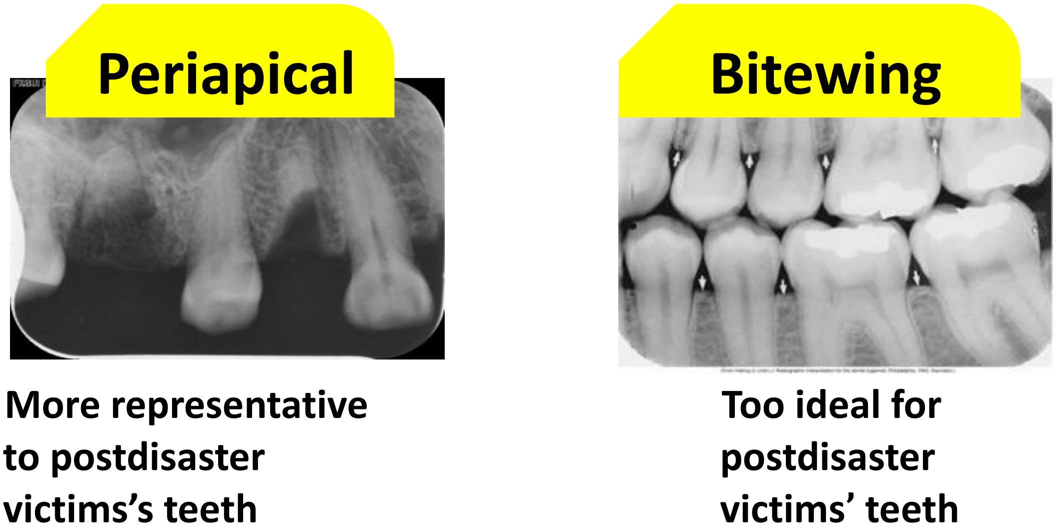
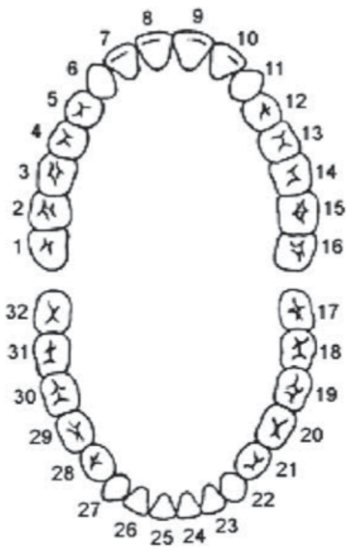


Fig. 1.8. Comparison between periapical and .bitewing radiograph. Note that in some cases, the lower and upper jaws of the victims are separated, therefore it is difficult to reconstruct bitewing image from the victims.



1. 3rd Molar (wisdom tooth)	17. 3rd Molar (wisdom tooth)
2. 2nd Molar (12-yr molar)	18. 2nd Molar (12-yr molar)
3. 1st Molar (6-yr molar)	19. 1st Molar (6-yr molar)
4. 2nd Bicuspid (2nd premolar)	20. 2nd Bicuspid (2nd premolar)
5. 1st Bicuspid (1st premolar)	21. 1st Bicuspid (1st premolar)
6. Cuspid (canine/eye tooth)	22. Cuspid (canine/eye tooth)
7. Lateral incisor	23. Lateral incisor
8. Central incisor	24. Central incisor
9. Central incisor	25. Central incisor
10. Lateral incisor	26. Lateral incisor
11. Cuspid (canine/eye tooth)	27. Cuspid (canine/eye tooth)
12. 1st Bicuspid (1st premolar)	28. 1st Bicuspid (1st premolar)
13. 2nd Bicuspid (2nd premolar)	29. 2nd Bicuspid (2nd premolar)
14. 1st Molar (6-yr molar)	30. 1st Molar (6-yr molar)
15. 2nd Molar (12-yr molar)	31. 2nd Molar (12-yr molar)
16. 3rd Molar (wisdom tooth)	32. 3rd Molar (wisdom tooth)

Fig. 1.9. Universal numbering system [9]

As for the challenges to identify the victims of massive disasters, the inherent challenges persist such as the condition of the postdisaster area that has been destroyed hit by the direct impact or indirect impact such as fire, flood, etc. The physically unrecognized victims also give difficulties to the working forensics as well as the physiological stress and lack of convenience in the working area may even further negatively affect the identification process. Fig. 1.10 depicts the mentioned conditions.

Fig. 1.10. Top: Condition of a postdisaster spot and a victim (facially unrecognizeable); Bottom: Portable X-Ray device for forensics

From technical point of view, the radiograph image itself may have problem with the irregular arrangement of the teeth, occlusion, or unclear position due to the improper angle or quality limitation when the radiograph picture is taken. Fig. 1.11 shows the example of the mentioned technical challenges.

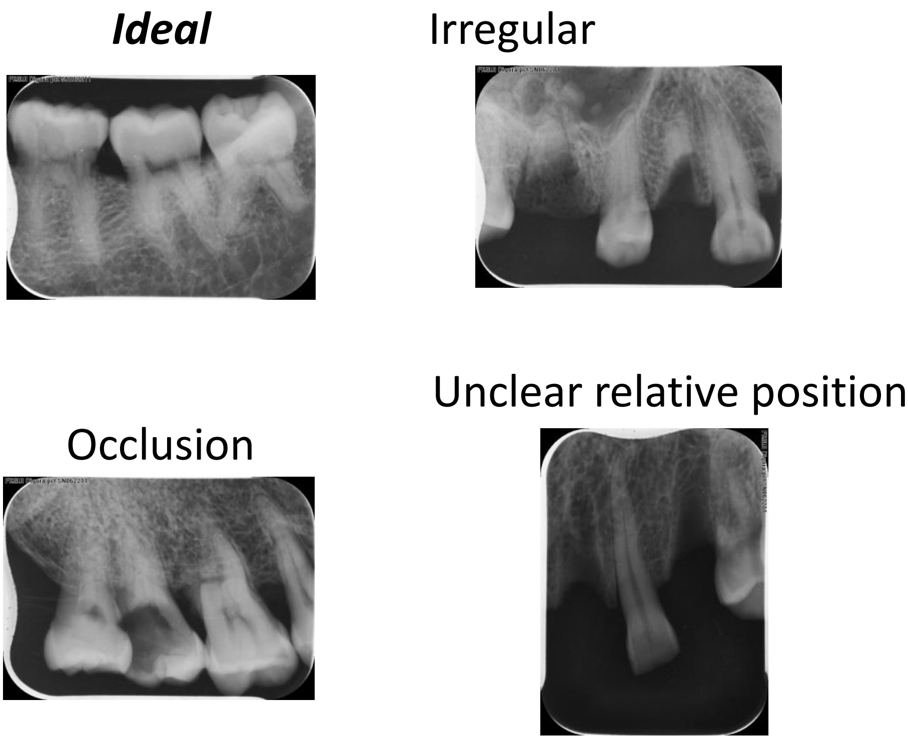


Fig. 1.11. Challenges in the arrangement of teeth in periapical radiograph

In order to realize an automatic dental based identification system, dental classification is a necessary subprocess to isolate and extract features of individual tooth. In the holistic point of view, dental classification enables indexing and efficient search for identification purpose. Research on dental classification and numbering is done using teeth region and contour information for dental bitewing [5]. Jain and Chen [4] propose a semi-automatic tooth segmentation using contour extraction method. Dental segmentation using fuzzy logic based emotional multi agent system is proposed in [6]. Research on multiscale image aggregation [7, 8] provides another insight to radiograph segmentation. Rresearch on dental classification, however, in periapical radiograph is still lacking and, therefore, it becomes the focus of this research.

Dental Classification based on Multiple Fuzzy Attribute for Automatic Dental Numbering System is proposed to classify periapical image based on the fuzzy value and is able to deal with orientation problem, missing teeth, or ambiguity by allowing probabilistic value to be included in the output if the automatic system cannot judge firmly based on certain criteria and leave the task to the expert to be done manually. The use of ratio value of the tooth size also enables the system to cope with various size periapical radiograph that may happen depending on angle and distance when taking the radiograph.

The two main advantages of this research are, (1) the proposal handles periapical radiograph and (2) the use of multiple fuzzy attributes improves classification accuracy without making speculative classification. Among various types of dental radiographs in best practice, extensive research has been done on bitewing and panoramic radiograph [9, 10, 11], however, the research of dental classification in periapical radiograph is still lacking and the existence of this research might contribute and complement the existing research while paving the way to completing dental based identification system. Since the periapical radiograph image consists only either upper or lower series of tooth, this type of radiograph is more representative to postdisaster conditions. For example, the upper and lower jaws of a victim are disintegrated in the flight accident in Gunung Salak, Indonesia 2012. Moreover, it is more practical for the forensics to reconstruct periapical radiograph during the postmortem examination.

Multiple fuzzy attribute offers advantage against uncertain condition of tooth that is difficult to categorize well. Instead of offering clear classification, which might decrease overall accuracy, the system offers multiple possibility of classification with its fuzzy value (referred as fuzzy attribute in this article). The proposed method provides full automatic classification results when it is certain. In uncertain case, the proposal provides classification as multiple fuzzy attributes so that the system still functions to provide assistance to expert without making speculative classification. The proposed method also employs integral projection for isolating each individual tooth. This method is selected because of its low computational complexity. As the result, the system has better accuracy result without sacrificing performance.

In order to confirm the performance, experiments on 78 periapical radiographs, which consist of lower and upper jaw, are conducted. The radiographs dominantly consist of molar and premolar teeth. The classification accuracy of each individual tooth is assessed. In addition to that, the classification accuracy over input radiograph is also evaluated statistically. To complement the numerical result, examples of classification results are also provided to give the visual grasp of the proposed method.

This research contributes to addressing issues on dental based personal identification system by broken down the process into three submodules, dental segmentation, dental classification, and dental matching. Fuzzy inference and various techniques are presented in each of the submodules. In relation to its subproblems, This dissertation is organized into three chapters in accordance to the three mentioned submodules.

In chapter 2, an experiment of fuzzy logic based emotional multi agent system for dental segmentation is conducted, which leads into the construction of the proposed method, called Multiscale Image Aggregation (MIA) for dental radiograph segmentation. MIA improves segmentation accuracy result with improved visual result regardless of contrast variation among radiographs. This capability is obtained by the automatic parameter tuning for fuzzy membership functions, therefore it has adaptability against the noisy and uneven contrast of radiograph. In order to give the quantifiable result, an experiment on 122 ill-conditioned radiographs from Faculty of Dentistry University of Indonesia is done. In order to justify the increased performance, statistical T-Test is applied to measure its statistical significance. As the result, the segmentation method is proposed and the segmentation result can be applied in the next phase for dental classification.

In chapter 3, the research on dental segmentation is continued on the development of Multiscale Image Aggregation method where the further experiments are conducted by comparing the segmentation result with the fuzzy logic based emotional multi agent system and otsu method.

In chapter 4, the dental classification based on multiple fuzzy attribute is presented for periapical dental radiograph. The two main advantages of this research are, (1) the proposal handles periapical radiograph and (2) the use of multiple fuzzy attributes improves classification accuracy without making speculative classification. In order to confirm the performance, an experiment on 78 periapical radiographs, which consist of lower and upper jaw, are conducted. The radiographs dominantly consist of molar and premolar teeth. The classification accuracy of each individual tooth is assessed. In addition to that, the classification accuracy over input radiograph is also evaluated statistically. To complement the numerical result, examples of classification results are also provided to give the visual grasp of the proposed method

In chapter 5, the application of fuzzy guided segmentation and labeling for dental matching and other expansion possibility is mentioned. The labeling process enable shortlisting, which enabling the system to do fast matching only on selected attributes relevant features of the radiograph and present the result to the user. Finally, chapter 6 presents conclusion and future works. The road map is shown in figure 1.12.

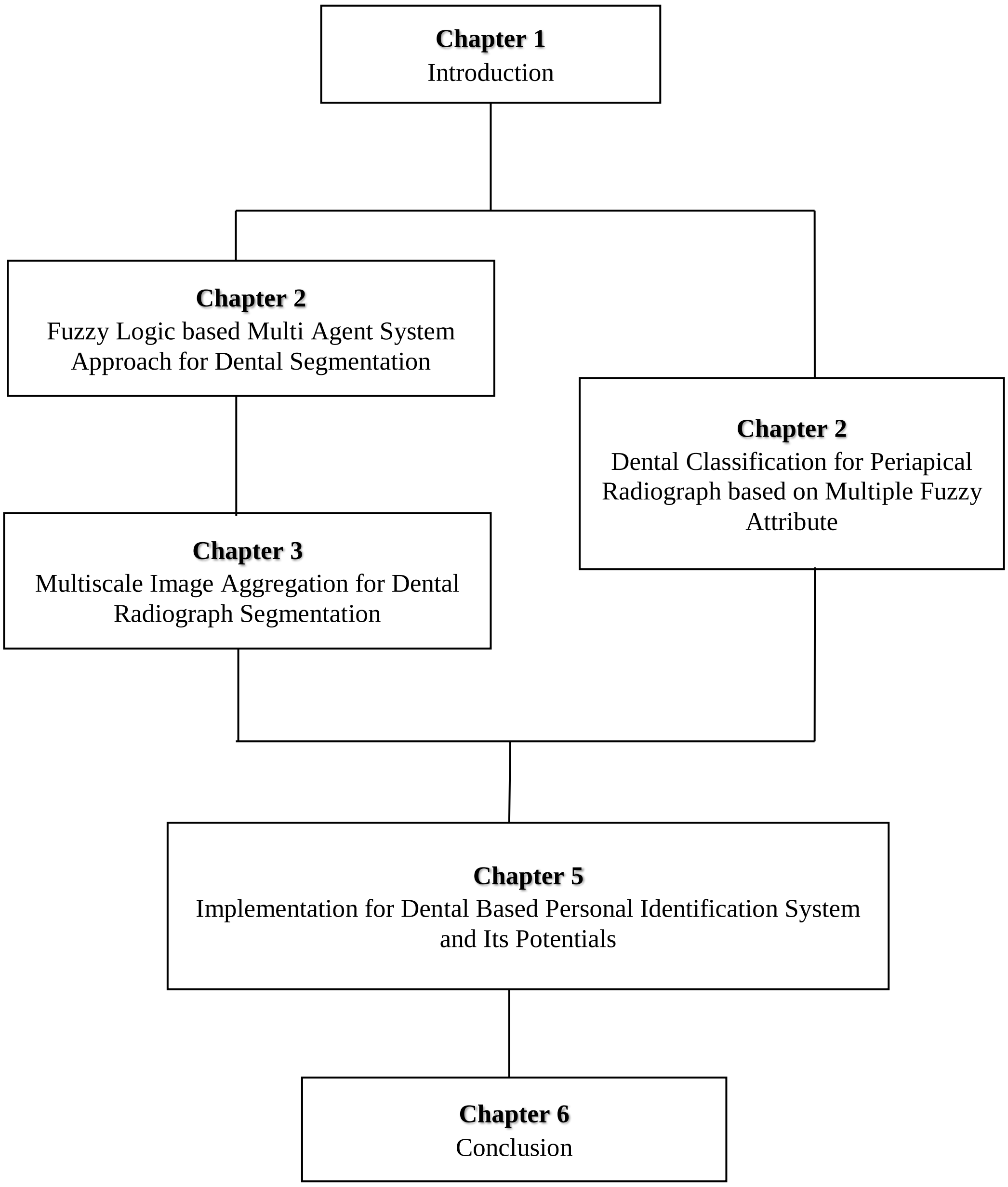


Fig. 1.12. Research roadmap

Chapter 2

Fuzzy Logic based Multi Agent System Approach for Radiograph Segmentation

In terms of techniques involved, dental based personal identification system utilizes computer vision [12], segmentation [13], statistics to test its statistical significance [14]. In addition to that, several image processing techniques might be utilized as well for pre-processing or even as main modules such as introduced in [15, 16, 17, 18, 19, 20]. This chapter focuses on the segmentation part.

Fuzzy logic based emotional multi agent system is computational entities that sense their local conditions and react to the sensed conditions by performing certain behaviors based on their emotion. The emotion of an agent is computed by using fuzzy logic that takes two parameters. The first parameter is the grayscale intensity of a pixel that is occupied by the agent. This parameter is used to decide the feeling of the agent. This feeling represents the internal emotion of an agent regardless the surrounding condition. The second parameter is the ratio of pixels occupied by living agents over total pixels from observation area (see Fig. 2.1). This parameter is used to decide the atmosphere of the local area under observation of an agent. The atmosphere represents the external affect for an agent.

The idea of combining multi agent system approach with fuzzy logic is based on the following points:

1. From the perspective of data.

   The possessed radiographs are grayscale X-ray images constructed from pixels with value ranging from 0 (black) to 255 (white pixel). The radiograph itself consists of blurred areas, which that is challenging to decide the degree of belonging of one pixel. Moreover, the belonging degree of a pixel depends on its neighboring pixels. Based on this fact, fuzzy logic can be employed to deal with ambiguity and multi agent system approach can be utilized to analyze a pixel's belonging relative to the local area of its neighboring pixels.

2. From the perspective of multi agent system approach.

   Multi agent system approach enables the use of multiple agents' characteristics and aspects of modularity of the development for general segmentation image method. Moreover, the use of multi agent system approach enables us to do pixel-based segmentation with consideration of one pixel's local relative values of its neighboring pixels

3. From the perspective of fuzzy logic.

   Fuzzy logic is employed to simulate the emotional states of an agent. Since an agent should react to its surrounding, the use of fuzzy logic is proper if it is related to the ambiguous surrounding pixel values. Moreover, by combining the fuzzy logic into multi agent system approach, an original proposal is created and demonstrated to achieve the defined objective to do dental segmentation on the dataset.

The matching capability and dental alignment [21, 22] usually needs segmentation in the first place. While this chapter explains a method to employ multi agent system approach for segmentation, the foundation research work about multi agent system approach [23, 24, 25] and especially its use on image is studied in [19], while the computer-assisted system for dentistry is surveyed in [20,21].

The proper segmentation result can be used for dental classification [26] and dental based personal identification system as shown in [27].

Given the mentioned three points, the proposal has been used and demonstrated to be able to cope with the defined problems. The proposal is explained in the sequence below and the results (accuracy and cost) are also presented.

2.1 Challenges Related with Grayscale X-ray Dental Image

This subchapter introduces the characteristics of the digital dental image and the possible extracted features from it. Since the radiograph is available only in grayscale image to picture gum, teeth, dental work, background (at least four different objects), this limitation poses its own challenges that should be handled in a specific way that is well suited to this domain problem. This subchapter explains the problems sequentially, started by the nature of the dental image, possible value to be extracted from the image, and then various problems and challenges that is commonly faced by both dentists and forensics are presented. that is commonly used.

2.1.1 Characteristics of Dental Image

X-Ray radiography is widely used in medical diagnosis because of its non-invasiveness and depicting changes [28]. As introduced in the previous chapter, a radiograph consist a range from white to black. The grayness of an area represents a region/object. An area consists of pixels. Assume an area belongs to either an object or background, then we can derive that a pixel belongs to either an object or background. This statement makes sure that a pixel based segmentation or classification is a working method, as explained in the next chapters. An area in a radiograph can be classified as follows (ordered from the brightest to the darkest area):

1. Object
   - ① Dental Work
   - ② Tooth
     1. Crown
     2. Root
   - ③ Gum

2. Background

Note that each area usually has its own range of brightness, where the relative brightness among images may change and expose unique challenges to accurately do segmentation or classification. In terms of a digital image, a radiograph is represented as a grayscale digital image. Since an image is composed of pixels, a grayscale image is an image where each pixel consists of a value in range [0, 255] to represent the grayness of a pixel. The illustration of a matrix representing a grayscale image of a radiograph is shown in Fig. 2.4.

2.1.2 Possible Extracted Features and Various Problems with Radiograph

The values that can be extracted from a grayscale image is the information of an intensity value [0, 255] for each pixel. This single information of each pixel poses challenges as the extracted value is rather limited. Given this circumstances, however, several features can be obtained if a set of values is taken. Therefore, a derivative information of a radiograph helps the process of segmentation.

There are possible information can be obtained by taking the neighboring pixels into account. The information such as:

1. Mean of the center of pixel and its neighboring pixels
2. Variance of the center of pixel and its neighboring pixels
3. Edge information of the suspect object in the image
4. Orientation of the object
5. Classification/dental type of a tooth.

As for the segmentation itself, the purpose is to obtain the edge of teeth objects by utilizing the value of a pixel, mean, and variance. Therefore, from numerical point of view, this problem can be modeled as converting an image with pixels values [0, 255] into {0,255}, where an area is crisply divided into object and background..

However, given the goals, several types caused by the condition of a radiograph exist. For example, the existences of unimportant details, unclear boundaries, noise, and inconsistent contrast make even difficult for human to clearly divide between the teeth and background firmly. The samples of these radiographs are shown in Fig. 2.1.

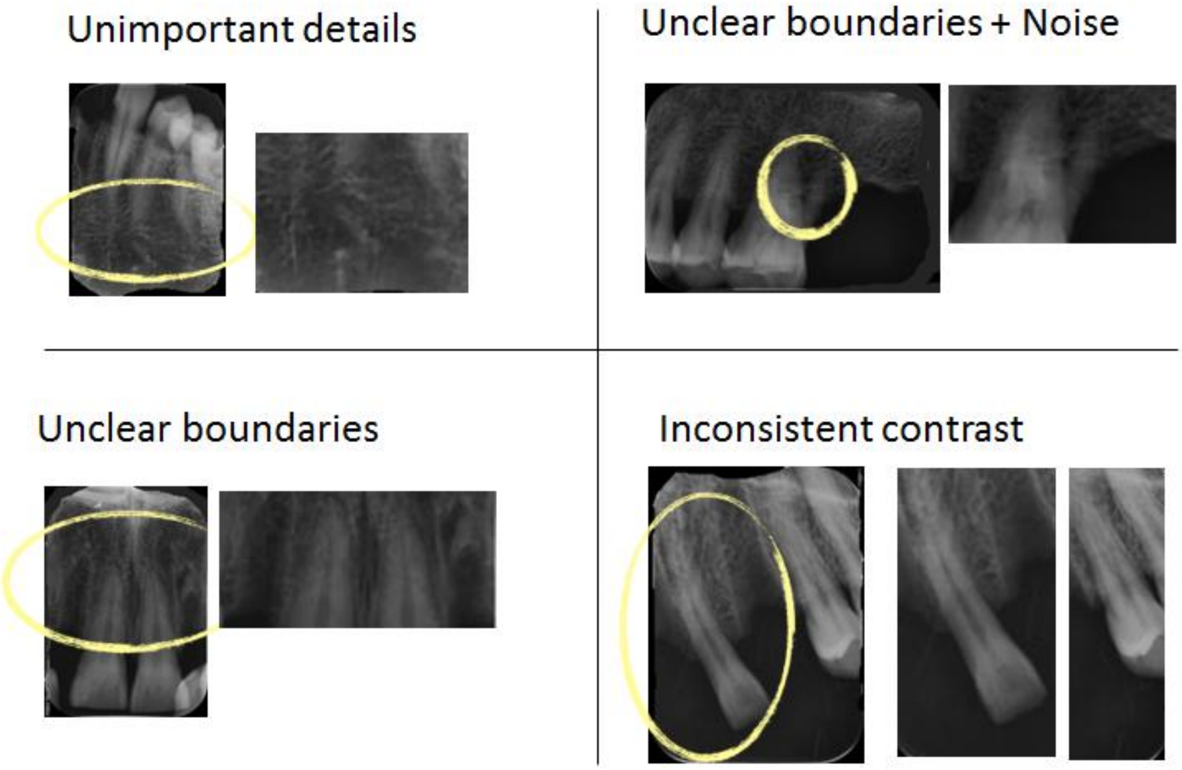


Fig. 2.1. Four categories of common visual challenges with the radiographs.

2.1.3 Challenges on Segmentation

As previously mentioned that segmentation is about converting an image with pixels values [0, 255] into {0,255}, where an area is crisply divided into object and background, the illustration is given in Fig. 2.2.

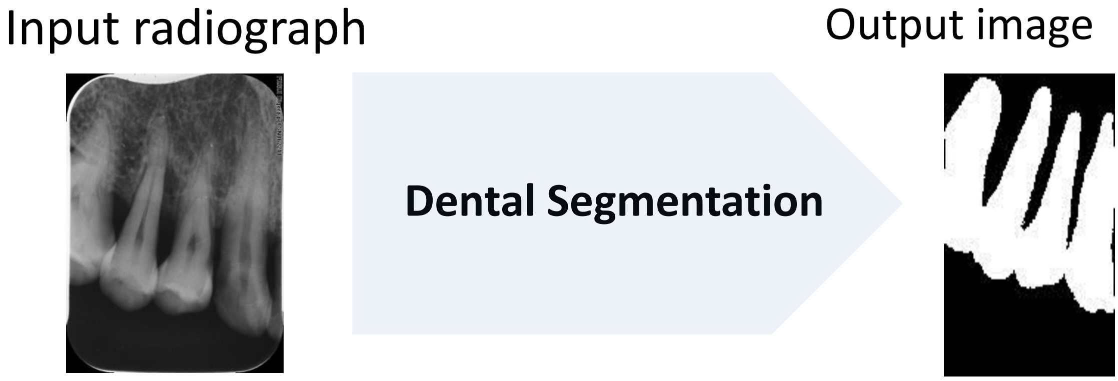


Fig. 2.2. Example output of an image after segmentation.

The challenges of dental segmentation, apart from the mentioned four categories mentioned in Fig. 2.2., lie on the fact that the contrast between gum and tooth is not clearly distinguishable, and it varies depending on the angle the radiograph is taken. This affects the quality of the produced radiograph, as well as the quality of the segmentation if an automatic system is built. In order to cope with the challenges with pixel based radiograph segmentation, the first proposal, a fuzzy logic based multi agent system approach is proposed.

2.2 Pixel based Radiograph Segmentation

The massive use of pixel data for segmentation may supports discovery and characterization of biomarkers for incidence and progression of the bone structures [29]. Survey on various segmentation methods has been done in [30]. However, in the dental radiograph, the 4D (3D + time) information is not available like those in MRI, therefore, it lacks of changing data [31].

The next subsequent subchapters explain the representation of pixels in a matrix with illustration. In addition to the general matrix concept in the image processing, some short illustrations on how an agent is put in a pixel are provided. The states of the agents, and how it will react to their environment is also addressed.

2.2.1 Representation of Pixels in a Matrix

The grayscale image is represented as a 2D-Cartesian coordinate of pixels intensity. Each grayscale value of the pixels contributes to the agent's feeling. Meanwhile the neighborhood condition within range of the observation area of the agents is used to determine the agent's atmosphere (see Fig. 2.3). An agent that is placed into a pixel will take the pixel's greylevel value and interact with the surroundings agents. An agent can only observe the pixels within his observation area.

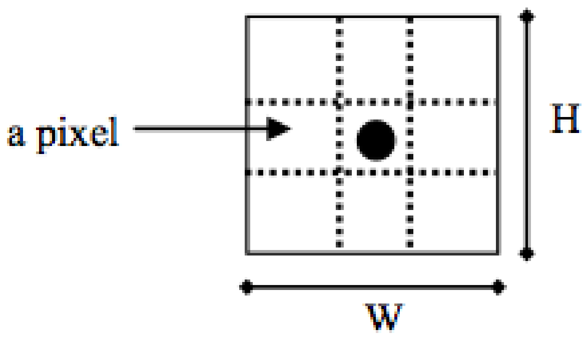


Fig. 2.3. 3 X 3 neighborhood blocks in a matrix sensed by an agent

Each agent has three states: active, immobile, death. Every agent is initiated as an active agent; they can be immobile if they are satisfied with the condition and start reproducing other agents. An active agent may also switch from active state to death state due to the poor emotion state. The pseudocode is explained in Fig. 2.5.

The action decided by each agent is computed based on fuzzy membership function and fuzzy rules that are described in Fig. 2.6 and Table. 2.1 respectively. The membership function is obtained based on experiment done on dental X-Ray images. To represent the surrounding (ratio living agents over observation area), three measures: fearful, neutral, and joyful are employed. Meanwhile, to represent the internal feeling, it is classified into four measurements: very disappointed, disappointed, comfortable, and very comfortable.

2.2.2 Values of a Pixel

The value that can be extracted from a pixel in a radiograph is a numerical value ranging from [0, 255] where 0 represents black, 255 represents white, and the value in between 0 to 255 represents gradient from black, dark grey, light gray, and white. In matrix representation, each value is held in each element of the matrix as shown in Fig. 2.4.

$$R=\begin{bmatrix} i(1,1) & i(1,2) & \dots & i(1,N) \\ i(2,1) & i(2,2) & \dots & i(2,N) \\ . & . & & . \\ . & & . & . \\ . & & & . \\ i(M,1) & i(M,2) & \dots & i(M,N) \end{bmatrix}$$

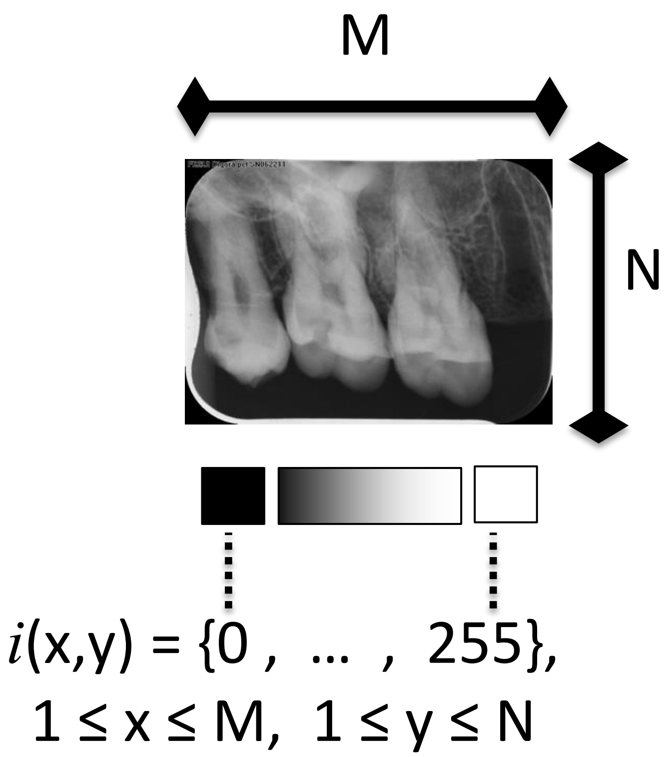


Fig. 2.4. Illustration of a grayscale image matrix representing a radiograph.

Refer to Fig. 2.4, suppose there is a radiograph image with M X N size, then mathematically, this can be modeled into a matrix with M column and N row where each element represents grayness of a pixel.

2.3 Radiograph Segmentation using Multi Agent System Approach

Pixel based radiograph segmentation is chosen in this research. Since the radiograph consists of visual challenges mentioned previously, the specific method is proposed to cope with the need to deal with the visual challenges by enabling group segmentation based on the neighboring pixels. Various segmentation techniques are studied such as using swarm intelligence approach [32], mathematical morphology [33], level set [34]. In addition to the mentioned techniques, several approaches to enhance the process in general segmentation are studied in [35, 36, 37, 38, 39, 40]. As the result of the research, a method called radiograph segmentation using fuzzy logic based multi agent system approach is proposed due to its capability to segment the object based on the proximities among agents that enables group segmentation.

2.3.1 Architecture of Proposed Multi Agent System Approach

The fuzzy logic based multi agent system approach is intended to simulate agents occupying pixels in an image. The general rules applied in the process are as following:

1. One pixel can only be occupied by one agent.
2. Agents are spread randomly in the 1/3 of the total pixels in the image.
3. Three actions can be taken by the agent: vanish, diffuse, reproduce.

4. The higher the intensity value of a pixel, the happier the occupying agent is.
5. Agent tends to live in a group.
6. These processes from 2) to 5) are iterated until no agent moves.
7. The pixel occupied by a living agent is considered as a pixel of an object.

Based on this architecture, it can be concluded that the process relies heavily on the iteration to reach consensus / convergence condition. The aim of this method is to make sure that the detected pixel objects are detected as a neighboring group. This is preferable as it conforms the nature of the radiograph topography. As for the drawbacks, this method on the other hands depends on the random agent initialization to reach consensus in the end. This drawback can be handled, however, by limiting the number of allowed iterations.

2.3.2 Fuzzy Logic Based Multi Agent System Approach

By applying the pseudocode in Fig. 2.5, the agents that are initially randomly distributed on the image will wander through the image and calculate the internal feeling and atmosphere based on the membership functions in Fig. 2.6. The immobile agent will reproduce agents for once, so that the number of agents around the immobile agent will grow and the same process might be repeated by the new generated agents. As the stopping criteria are met, the pixels with active agents or immobile agents upon them are labeled as object. The rest of the pixels are labeled as background.

Input: a grey-level digital image of size U_1 X U_2

Output: a segmented digital image of size U_1 X U_2

Initial active agents: $|A| = \frac{|U1 \times U2|}{3}$

Observation area: 20 X 20 pixels

Convergence criteria: No agent moves

prepare a set of **death agents D = {}**

prepare a set of **immobile agents I = {}**

Distribute an initial set of **active agents A = {a}** over the radiograph, one agent every three pixels uniformly

While not convergent **do**

    For each **a** ∈ A do

    a.decide_action(pixel greyvalue, observation area)

    if a.nextAction = **vanish**

        A = A - a

        D = D U {a}

    else if a.nextAction = **diffuse**

        move a to unoccupied lighter pixel within an observation area

    else if a.nextAction = **reproduce**

        reproduce a set of new agents N = {n} in the unoccupied pixels within an observation area

        A = A U N

        a.become_immobile()

        A = A - a

        I = I U {a}

    End if

    End for

End while

All Pixels occupied by immobile agents are **labeled** as **object**

Otherwise, labeled as background

Fig. 2.5. Pseudocode of the proposed multi agent system

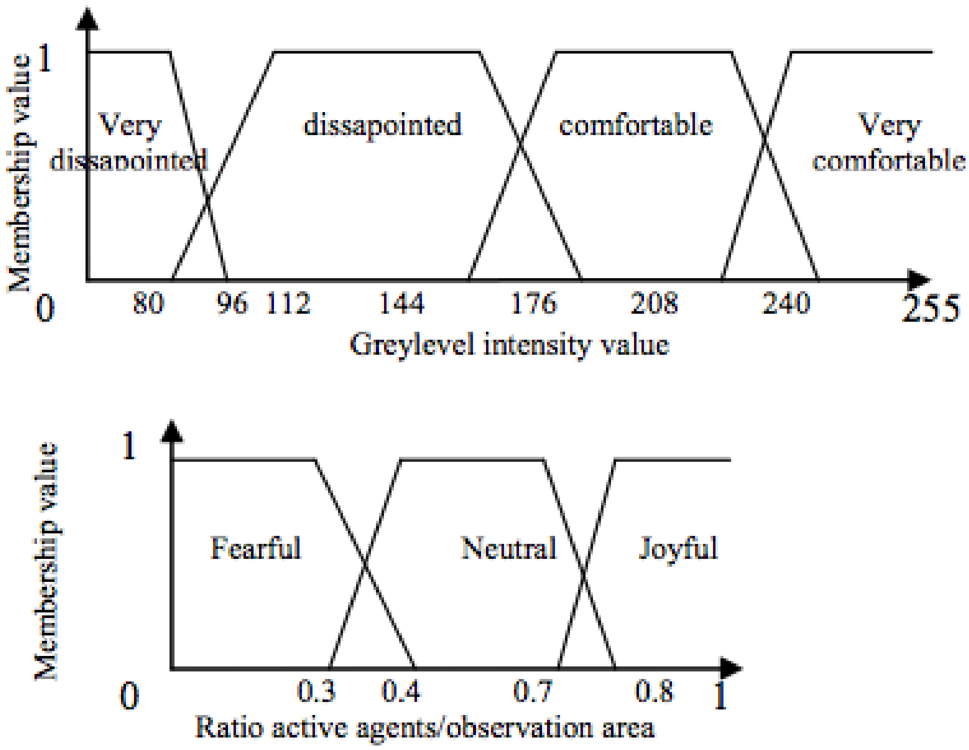


Fig. 2.6. Membership functions for internal feeling (upper) and atmosphere (lower)

Table 2.1. Fuzzy rules and its decisions

if	feeling	operator	atmosphere	Next action
	very disappointed			vanish
	disappointed	and	fearful	vanish
	comfortable	and	joyful	reproduce
	very comfortable			reproduce
	comfortable	and	joyful	diffuse

In order to measure the image segmentation accuracy and efficiency of the proposed approach, experiments are carried out with nine dental X-Ray images from Faculty of Dentistry University of Indonesia. Image segmentation accuracy is measured by comparing the number of pixels that are labeled as object pixels between the proposed approach and the classical multi agent approach. In addition to the accuracy, the efficiency of the proposed approach is measured by comparing the number of iterations needed in order to reach the stopping criteria.

2.4 Performance Measurement by Comparing Iterations and Object Pixels.

The performance of the proposal is quantitatively measured by calculating its iteration needed to segment an image and also the quality of the segmentation by comparing the produced output with the manual segmentation result is presented. The iteration describes the efficiency of the proposal while the accuracy talks about the effectiveness of the proposal to reach the goal to do accurate segmentation.

2.4.1 Iteration Comparison Results

The experiment is done on a PC with AMD Turion X2 2.2 GHz, 3 GB RAM, and Windows XP operating system. The programming language used is Java with Java 2 Platform, Standard Development Kit version 1.4.2. The result is shown in Table 2.2.

The result suggests that the proposed method can distinguish between gum and tooth part with higher accuracy compared with the one that does not use fuzzy logic. The radiograph that is heavily ill-defined and low contrast leads the system into making segmentation error when it attempts to segment between tooth and gum.

To measure the accuracy of image segmentation results and the iteration efficiency to reach stopping criteria of both approaches, numerical comparison is shown in table 2.2 while visual comparison is shown in Table 2.3. The segmentation results of classical multi agent approach yield over segmented image, where there are some cases in which gum is also classified as teeth. On the other hand, the proposed idea overcomes this problem on several cases. Therefore, in order to show the effectiveness, the difference between numbers of pixels labeled as object in classical multi agent system and fuzzy logic based emotional multi agent system are also indicated

Table 2.2. Iteration and the number of segmented pixels.

Image # and Size		Multi agent system (MAS) [10]		Fuzzy logic based Emotional MAS		% O1 – O2
		Σ Iteration	Σ object pixels (O1)	Σ Iteration	Σ object pixels (O2)	
1	149 x 203	13	16755	14	10661	20.14
2	207 x 148	10	20208	10	16245	12.93
3	203 x 148	10	17040	10	14203	9.44
4	204 x 148	10	23015	10	19471	11.73
5	147 x 203	10	20845	10	13982	22.99
6	203 x 146	10	26923	9	20250	22.51
7	202 x 148	10	25891	10	19827	20.28
8	148 x 202	13	20943	13	17898	10.18
9	124 x 115	9	14259	9	11812	17.15
Average		10.55		10.55		16.36
Variance		2.02		3.02		28.92
Standard Deviation		1.42		1.74		5.38

One of the advantages of using these proposed multi agent approaches is no image preprocessing is required. From numerical point of view shown in table 2.2, it is indicated that the proposed approach outperforms the classical approach by 16.36 % in average O1-O2, due to the capability of the proposed approach to distinguish the gum and teeth.

As for the efficiency, it is calculated based on the number of iteration needed in order to reach the convergence of the agents, so that the stopping criteria are met. From the result in Table 2.2, approximately 11 iterations are needed for these test case images. The standard deviations from both approaches are small, which means these multi agent system approaches reach stopping criteria within predictable iterations. Both of the approaches reach the stopping criteria in almost the same number of iteration. Therefore, the proposed idea improves the segmentation accuracy without sacrificing efficiency

Table 2.3 and Table 2.4 show the visual experimental results. Table 2.3 shows the segmentation results between multi agent system approach and fuzzy logic based emotional multi agent system approach. From this comparison, the proposed method shows visual improvement result, where the proposal can distinguish gum and teeth better.

Table 2.4 shows more samples of original radiograph and the segmentation results of the proposal. This table of visual segmentation results complements the numerical result and provides another perspective to inspect the results.

Table 2.3. Example of segmentation results in comparison with multi agent system without the use of fuzzy logic.

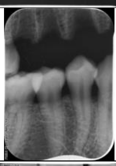
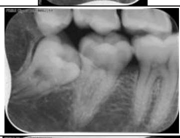
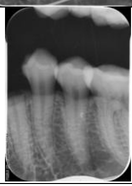
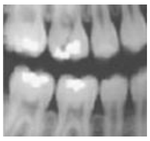
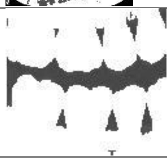
#	Original image	Multi agent system (MAS)	Fuzzy logic based Emotional MAS
1			
2			
3			
4			
5			
6			
7			
8			
9			

Table 2.4. Samples of original radiograph and the segmentation results of the proposal respectively.

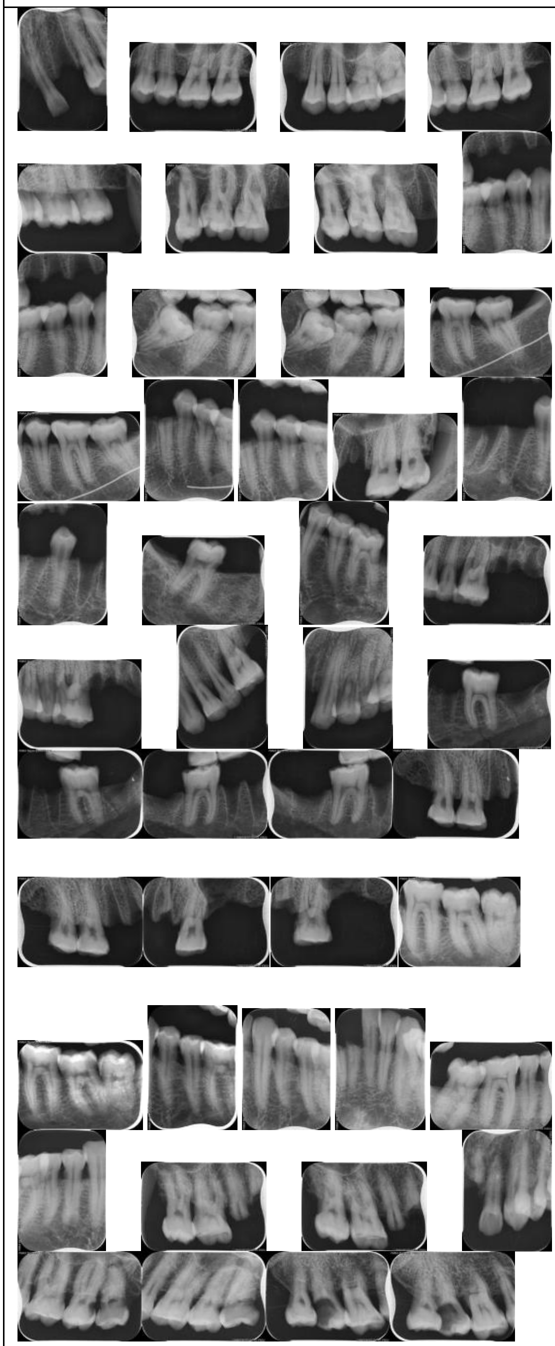
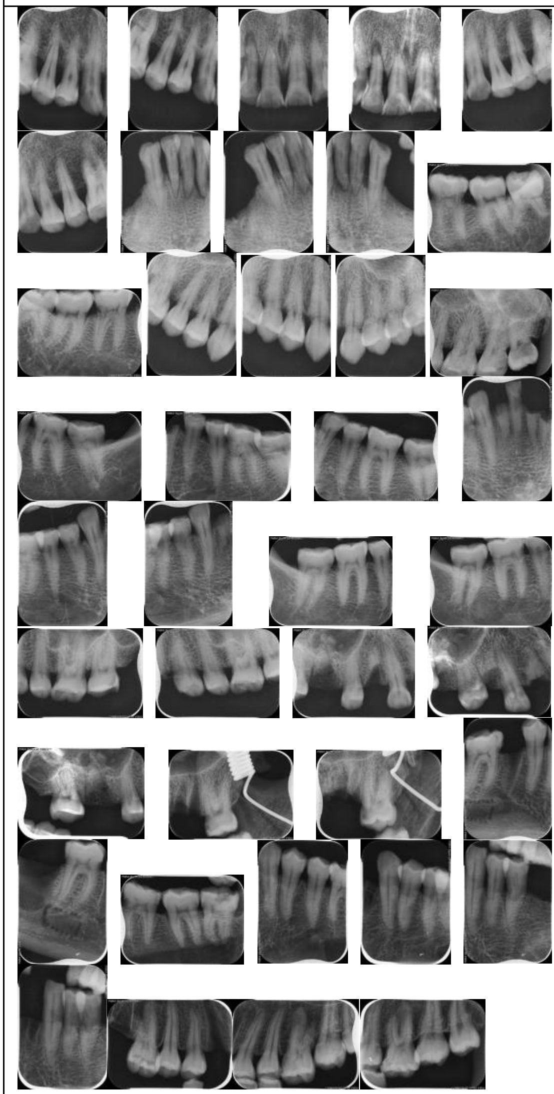
Original	Fuzzy Logic Emotional Multi Agent System
	

Table 2.4 (cont.). Samples of original radiograph and the segmentation results of the proposal respectively.

Original	Fuzzy Logic Emotional Multi Agent System
	

2.4.2 Statistical Performance for Segmentation Accuracy

The segmentation accuracy of the proposal is measured by comparing it with the manual segmentation result done by hand. The manual segmentation result is considered as a reference with 100% accuracy. Therefore, in order to measure the accuracy, the method used is image subtraction between the produced segmentation result automatically by the proposal and the manual segmentation result.

The compilation of the segmentation quality in quantitative measurement is provided in Table 2.5. In this table, the average, standard deviation, maximum, and minimum accuracy spread on 122 data are measured. In addition to the previous numerical data, the average error of false positive error and false negative error are calculated and the results are presented in Table 2.6.

Table 2.5. Statistical data of accuracy

	Multi-agent
Average (%)	71.91
Standard Deviation (%)	9.28
Maximum (%)	89.37
Minimum (%)	32.59

Table 2.6. False Positives-False Negatives Error (FPE and FNE)

	Multi-agent	
	FPE	**FNE**
Average error (%)	14.54	13.53
Maximum (%)	62.46	45.76
Minimum (%)	3.51	2.11

In order to show the spread of the accuracy of the system relative to each segmentation result, Fig. 2.7 serves the factual accuracy result. It is marked that more than 50% of the data are segmented with accuracy more than 70%. In addition to that, around 25 images are successfully segmented with accuracy more than 80%. This proves the feasibility of the method and leads the conclusion that the use of intensity and neighboring pixels is sufficient for pixel based segmentation in this domain problem as will be shown in chapter 3.

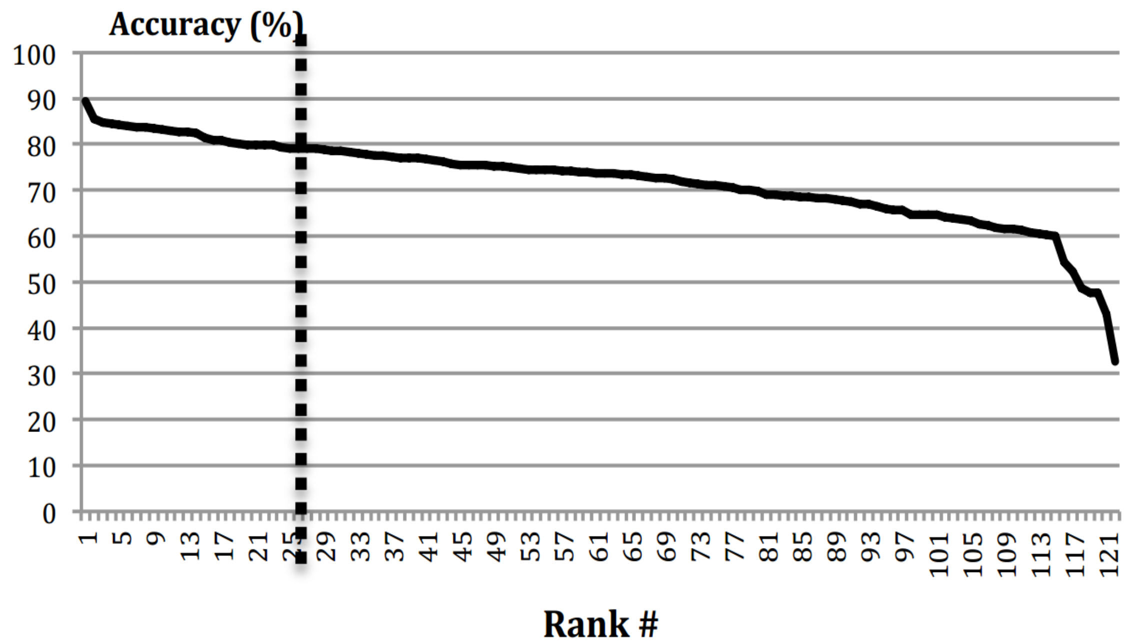


Figure 2.7. The Accuracy of Fuzzy Logic based Emotional Multi Agent's Segmentation Results Sorted Descending. The dotted line shows its accuracy is below 80% on the specific rank

2.5 Chapter Summary

The outcome of this research shows the capacity of fuzzy logic based multi agent system approach to accomplish dental image segmentation. The points confirmed from the experiment results are as follows:

1. It is indicated that the proposed approach outperforms the classical approach by 16.36 % in average due to its capability to distinguish gum and teeth.
2. The interaction among agents and pixels enables gradual segmentation, which is expected to improve the visual quality and accuracy of segmentation, especially in the setting of gradual uneven contrast in the radiograph.
3. Emotional model enables interaction among agents with their terrains (pixels) and takes actions to simulate the exploration of the pixels in the image.
4. Simulation based segmentation requires some iterations before converge (the situation where no agent moves).
5. The feasibility of the segmentation using this proposal confirms the use of mean and variance of the pixel values. This study gives a valuable insight for the next proposal, multiscale image aggregation.

The result suggests that the proposed method can distinguish between tooth part and other parts. The result also suggests that the proposed multi agent system approach is able to cope with gradual changes of pixel values in the gray area of the radiograph and makes segmentation based on the group of pixels.

Chapter 3

Multiscale Image Aggregation for Dental Radiograph Segmentation

The framework for automatic dental-based personal identification system consists of two main processes: dental segmentation and dental matching (shown in Fig.3.1). The present work focuses on the dental segmentation process, as the dental matching will be the focus of future work.

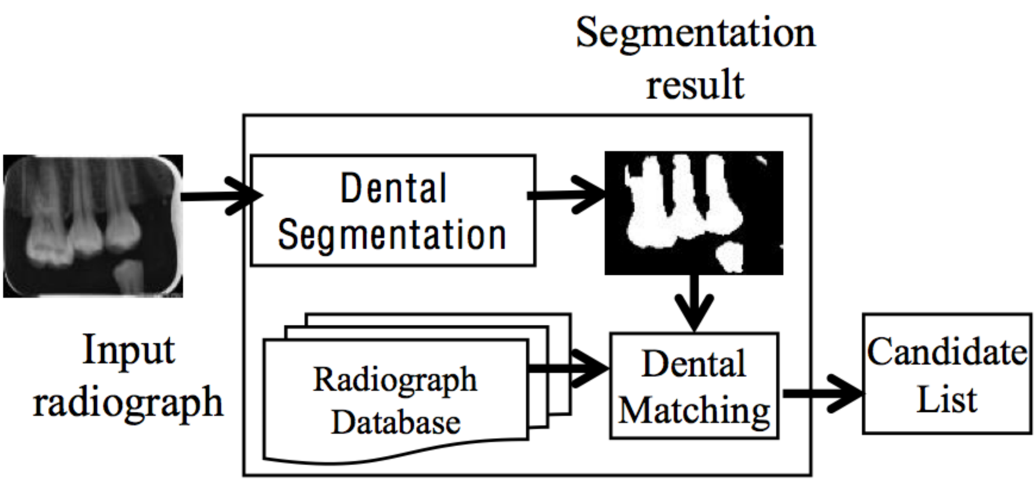


Fig. 3.1. General scheme of dental-based personal identification system and location of dental segmentation.

3.1 Outcome from Pixel Based Segmentation

The previous research done on pixel based segmentation using multi agent system approach gives insight on the next level challenges that lead to the improvement of the next method called multiscale image aggregation that is explained in this chapter.

3.1.1 Outcome from Multi Agent System Approach

The previous research on fuzzy logic based multi agent system approach presented an alternative to enable dental segmentation using the intensity information of the pixel. Moreover, this research also gives insight that mean and variance of the neighboring pixels are useful as well since they state the gradual change of grayness that implies different area/cluster in the radiograph.

This outcome is indeed valuable as will be shown in the subsequent, that this approach leads the improvement by the creation of the introduced method in this chapter, multiscale image aggregation. Some issues that need to be addressed are the iteration of multi agent system approach that lowers down the efficiency of the segmentation. To sum up, the outcome of the multi agent system approach leads to the improvement on pixel based segmentation approach, which is explained in the next subsequence.

3.1.2 Improvement on Pixel Based Segmentation Approach

The problems arise from the multi agent system approach are as follows:

1. This approach needs non-uniform iterations to reach convergence (in this case,

this means segmentation process for the same size of image may take different time)

2. The process of interaction among agents takes computing resource.

In order to deal with those mentioned problems, another method called multiscale image aggregation that employs several scaled-down images is proposed. The explanations are ordered from the idea, implementation, and the experiments..

3.2 Idea of Multiscale Image Aggregation

Dental radiograph segmentation refers to the process of partitioning a dental X-ray radiograph into teeth and background parts by assigning a label to every pixel of the radiograph. This process aims to simplify the representation of an image [12]. In terms of application, dental radiograph segmentation is a sub-module of automatic dental-based identification system, since the segmented teeth is used in the further stage of shape matching process for identification. It is shown that the identification rate of missing people with dental records is higher [1]. As a starting point, an accurate segmentation method is necessary to improve the recognition rate of the automatic dental-based identification system [2, 3, 4].

Segmentation of dental radiograph, however, is challenging because of radiograph characteristics [5,13] such as overlapping teeth, unclear boundaries between a tooth and its surroundings, topological change and branches of the tooth contour in root and crown regions, size variation, and noise due to limitation of the radiation dose, suffering from low contrast, and uneven exposure. These problems make finding the threshold value between teeth and background difficult. Consequently, the gum-pixel may be frequently misclassified as tooth and conversely, which decreases the accuracy of segmentation.

Multiscale image aggregation (MIA) is proposed to overcome the mentioned challenges. This method downscales the input radiograph into 50%, 25%, and 12.5% of its original size and statistically analyzing the pixel's intensity value, the pixel and its neighbors' mean intensity, and intensity variance. The results of this statistical analysis are used as parameter values of dynamic membership functions depending on the intensity distribution of the radiograph. After applying pixel based image segmentation using fuzzy inference to each radiograph, the segmentation results from various sizes are rescaled back to original size and aggregated into a single output image. This single output image is segmented by setting a threshold value.

MIA minimizes the error probability of oversegmentation by taking into account the neighboring pixels and reduces undersegmentation by aggregating the segmentation result from various scales of segmentation results. In order to quantify the segmentation accuracy, each segmentation result is compared with the manual segmentation result. The manual segmentation result is done manually by the author and is assumed it has 100% segmentation accuracy. The experiment is done on all 122 radiographs provided by the Faculty of Dentistry University of Indonesia for this research that contains periapical and bitewing view that is widely used by dentist or forensic. The experiments show that the proposed method increases the accuracy of segmentation and its statistical significance is confirmed by t-test. As for the environment setting, the experiment is done in a Windows 7 environment and MIA is implemented in Matlab 7.9.0.529.

3.3 Implementation of of Multiscale Image Aggregation

The implementation of Multiscale image aggregation (MIA) is explained from the way the radiograph is represented in a matrix, statistical test during the preliminary phase, and finally, the construction of the algorithm itself In order to prove the feasibility and improvement, comparison is done during the experiment with t-test..

3.3.1 Dental Radiograph Representation and Multiscale Image Aggregation

Automatic dental-based personal identification system takes radiograph as an input and matches the pattern of teeth to the radiograph database in order to find the candidate identities of the input radiograph as shown in Fig. 3.1. This identification process requires dental segmentation process, the focus of this research, to extract the shape of the teeth. Technically, dental segmentation works as the first sub-process as presented in [5].

The dental radiograph is a digital image of the teeth (tooth), bones, and surrounding soft tissues that is formed by a controlled discharge of X-ray radiation [6]. The radiograph is a digital gray scale image, where each pixel has a value ranging from 0 (black) to 255 (white). Formally, a dental radiograph R with size M X N can be represented as a matrix of intensity

$$R=\begin{bmatrix} i(1,1) & i(1,2) & \dots & i(1,N) \\ i(2,1) & i(2,2) & \dots & i(2,N) \\ . & . & & . \\ . & & . & . \\ . & & & . \\ i(M,1) & i(M,2) & \dots & i(M,N) \end{bmatrix}, \quad (1)$$

where i(x,y) = {0, … , 255}, for $1 \le x \le M$ and $1 \le y \le N$.

As a matrix, basic matrix operations such as addition, subtraction, multiplication, etc. can be applied on R as a part of image processing. One of the most crucial concepts in analyzing the composition of pixels' intensities is a neighborhood block consisting of its neighboring pixels. A pixel's neighborhood is a set of surrounding pixels defined by their relative location to a pixel called center pixel. The neighborhood block used for this study is a 3 X 3 rectangular block as shown in Fig. 3.2, the center pixel is denoted with black dot.

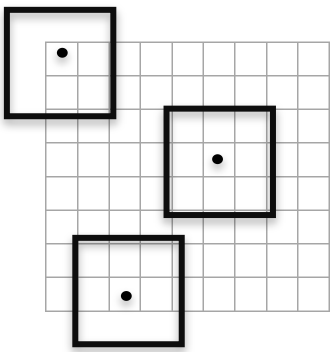


Fig. 3.2. 3 X 3 neighborhood blocks in a matrix

Given any matrix, the variance and mean of intensities of all 3 X 3 blocks is calculated as follows:

1. Select a single pixel (x,y) as a center pixel.
2. Determine its neighborhood.
3. Apply a function to calculate the mean and variance of corresponding block. The obtained mean and variance are stored in the matrices of mean and variance respectively.
4. Repeat steps 1-3 until all the pixels of the radiograph have been processed.

The functions used for dental radiograph segmentation are averaging and variance functions. As the results are obtained from these functions, they are stored in the output matrices of average and variance respectively.

3.3.2 Statistical Test and Multiscale Image Aggregation

The goal of dental radiograph segmentation is to classify the image into teeth and background areas. In the pixel-based segmentation, this goal can be achieved by deciding whether a pixel belongs to a tooth or background. Since the parameters of mean and variance of input radiograph are used in the fuzzy inference based image segmentation, Wilcoxon test [14] is necessary to prove the capability of the use of these parameters to separate the background, gum, and teeth of the image. Therefore, statistical test on intensities is done.

The test is done by sampling small size images from background, gum, tooth, and special case overlapping teeth (shown in Fig. 3.3). From visual inspection, it is shown that white pixel can be associated with tooth, black with background, and striped white-black with gum.

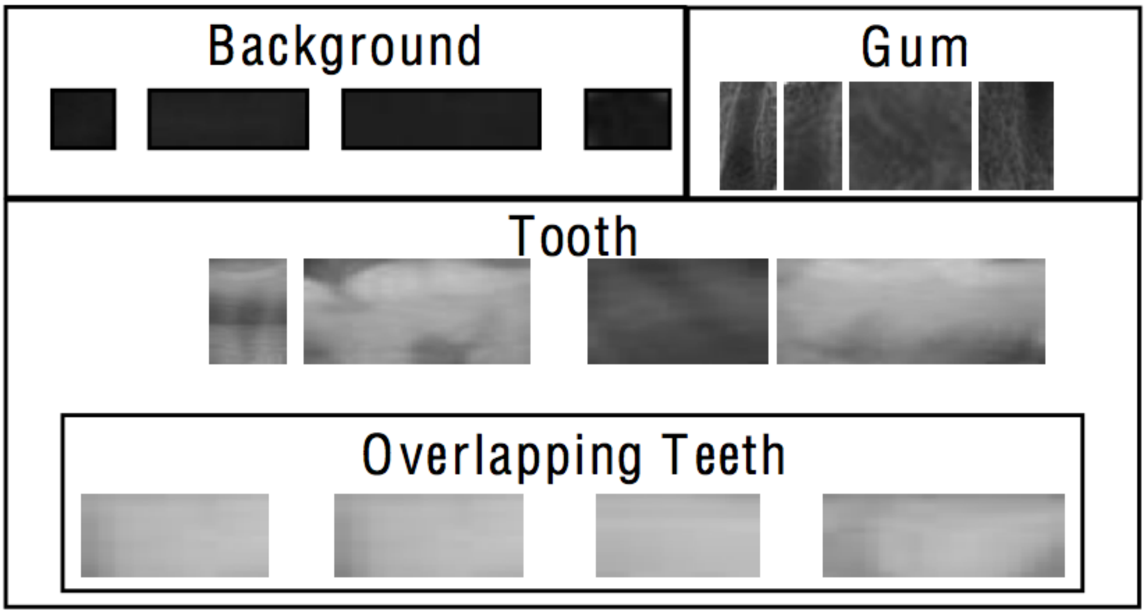


Fig. 3.3. Texture samples of background, gum, tooth, and overlapping teeth

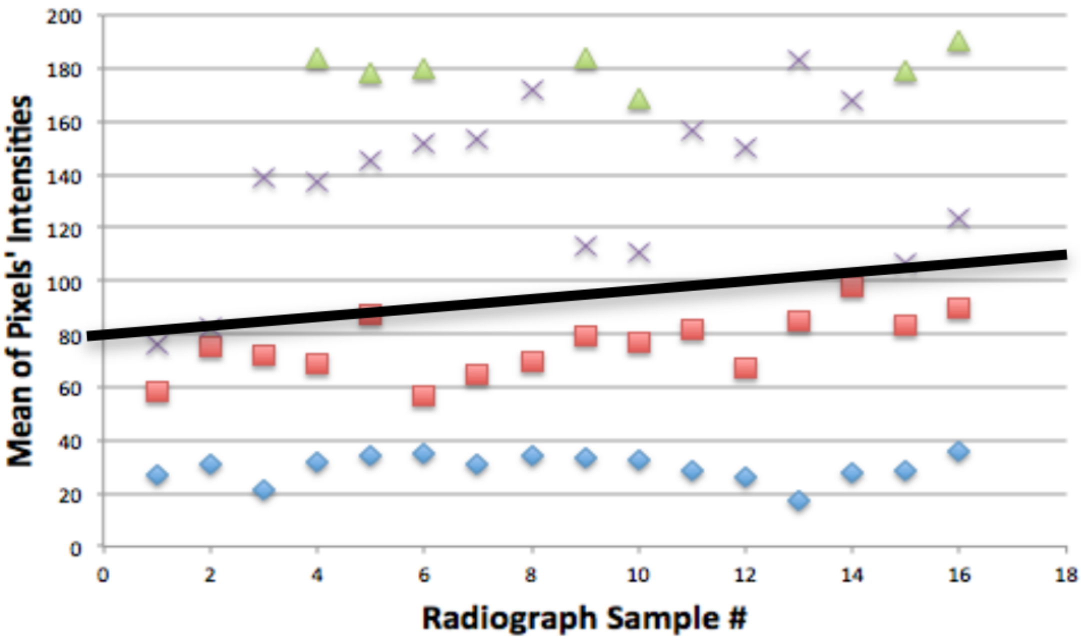


Fig. 3.4. (cont.) Plot of means & variances of pixel's intensities from samples of background, gum, tooth, and overlapping tooth. The separations are shown with bold lines. These diagrams show separabilities between teeth and non-teeth area

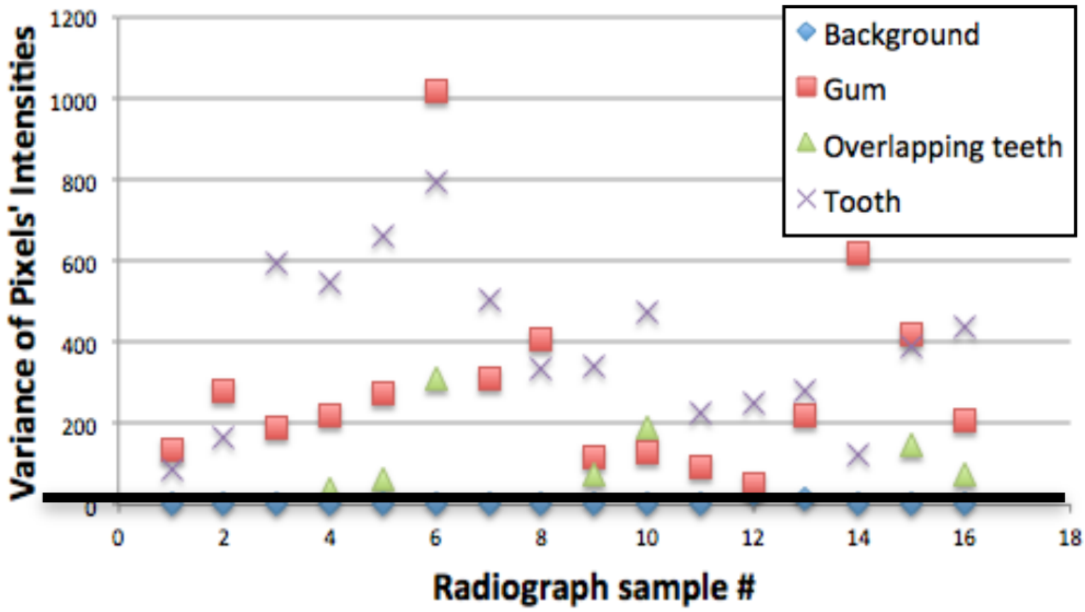


Fig. 3.4. Plot of means & variances of pixel's intensities from samples of background, gum, tooth, and overlapping tooth. The separations are shown with bold lines. These diagrams show separabilities between teeth and non-teeth area

The Wilcoxon test is done on 16 representative samples of dental radiographs. The background, gum, and tooth area of each radiograph is sampled (shown in Fig. 3.3). Based on Wilcoxon test, it has been shown that the background area and non-background area (gum, tooth, and overlapping tooth) are separable using the mean and variance of intensity through the rejection of the null thesis (shown in Fig. 3.4). Meanwhile, the gum and tooth are only separable using mean of intensity. Based on this result, the mean and variance are used as decisive parameters in the fuzzy inference for pixel based segmentation. Besides these two parameters, the individual pixel value is also taken into account in the fuzzy inference.

After the test is done, the general scheme of Multiscale Image Aggregation is constructed. in general, the three steps used in this radiograph segmentation are: image rescaling, segmentation process, and images aggregation. The architecture of this method is shown in Fig. 3.5 and its explanation is presented in the sequel.

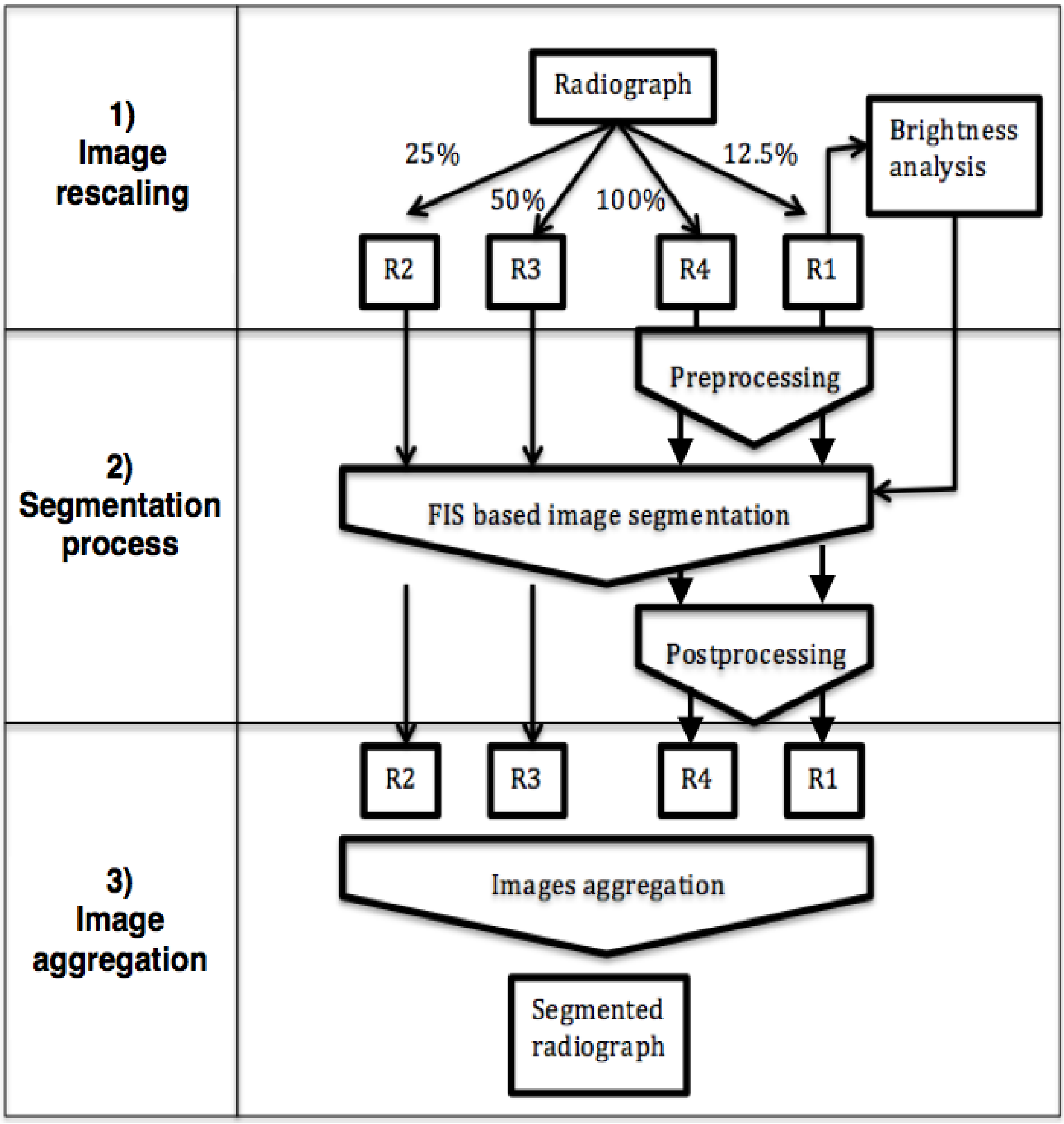


Fig. 3.5. Multiscale image aggregation algorithm for dental radiograph

3.3.3 Image Rescaling using Nearest-Neighbor Interpolation

The input radiograph is copied and rescaled into four radiographs of 100%, 50%, 25%, and 12.5% of its original size (shown as R4, R3, R2, and R1 respectively in Fig. 5). The brightness analysis is done to obtain the value of three quartiles. The purpose of rescaling the input radiograph into smaller radiographs is to minimize unimportant details that exist in the input radiograph. Image rescaling is known to decrease the detail of the image (often associated with decreasing the image quality), but for this purpose, this rescaling feature is utilized to ignore the unimportant details such as noise. Thus, it increases the whole segmentation result after all the rescaled radiographs are aggregated.

The rescaling factors 100%, 50%, 25%, and 12.5% are chosen based on the consideration of computational complexity. By halving the size on the next radiograph, the computational complexity will be reduced into 25% of the previous bigger size since the complexity of segmentation this algorithm is quadratic. The relations are shown in Table 3.1 and Fig. 3.6 through experiments on 18 representative radiographs. Based on this advantage and the fact that image calculation is computationally expensive, therefore the rescaling factors 100%, 50%, 25%, and 12.5% is chosen.

Since the complexity of image calculation is quadratic, any x% size-reduction from the original image means $(x\%)^2$ complexity reduction. The complexity factor in the Table 3.1 is obtained by adding $(R1)^2 + (R2)^2 + (R3)^2 + (R4)^2$.

The radiograph rescaling method uses Nearest-neighbor interpolation, a method for approximating the value for a non-given point in some space by selecting the value of the nearest point given from points around that point. This algorithm interpolates proportionally to the scaling factor on the basis of the nearest single point (using the same value of the single point). Since the process of rescaling an image changes almost all of the pixels' position, a value approximation for each affected pixel is interpolated.

Table 3.1. Comparison among down-scaling, complexity factor, and accuracy. The bold one is the proposed down-scaling factor.

Down-scaling factors				Complexity factor	Accuracy (%)
R_1	R_2	R_3	R_4		
1	0.3	0.15	0.075	1.118125	83.114
1	0.3	0.2	0.1	1.14	83.457
1	0.4	0.2	0.1	1.21	83.755
1	**0.5**	**0.25**	**0.125**	**1.328125**	**84.419**
1	0.6	0.3	0.15	1.4725	84.365
1	0.6	0.4	0.2	1.56	84.397
1	0.7	0.4	0.1	1.66	84.518
1	0.6	0.5	0.4	1.77	83.639
1	0.7	0.5	0.3	1.83	83.864
1	0.75	0.5	0.25	1.875	84.591
1	0.8	0.5	0.2	1.93	85.014
1	0.9	0.5	0.1	2.07	85.268
1	0.8	0.6	0.4	2.16	83.601
1	0.9	0.6	0.25	2.2325	84.44
1	0.85	0.7	0.4	2.3725	83.474

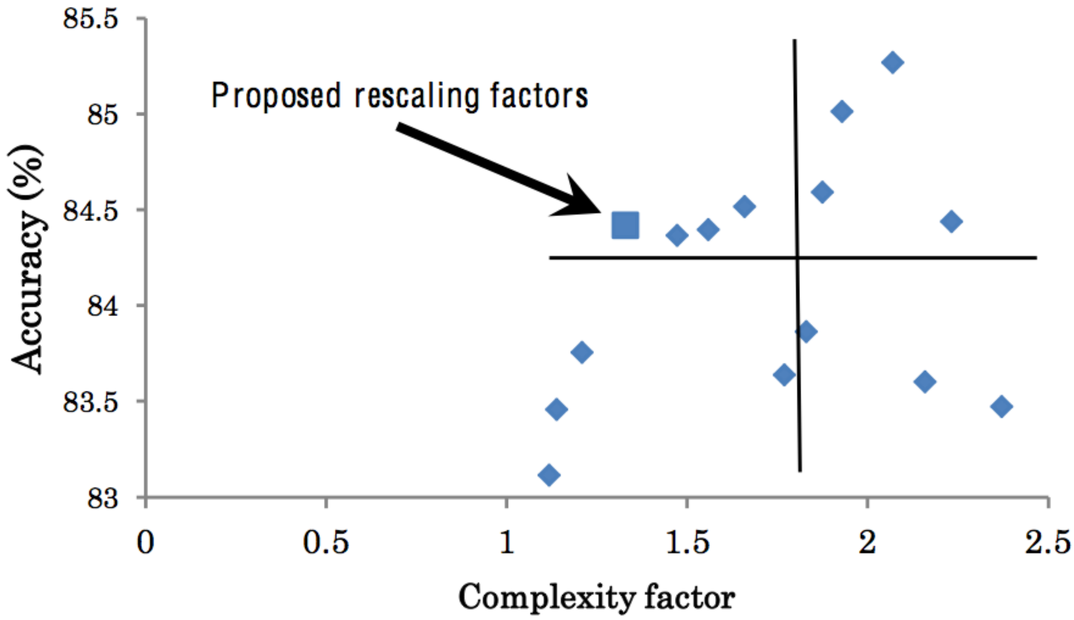


Fig. 3.6. Proposed rescaling factor shown in terms of accuracy/complexity

Two radiographs are preprocessed (R1 and R4 in Fig. 5) using adaptive local contrast [15] and adaptive histogram equalization [16] in order to increase the clarity of the boundary on the radiograph.

3.3.4 Fuzzy Inference for Teeth Segmentation

Fuzzy inference is constructed for deciding pixel's belonging to the tooth or background area. Since the contrast level distributions vary among radiographs, an automatic parameter tuning for building an adaptive membership function is needed so that the proposed method can deal with different contrast levels among radiographs. Following the automatic parameter tuning, fuzzy rules are applied to classify the input pixel.

Automatic Parameter Tuning for Membership Function

The parameters for membership function are decided by the statistical variables of three quartiles, Q1, Q2, and Q3. Q1, Q2, and Q3 representing the 25th, 50th, and 75th percentile of R1's (25% size of the original input radiograph) pixel intensities respectively. The values of Q1, Q2, and Q3 are used to determine the low, medium, and high value of pixel intensity and mean intensity. In this fuzzy inference, a trapezoidal fuzzy membership function is used, with formula

$$\mu\ \ (x,a,b,c,d) = \begin{cases} 0, & x \le a, x > d \\ \dfrac{x-a}{b-a}, & a < x \le b \\ 1, & b < x < c \\ \dfrac{d-x}{d-c}, & c < x \le d \end{cases} \quad , (2)$$

Where x, a, b, c, and d are real numbers.

Define IQR = Q3 - Q1 as interquartile value, the values of a, b, c, d for μ_low, μ_med, μ_high are shown in Table 3.2. By using the variable of quartile and interquartile, the automatic parameter values can be adjusted for each different radiograph.

Table 3.2. Parameters for membership functions of pixel and mean intensity

Parameters	$\boldsymbol{\mu_{low}}$	$\boldsymbol{\mu_{med}}$	$\boldsymbol{\mu_{high}}$
a	0	$Q_1 + \frac{1}{8}IQR$	$Q_1 + \frac{5}{8}IQR$
b	0.1	$Q_1 + \frac{3}{8}IQR$	$Q_1 + \frac{6}{8}IQR$
c	Q_1	$Q_1 + \frac{5}{8}IQR$	255
d	$Q_1 + \frac{1}{4}IQR$	$Q_1 + \frac{7}{8}IQR$	256

As for the variance membership functions, since the variance value does not vary, an automatic parameter tuning is not needed. Therefore, the values of trapezoidal membership functionsμ_low, μ_med, μ_high of variance are predetermined as shown in Table 3.3.

Table 3.3. Parameters for membership functions of variance

Parameters	μ_{low}	μ_{med}	μ_{high}
a	0	10	700
b	0.1	30	1000
c	1	700	5020
d	20	1000	6360

The values in Table 3.3 are obtained from statistical test done on the sample parts of background, gum, and tooth. Variance is used for assessing the degree of contrast in an area, where the value can be used to classify a pixel.

Fuzzy Rules for Dental Radiograph Segmentation

Fuzzy rules are constructed for each pixel, by extracting three values: pixel intensity, mean intensity, and variance intensity. The value of mean and variance are calculated from the value of its pixel and its 3 X 3 neighboring pixels as explained in Fig. 3.2. The fuzzy rules are shown in Table 3.4.

Table 3.4. Fuzzy rules for dental radiograph segmentation

	Intensity		Mean		Variance		Output
If	LOW	and*	LOW	and*	LOW	Then*	BG
	MED	or*	MED	or*	MED		GUM
	HIGH	and*	HIGH	and*	HIGH		TOOTH

*)and, or, and then refers to T-Norm, T-Conorm, and implication in fuzzy logic concept

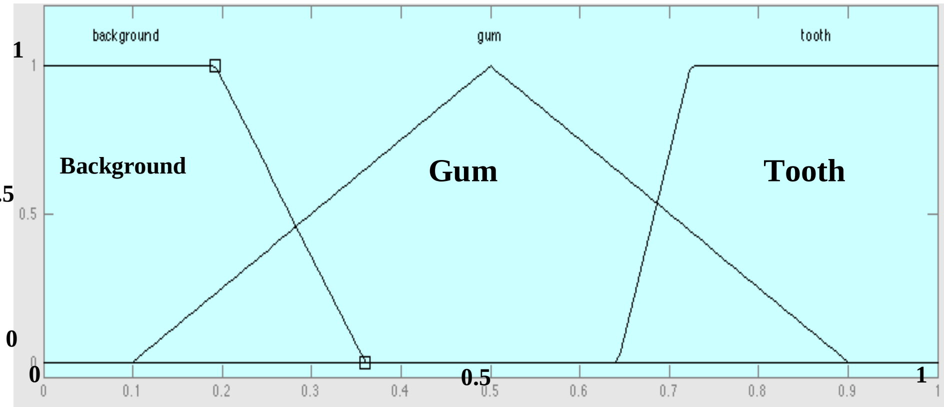


Fig. 3.7. Membership functions of output variable

The output value is then calculated using center of gravity method. If the value is larger than 0.58, the corresponding pixel is classified as tooth-pixel. Otherwise, the pixel is classified as background. This process is done for all of the pixels of the radiograph.

The membership functions of output variable and the chosen threshold value are obtained from experiments that reach the most optimal result.

Gap Filling and Small Objects Removal

After each pixel has been classified either as background or tooth, still there are some noise disperses on to the radiograph causing misclassification due to its dominant brightness level compared to the surrounding. This situation yields an isolated small group of misclassified pixel to the surrounding. In order to deal with this problem, a gap-filling algorithm is employed to remove the tooth part that is misclassified as a background. Gap-filling algorithm works in the binary image using flood-fill operation on background pixels with certain pixels connectivity [17].

After the gap has been filled, however, the segmentation results sometimes contain small-misclassified pixels as tooth on the background area. In order to deal with this issue, morphological opening is applied to the image in order to remove connected pixels that are fewer than predetermined number of pixels. By applying these two methods, the segmented radiograph is classified into two large areas comprising of teeth and background.

Output Aggregation and Final Segmentation Result

Output aggregation is taken from four different sizes of the segmented radiographs (binary image format). The segmented radiographs with size 12.5%, 25%, and 50% are resized back to their original sizes using nearest-neighbor interpolation. Along with the original size segmented radiograph, the rest three segmented radiographs are averaged in order to get the aggregated result of input radiograph (shown in Fig. 3.8). The aggregation of the four radiographs is a summation of the four matrices (also shown in Fig. 3.8), after that each element of the matrices output is divided by a scalar value 4 in order to get the average value of each element of the matrix. Since the aggregated result of binary images is a matrix with each element has a value ranging from 0 to 1. Then a threshold value 0.5 is applied to this radiograph in order to get the final result. The pixel that has value above 0.5 is considered as a tooth pixel. In experiment, the segmentation using Otsu method [18] is also applied and the result is presented in Table 3.7.

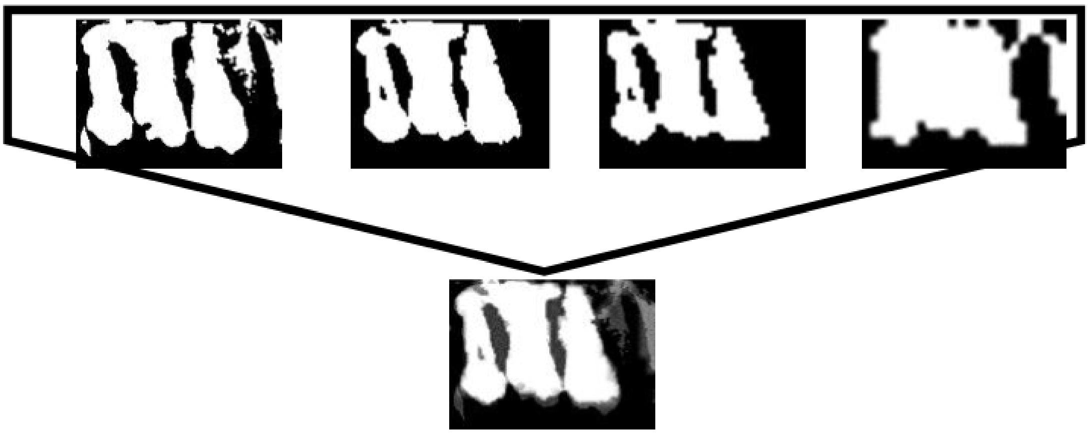


Fig. 3.8. Aggregation results from four various image sizes

3.4 Experiments with 122 Dental Radiographs

In order to test the capabilities and improvement of the proposed method, experiments with 122 dental radiograph from the faculty of dentistry University of Indonesia are conducted.

To measure quantitatively, the segmentation accuracy is measured from statistical point of view where several statistical measurements such as average, standard deviation, and p-value are used.

3.4.1 Segmentation Accuracy of MIA

The accuracy of segmentation results from the proposed method is validated by comparisons with manually segmented results. A sample of a manually segmented radiograph is shown in Fig. 3.9.

Fig. 3.9. Radiograph and its manual segmentation result

The manual segmentation is done by marking the tooth area on the radiograph [7]. By having it manually segmented, the accuracy rate can be quantified. The evaluation method is calculated by subtracting the manual segmentation result with the segmentation result of the proposed method. Specifically, the subtraction is the absolute difference between two corresponding pixel values. From the mathematical point of view, this process is a subtraction of matrices. An example of the evaluation result is shown in the Fig. 3.10.

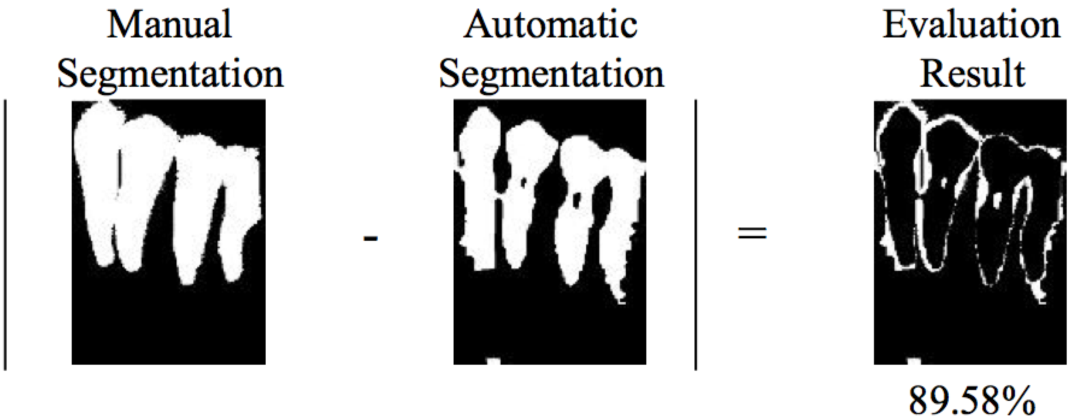


Fig. 3.10. Evaluation method to calculate accuracy. The accuracy is ratio of black area to image size of the evaluation result

Segmentation Results of Radiograph

The segmentation results are obtained by using 122 input radiographs from University of Indonesia consists of periapical radiographs (Fig. 3.11). The sizes of the radiographs vary within approximately 150 X 200 pixels. The method is implemented using Matlab 7.9.0.529 in a Windows 7 PC with Intel Pentium core 2 duo 2.53 GHz and 2 GB RAM. As for the result, the proposed method reaches up to 77.7% accuracy in average. The segmentation performance of MIA is shown in Table 3.5.

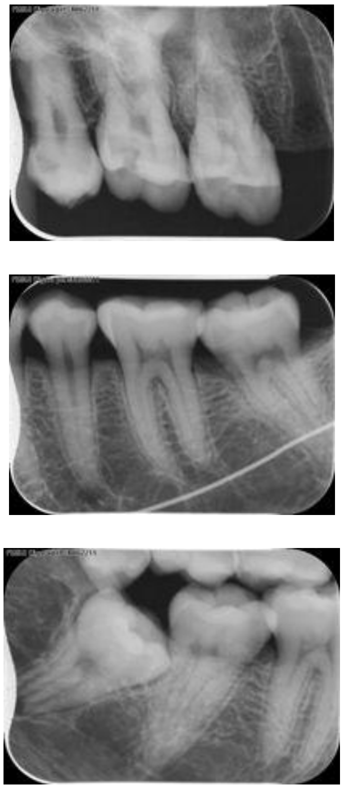


Fig. 3.11. Sample of dataset from University of Indonesia

The misclassification is broken down into false positive error (the percent of area reported as a tooth by the algorithm, but not by manual segmentation) and false negative error (the percent of area reported by manual segmentation, but not by the algorithm). These misclassifications are shown in Table 3.6. The five most accurate segmentation results by MIA are shown in Table 3.7. Based on the experimental results, although MIA does not reach the perfect accuracy, the consistency shown in the segmentation results makes this method suitable as a supporting module of dental-based identification system, which are being developed.

Table 3.5. Statistical data of accuracy

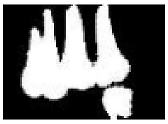
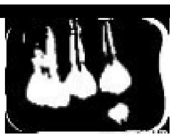
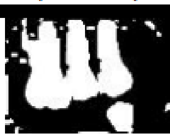
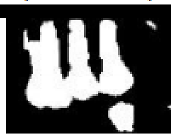
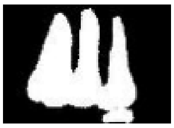
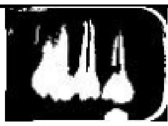
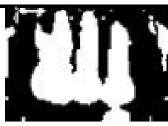
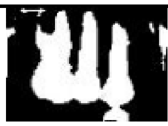
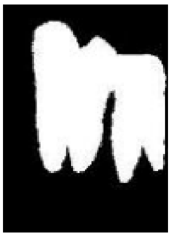
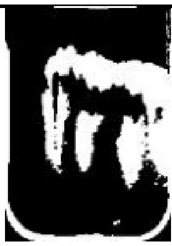
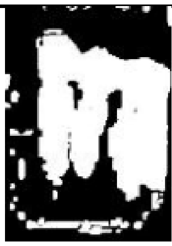
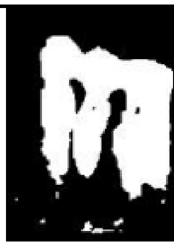
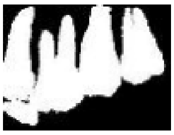
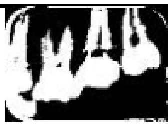
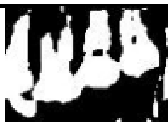
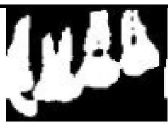
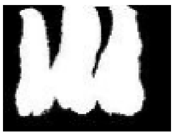
Radiograph	**Manual**	**Otsu**	**MIA (T=0.5)**	**MIA (T=Otsu)**
		 Acc = 77.58%	 Acc = 89.42%	 Acc = 92.02%
		 Acc = 80.07%	 Acc = 89.19%	 Acc = 90.85%
		 Acc = 74.69%	 Acc = 87.94%	 Acc = 91.16%
		 Acc = 81.06%	 Acc = 87.49%	 Acc = 87.09%
		 Acc = 84.05%	 Acc = 87.47%	 Acc = 88.42%

Table 3.6. False positives – false negatives' error (FPE – FNE)

	Otsu		**MIA*)** (T=0.5)		**MIA*)** (T=Otsu)	
	FPE	**FNE**	**FPE**	**FNE**	**FPE**	**FNE**
Average (%)	15.62	11.92	16.46	8.35	12.29	9.99
Max (%)	60.17	46.68	51.62	24.58	42.15	24.53
Min (%)	2.77	1.71	1.56	0.9	4.21	1.05

Table 3.7. Top 5 segmentation results for MIA (T=0.5)

	Methods		
	Otsu	**MIA*)** (T=0.5)	**MIA*)** T=Otsu)
Average (%)	72.44	75.17	**77.70**
Std Dev (%)	9.98	10.92	9.37
Maximum (%)	90.5	89.42	**92.02**
Minimum (%)	33.36	**45.29**	43.55

*) MIA: Multi Image Analysis; T: Threshold value

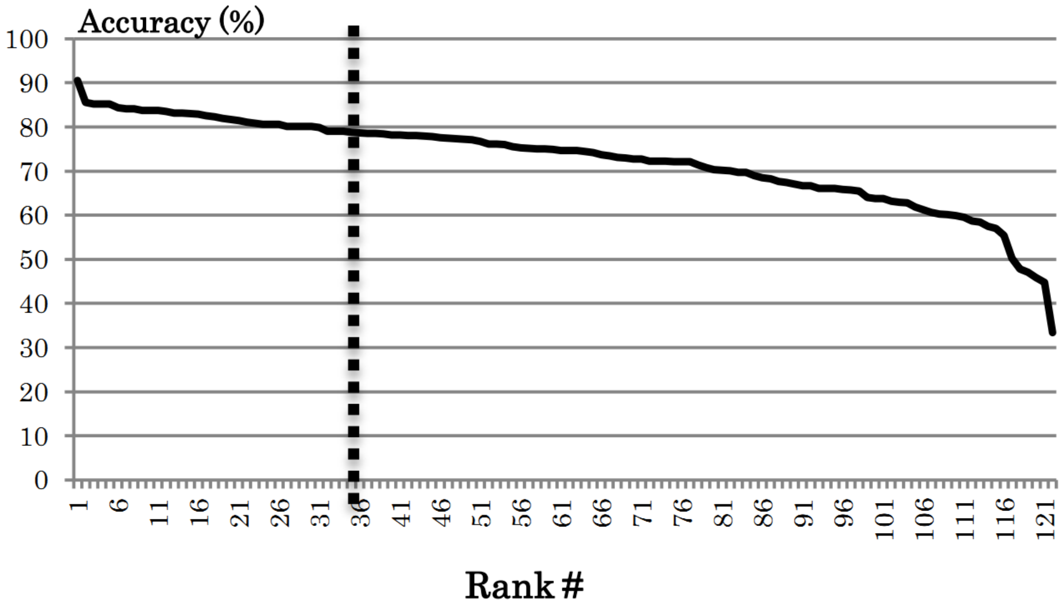


Fig. 3.12. The accuracy of Otsu method segmentation results sorted descending. The dotted line shows its accuracy is below 80% on the specific rank.

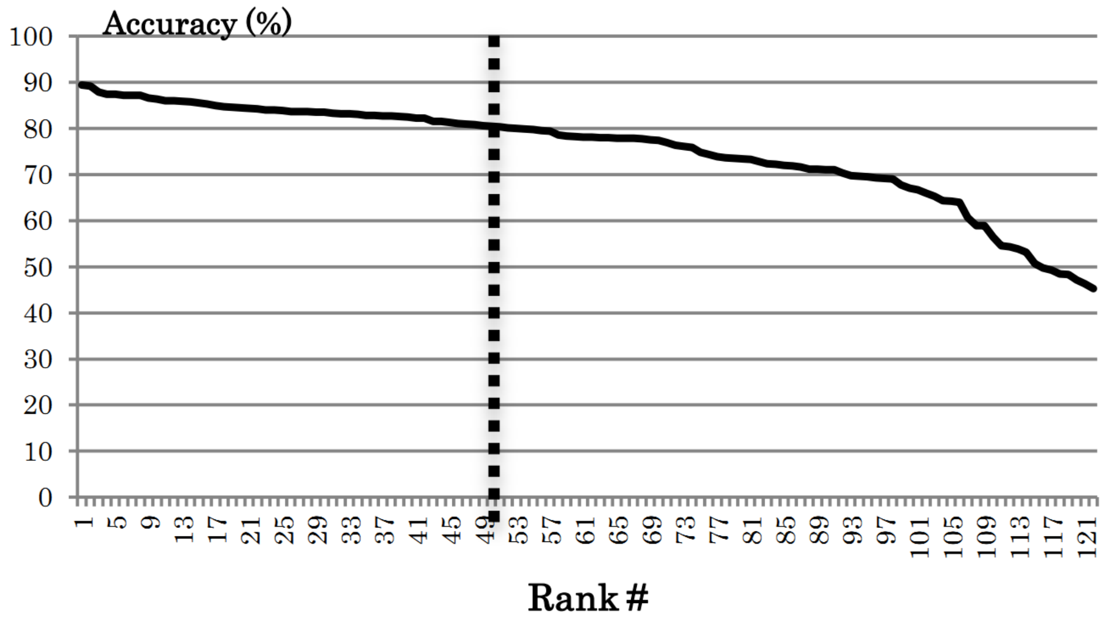


Fig. 3.13. The accuracy of multiscale image aggregation's segmentation results with threshold = 0.5, sorted descending. The dotted line shows this method successfully segment the radiograph above 80% for almost half of the dataset.

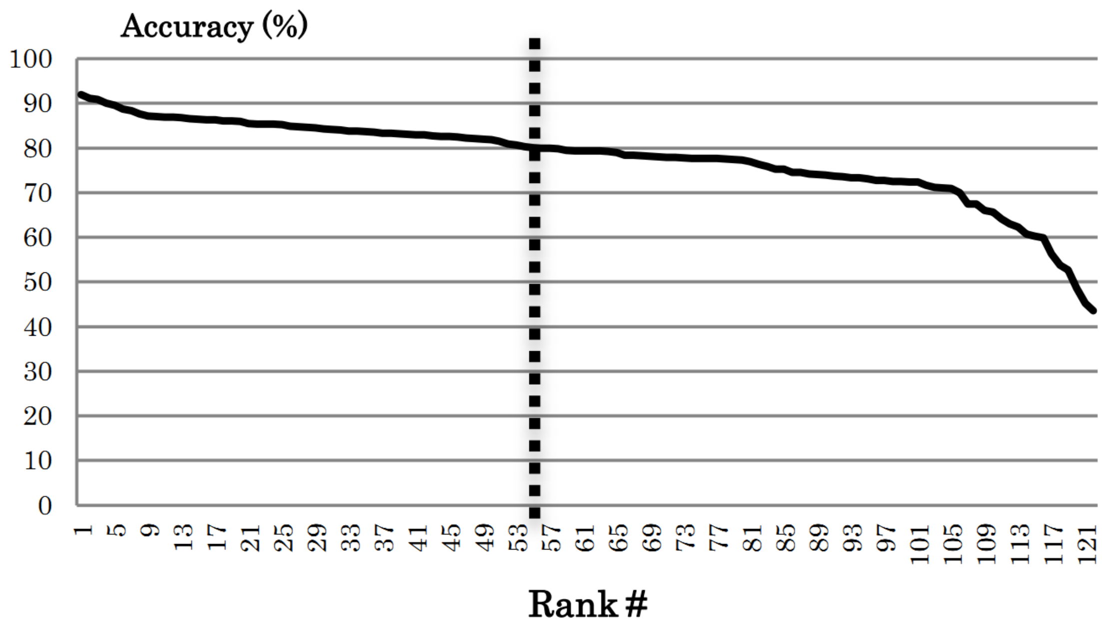


Fig. 3.14. The accuracy of multiscale image aggregation combined with Otsu method segmentation results sorted descending. The dotted line shows the proposed method successfully segment the radiograph above 80% for more than half of the dataset.

Figs. 3.12 – 3.14 show the improvement of the accuracy segmentation results sorted by accuracy. The multiscale image aggregation using Otsu thresholding method yields more than 80% accuracy for more than half of the dataset. The box plot visualization of the segmentation accuracy is summarized in Fig. 3.15.

In order to give visual aspect of the segmentation result, Table 3.8 - Table 3.11 are shown in the subsequent pages. Table 3.8 shows the least accurate segmentation result ordered from the segmentation result of MIA (T = 0.5). To give the balance view, Table 3.9 shows top five of most accurate segmentation result ordered by MIA (T=0.5). Meanwhile, for the complete segmentation result of MIA method both using T = 0.5 and T = Otsu, the results are presented in Table 3.10 and 3.11.

Table 3.8. Bottom 5 least accurate segmentation results

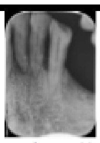
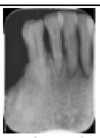
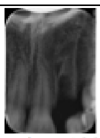
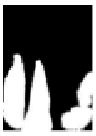
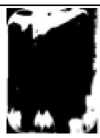
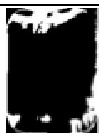
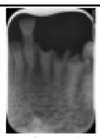
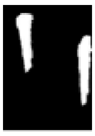
Radiograph	Manual Segmentation	Otsu	Multi Agent	MIA*) (Threshold=0.5)	MIA*) (Threshold=Otsu)
 Index: 69		 Accuracy = 44.83%	 Accuracy = 43.06%	 Accuracy = 48.46%	 Accuracy = 43.55%
 Index: 67		 Accuracy = 47.76%	 Accuracy = 47.55%	 Accuracy = 48.29%	 Accuracy = 48.62%
 Index: 122		 Accuracy = 66.07%	 Accuracy = 64.70%	 Accuracy = 47.12%	 Accuracy = 75.93%
 Index: 87		 Accuracy = 66.72%	 Accuracy = 70.99%	 Accuracy = 46.28%	 Accuracy = 53.83%
 Index: 80		 Accuracy = 33.36%	 Accuracy = 32.59%	 Accuracy = 45.29%	 Accuracy = 45.27%

Table 3.9. Top 5 most accurate segmentation results

Radiograph	Manual Segmentation	Otsu	Multi Agent	MIA*) (Threshold=0.5)	MIA*) (Threshold=Otsu)
Index: 116		Accuracy = 77.58%	Accuracy = 69.88%	Accuracy = 89.42%	Accuracy = 92.02%
Index: 115		Accuracy = 80.07%	Accuracy = 75.52%	Accuracy = 89.19%	Accuracy = 90.85%
Index: 108		Accuracy = 74.69%	Accuracy = 68.90%	Accuracy = 87.94%	Accuracy = 91.16%
Index: 119		Accuracy = 81.06%	Accuracy = 72.87%	Accuracy = 87.49%	Accuracy = 87.09%
Index: 7		Accuracy = 84.05%	Accuracy = 83.70%	Accuracy = 87.47%	Accuracy = 88.42%

Table 3.10. Segmentation results relative to the input radiographs using MIA (T = 0.5)

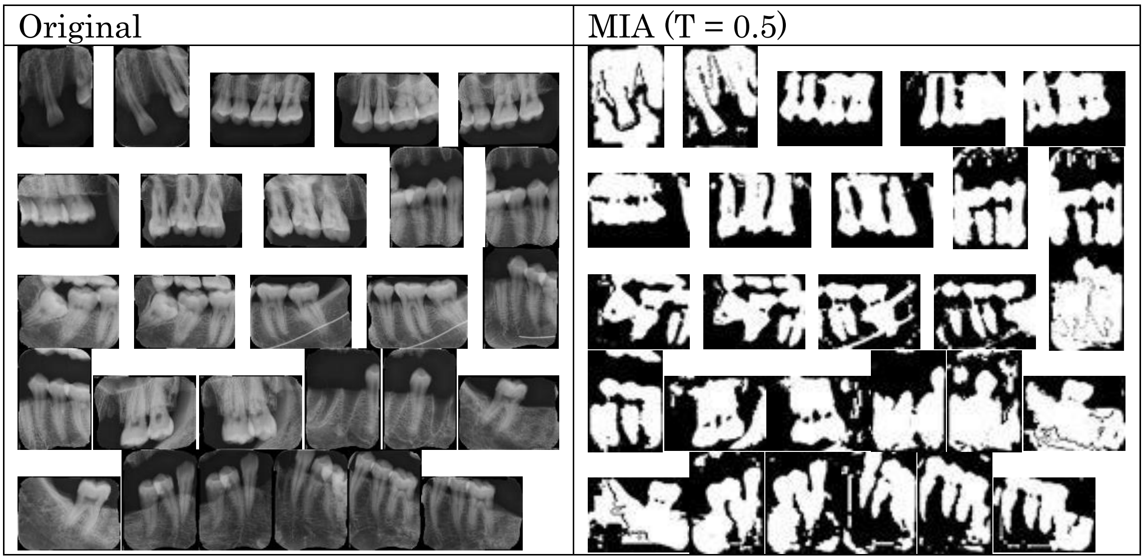


Table 3.10 (cont.). Segmentation results relative to the input radiographs using MIA (T = 0.5)

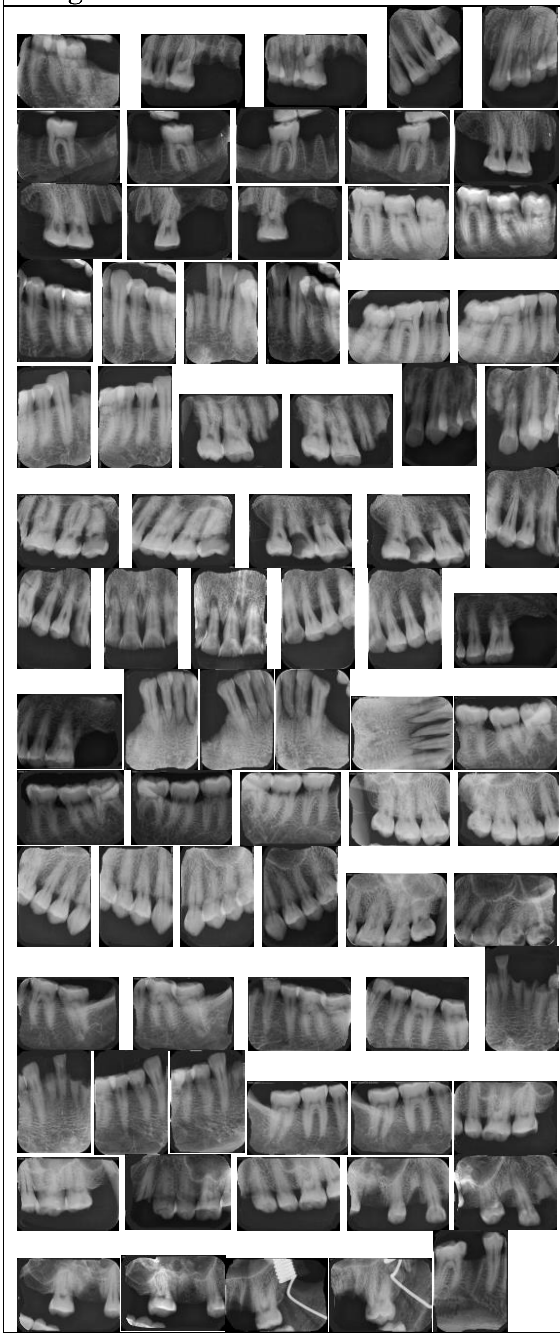
Original	MIA (T = 0.5)
	

Table 3.10 (cont.). Segmentation results relative to the input radiographs using MIA (T = 0.5)

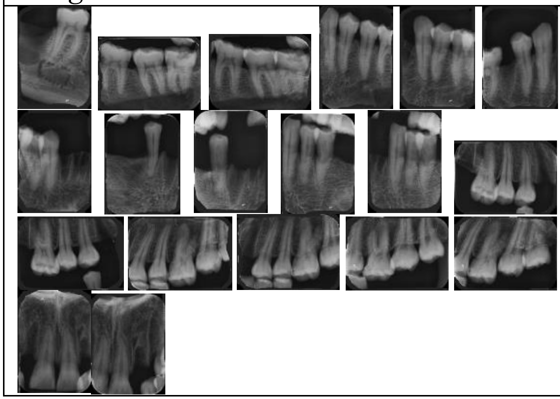
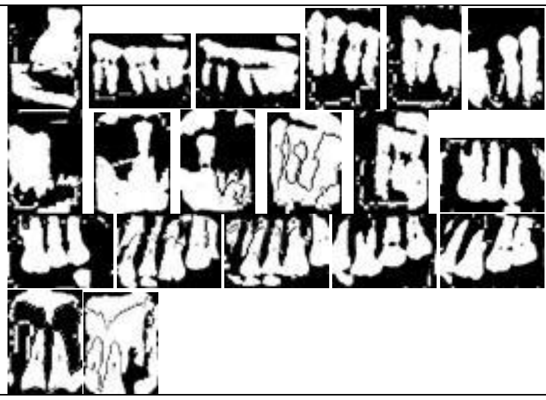
Original	MIA (T = 0.5)
	

Table 3.11. Segmentation results relative to the input radiographs using MIA (T =Otsu)

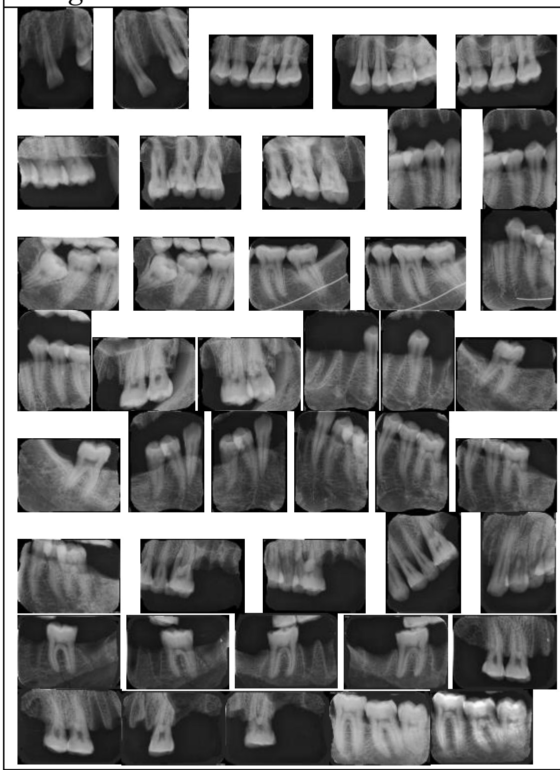
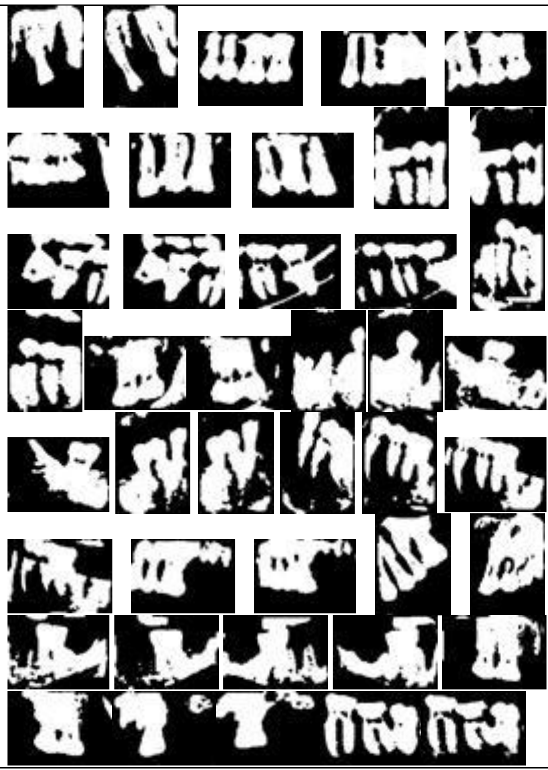
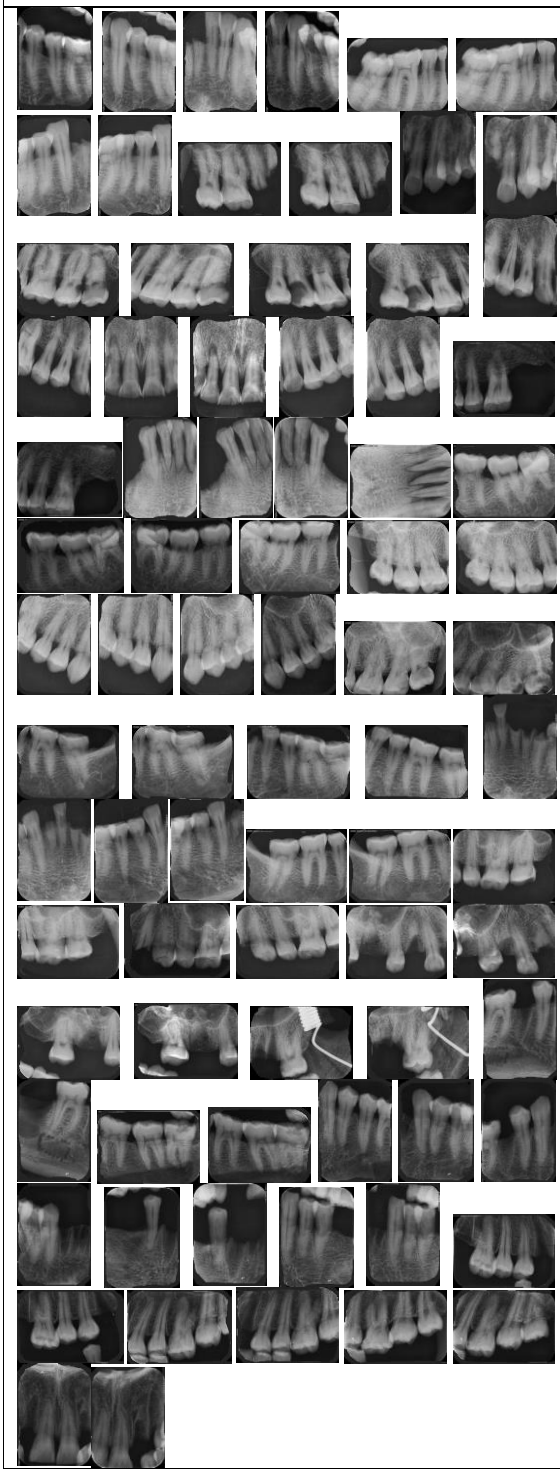
Original	MIA (T = Otsu)
	

Table 3.11 (cont.). Segmentation results relative to the input radiographs using MIA (T =Otsu)

Original	MIA (T = Otsu)
	

3.4.2 Statistical Test for Significance Measurement

The statistical test for significance measurement is done using t-test. The performance is analyzed as the following:

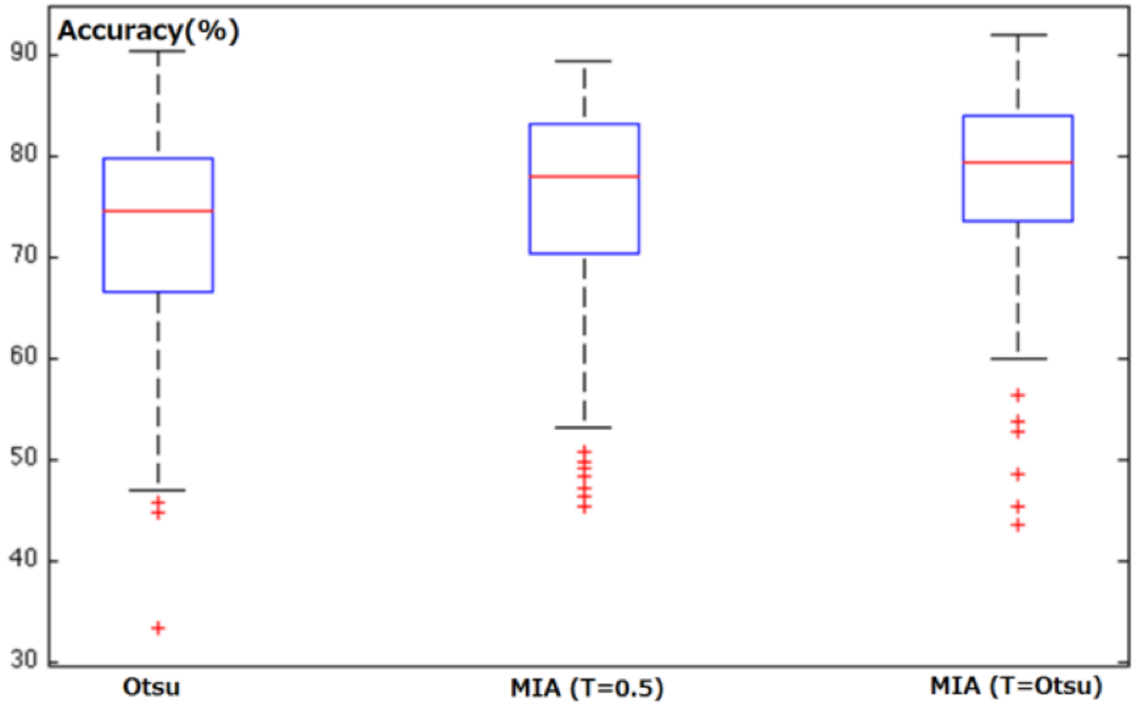


Fig. 3.15. Box plot of segmentation results' accuracies

Performance Analysis

Table 3.7 shows the accuracy of the proposed methods quantitatively. Although the proposed methods increase the segmentation accuracy between 3% and 5%, in order to show the significance of observed differences between means of the proposed methods and conventional method, paired t-test is used.

T-test is a statistical hypothesis test, which assesses whether the means of two tested groups are statistically different from each other. This test is proper if the analysis of the posttest experimental results consist of two groups [90]. The parameter measured as the outcome of this test is a p-value. P-value will be positive if the mean first category of the sample is larger than the second one, and negarive value is obtained if the mean of the second category of the sample is larger than the first one. The produced p-value can be compared with the table of significance to see if the difference between the likelihood if the difference is a chance finding. In most of the research, the rule of thumb set for p-test is the alpha level 0.05 (or also known as the risk level). 0.05 means five out of hundred a statistical difference between means would be found by ‘chance’. The smaller the value, the smaller the finding of statistical difference value by chance, therefore the more confident of the existence of statistical differences. The null hypothesis means there is no difference between the means.

The T-tests confirm that the null hypotheses are rejected for

1. T-test between multiscale image aggregation (with value generated by Otsu method) and Otsu method. The test yields p = 3.68 X 10-12.
2. T-test between multiscale image aggregation (with 0.5 threshold) and Otsu method (p = 0.001).

The p-value is the probability of being uncertain about the decision. This indicates that multiscale image aggregation method improves the segmentation accuracy in comparison with the other two methods.

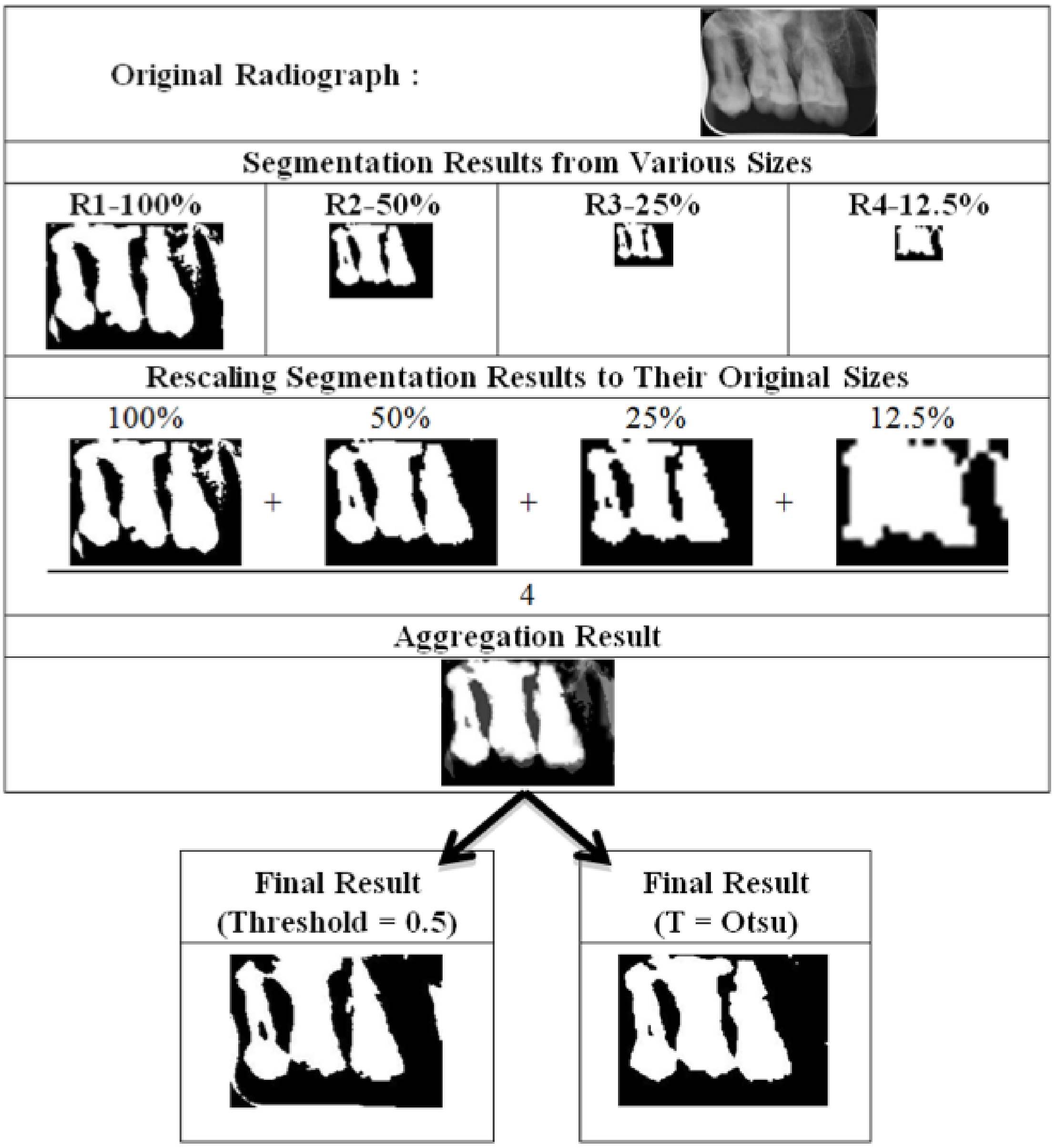


Fig. 3.16. Images aggregation

The importance of scaling down the three radiographs, where the final result of segmentation can classify teeth part correctly is shown in Fig. 3.16. If only the radiograph with its original size is taken into account, the method will misclassify the gum on the upper-right of the radiograph as a tooth, while combining the other sizes helps the system to avoid the false positive misclassification.

The complexity of the core proposed idea is analyzed as a summation of each scaled-down image segmentation complexity. The complexity for image with size M X N for a segmentation process is O(9*M*N) where 9 is obtained for counting 3 X 3 neighborhood block. The complexity of segmentation processes for 50%, 25%, and 12.5% scaled-down images are O(9*1/2M*1/2N), O(9*1/4M*1/4N), and O(9*1/8M*1/8N) respectively. By summation, the total complexity of the core algorithm is O(11.95*MN) which is quadratic.

Discussion on Misclassification Result

The misclassification results are caused by the contrast of the image that does not balance the statistical distribution of light and dark pixels. These radiographs are dominated by gum, teeth, and only a small portion of background. This situation leads the proposed method to segment the radiograph improperly. Given the consistency of the result from MIA, this dental segmentation module is suitable to be used in the dental-based identification system.

As for the analyses from the experiment, several points are synthesized:

1. Besides it is shown through T-test that the segmentation result is improved in the multiscale image aggregation, based on the visual evaluation, multiscale image aggregation also produces better contour of segmentation results.
2. False negatives in multiscale image aggregation method is smaller compared than Otsu method.
3. Most of the radiographs that are not properly segmented are dominated by the gum and teeth areas. This means the radiograph contains more light pixels than dark ones. This situations mislead the automatic parameter tuning for fuzzy membership function.

3.5 Chapter Summary

Multiscale image aggregation for radiograph segmentation improves the segmentation accuracy by scaling down the radiograph into three smaller sizes in order to reduce unimportant detail of the radiograph. The experiment on 122 ill-conditioned radiographs from Faculty of Dentistry University of Indonesia is done. The result shows that the proposed method yields 77.7% (using Otsu thresholding) and 75.17% (using a 0.5 threshold value) average accuracy by comparing every pixel with the corresponding pixel of manually segmented radiograph. The result suggests that the proposed method performs well on the radiographs with balanced proportion among teeth, gum, and background regardless of the varying contrast among radiographs as the automatic parameter tuning gives adaptability.

In addition to accuracy measurement, the significance of the proposed methods is also confirmed using t-test. Based on t-test result, it is concluded that multiscale image aggregation gives significance improvement compared with segmentation using Otsu method.

MIA will be used as a module of dental-based identification, which is being developed now. The automatic dental-based personal identification system is intended to be developed as the real system, which is useful in assisting forensics in the disastrous area by shortlisting the possible identities of a victim. As a result, it will save the forensics from strenuous effort identifying manually. This system could assist in identifying victims of massive disasters such as Indian Ocean tsunami (2004), Haiti earthquake (2010), and Tohoku earthquake (2011) where there were numerous physically unidentified victims.

From the technical point of view, since the database of radiograph images consist of huge datasets, a research focusing on dental matching's speed and efficiency will be carried out. Moreover, a further development of the multiscale image aggregation is intended to construct the capability of the segmentation method for general grayscale images.

In terms of comparison between multiscale image aggregation method with multi agent system approach, several points below are concluded:

1. MIA does not need iteration to converge
2. The segmentation speed of MIA is always the same for the image with same size.
3. The accuracy is better with the supplied data and is tested using t-test for its statistical significance.

Chapter 4

Multiple Fuzzy Attribute for Dental Classification on Periapical Radiograph

Identifying a physically unrecognizable deceased is a demanding task, especially when the problem is scaled up into identifying victims of massive disasters such as those victims of March 11th tsunami in Great-Tohoku Earthquake 2011 or Indian Ocean Tsunami 2004. Until now, several identification methods exist such as face, DNA, Iris, fingerprint, and dental based identification. Among them, it is shown that dental based identification has high identification with low cost to detect the victims with massive physical destruction [1, 2, 3]. In addition to that, tooth is also one of the most resistant against heat and time; in other words, dental based identification can be applied for the burned or decayed deceased which is commonly found in the post disaster area [4].

In order to realize an automatic dental based identification system, dental classification is a necessary subprocess to isolate and extract features of individual tooth. In the holistic point of view, dental classification enables indexing and efficient search for identification purpose. Research on dental classification and numbering is done using teeth region and contour information for dental bitewing [5]. Jain and Chen [4] propose a semi-automatic tooth segmentation using contour extraction method. Dental segmentation using fuzzy logic based emotional multi agent system is proposed in [6]. Research on multiscale image aggregation [7, 8] provides another insight to radiograph segmentation. Based on article in radiography and radiology [41, 42, 43], it is decided that periapical is the target of the study. Automatic classification of teeth in bitewing dental images is quite common as done in [44, 45, 46], however, the author choose to use periapical radiograph [47] which each tooth will be classified into standard referred in [48]. To reemphasize, research on dental classification, however, in periapical radiograph is still lacking and, therefore, it becomes the focus of this research.

Dental classification for periapical radiograph based on Multiple Fuzzy Attribute is proposed to classify periapical image based on the fuzzy value and is able to deal with orientation problem, missing teeth, or ambiguity by allowing probabilistic value to be included in the output if the automatic system cannot judge firmly based on certain criteria and leave the task to the expert to be done manually. The use of ratio value of the tooth size also enables the system to cope with various size periapical radiograph that may happen depending on angle and distance when taking the radiograph.

The two main advantages of this research are, (1) the proposal handles periapical radiograph and (2) the use of multiple fuzzy attributes improves classification accuracy without making speculative classification. Among various types of dental radiographs in best practice, extensive research has been done on bitewing and panoramic radiograph [9, 10, 11], however, the research of dental classification in periapical radiograph is still lacking and the existence of this research might contribute and complement the existing research while paving the way to completing dental based identification system. Identification system is actually can be modeled/viewed as image retrieval system which several extensive research has been done [49, 50, 51, 52, 53]. In spite of its popularity, the road toward automatic identification system is still challenging [54, 55, 56, 57, 58, 59, 60]. Various image processing techniques [61] and its use to scale-invariant object recognition [62] may help, however, the computing cost is indeed high. The existence of indexing system may help significantly to reduce the search space. This research focus on periapical radiograph since this type of radiograph image consists only either upper or lower series of tooth, this type of radiograph is more representative to postdisaster conditions. For example, the upper and lower jaws of a victim are disintegrated in the flight accident in Gunung Salak, Indonesia 2012.

Moreover, it is more practical for the forensics to reconstruct periapical radiograph during the postmortem examination.

Multiple fuzzy attribute offers advantage against uncertain condition of tooth that is difficult to categorize well. Instead of offering clear classification, which might decrease overall accuracy, the system offers multiple possibility of classification with its fuzzy value (referred as fuzzy attribute in this article). The proposed method provides full automatic classification results when it is certain. In uncertain case, the proposal provides classification as multiple fuzzy attributes so that the system still functions to provide assistance to expert without making speculative classification. The proposed method also employs integral projection for isolating each individual tooth. This method is selected because of its low computational complexity. As the result, the system has better accuracy result without sacrificing performance.

In order to confirm the performance, an experiment on 78 periapical radiographs, which consist of lower and upper jaw, are conducted. The radiographs dominantly consist of molar and premolar teeth. The classification accuracy of each individual tooth is assessed. In addition to that, the classification accuracy over input radiograph is also evaluated statistically. To complement the numerical result, examples of classification results are also provided to give the visual grasp of the proposed method.

The related concept of dental radiograph, image processing, dental segmentation, and statistical test is summarized in 4.1. A dental classification system is proposed in 4.2 whereby its each module is mentioned consecutively in subsections. Finally, the experiment results and the statistical analysis are presented in 4.3.

4.1 Dental Classification on Radiograph

The dental classification is a necessary step in this proposed identification scheme, since inside the classification process lies also feature extraction of the length, width, length/width ratio, area/perimeter ratio, and dental type. This information would be useful for the purpose of indexing, which will avoid the necessity of doing exhaustive search to the whole dental records; instead the search space can be greatly reduced during the identification process. Therefore, dental classification is a necessary step for shortlisting the possible victim candidates in an efficient manner.

In addition, the dental classification on radiograph is a necessary and common process done by the dentist or forensics for the purpose of documentation or archiving. This information is crucial for the identification process. In the subsequent chapter, the general purposes and the technical purposes of dental classification are explained more detailed.

4.1.1 General Purposes of Dental Classification

Dental radiograph is an intra or extra oral image that is taken using X-ray radiation. Dental radiograph consists of teeth, bones, and surrounding soft tissues. There are three types of dental radiograph that is commonly used in dentistry, they are periapical, bitewing, and panoramic (shown in fig. 4.1).

The radiograph types are different based on the purpose and the way the radiograph is taken. Periapical radiograph is useful to show the whole tooth from crown to beyond the end of the root. This can be used to detect abnormalities of the root surrounding bone structure. Bitewing radiograph shows detail of upper and lower part of teeth in certain area of the mouth. This radiograph can be used to detect decay between teeth and bone density changes caused by disease. Panoramic radiograph shows the entire mouth area, both upper and lower jaws, and it is useful in localizing fractures or pathologic entities. This research focuses on the periapical radiograph.

The dental universal numbering system and categories are shown in fig. 4.2. There are four types of teeth, i.e., incisor, canine, premolar, and molar. Assuming there is no missing tooth, it can be concluded that if the type of the tooth and the location of the jaw are known, the number can be assigned to a tooth.

Fig. 4.1 Categories of dental radiograph, top-left: periapical, top-right: bitewing, bottom: panoramic.

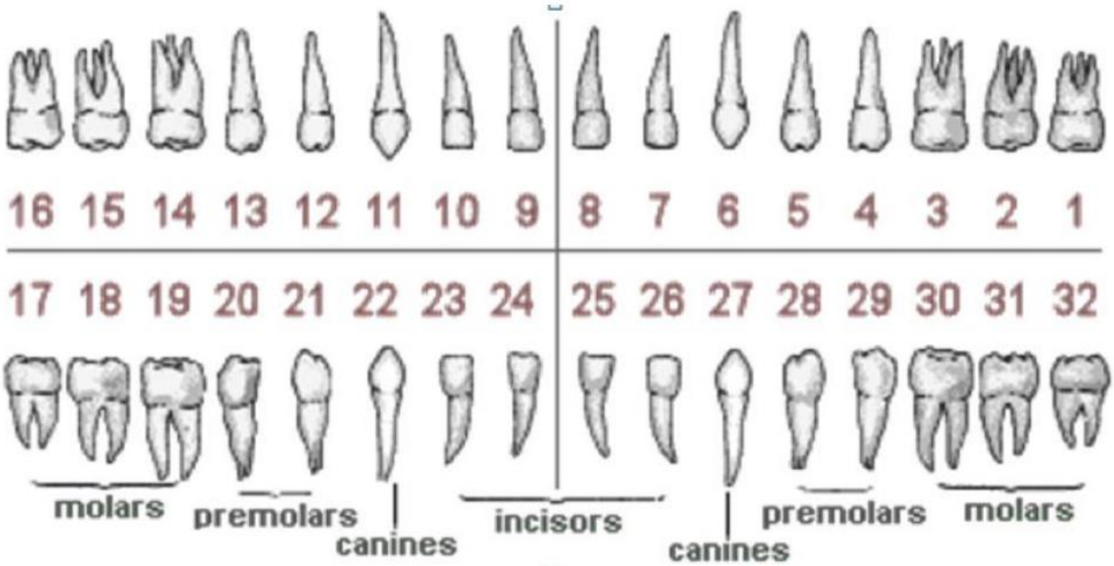


Fig. 4.2 Dental types and numbers shown in universal numbering system (note: it is shown in patient's view – patient's right corresponds to the chart's right).

Source: http://users.forthnet.gr

Researches on classification and numbering for dental on bitewing radiographs are also done in [26, 51, 52], most of them use shape analysis for classification [53]. Even though teeth numbering is useful for records and identification purposes, there are various way to identify victims using dental based approach such as tooth contour [63], automatic dental chart construction [64], dental works [65]. As an evidence of its feasibility, the dental based personal identification is adopted as indicated in [66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80]. Its use of identification purposes proves adding value in case of homicide [81, 82, 83, 84, 85]. Moreover, the development of the automated dental based identification system is done in [86, 87]

Dental Segmentation

The dental segmentation process used in this research is multiscale image aggregation [8]. This method is selected after considering the characteristics of radiograph, where there are pixel distortions inside the data. Multiscale image aggregation works by scaling down the radiograph into several scaled down sizes so that the distortions can also be removed to certain extent, therefore increase the segmentation accuracy overall.

4.1.2 Technical Purposes of Dental Classification and Their Challenges

The technical purposes of dental classification in this thesis refer to the technical use for identification process. The technical purposes are as follows:

1. For archiving the tooth based on the type of each tooth. This archive can be used for pruning by looking up to the relevant index while searching for the tooth based on the features.
2. For automatically divide the area of the tooth in a more defined way and extract the features that can be used as indices that will help the identification process. In this manner, the exhaustive searching can be avoided.

Considering the previously mentioned purposes, the idea of dental classification on periapical radiograph using multiple probabilistic attribute is proposed.

4.2 Dental Classification on Periapical Radiograph using Multiple Probabilistic Attribute

The main goal of dental classification is to classify each individual tooth in the image into 4 categories, i.e., incisor, canine, premolar, and molar. Dental classification is done through a sequence of modular process as explained in the sequential subchapters and shown in fig. 4.3. Classification can be done without segmentation. This process, however, may decrease the accuracy of the tooth isolation result due to the ambiguous area of gum in the data. Since the isolation process relies on the integral projection method, the projection result would be different especially in the local minima and may lead to the less accurate tooth-isolation.

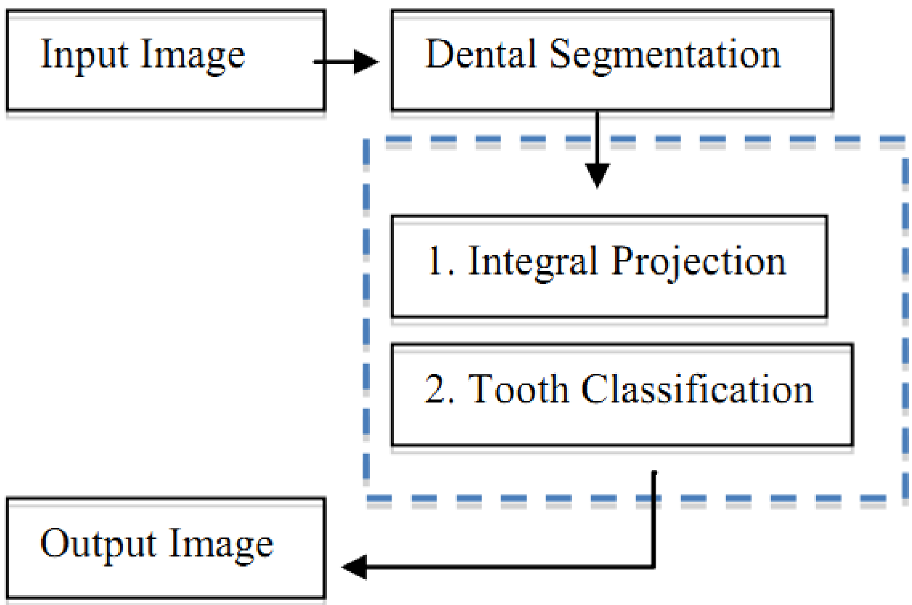


Fig. 4.3 The proposed dental classification process.

4.2.1 Integral Projection for Tooth Isolation

An integral projection is a one-dimensional signal derived from the summation of a set of pixels along a certain direction (e.g. vertical, horizontal, etc.). In relation with the purpose to isolate each tooth in periapical dental radiograph, horizontal (down) integral projection is employed since it matches the objects' locations characteristics that are spread horizontally. Horizontal integral projection of well-separated teeth in the periapical dental radiograph results a signal with clear local minimum. As the consequence, these local minima can be utilized to infer isolation area of a tooth in the radiograph (as shown in fig. 4.4).

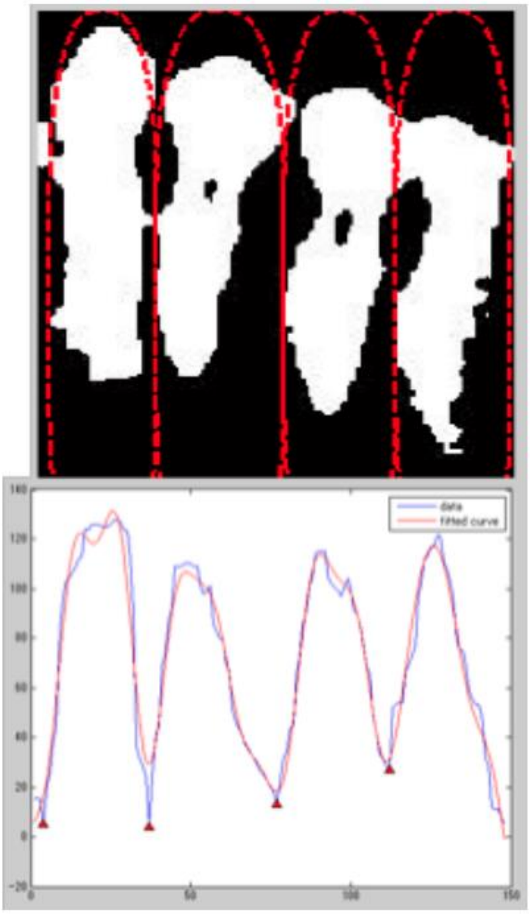


Fig. 4.4 Horizontal integral projection of lower teeth.

The integral projection is applied into the radiograph segmentation result obtained by applying multiscale image aggregation method [8]. Since the segmentation image consists only black and white pixels, and in this case the tooth object is indicated by a group of white pixels while the background is indicated in black pixels, the integral projection result can has contrast up and down value among certain regions of interest.

After the integral projection result is obtained, an interpretation for the result is necessary in order to pinpoint the separation between two adjacent teeth. Mathematically, this problem can be modeled as finding local minima problem. In this work, the finding local minima problem is approached using sorting method. Since the result of integral projection is an array of numbers, the array's values are sorted with quicksort algorithm while maintaining the original index value of the array. From the sorting result, a point in the integral projection can be picked as a local minima value if it fulfills two conditions: (1) The point has dominantly small value and (2) The point is distant within certain threshold value compared with the previously selected points.

Since integral projection only sum up the vertical pixel values along the horizontal line, integral projection is chosen because of its light computation. And based on observation, this method is enough to isolate the position of an individual tooth. After this step is fulfilled, feature extraction of an individual tooth can be done.

4.2.2 Feature Extraction from Isolated Tooth

Once an individual tooth is already isolated from the radiograph, the isolated pixel information from the estimated tooth area can be obtained. As a consequence, the feature extraction of each individual tooth can also be done.

The features extracted from an isolated tooth are area, perimeter, width, length (as shown in fig. 4.5), ratio of area/perimeter, and ratio of length/width. The advantage of using ratio of length/width is invariance to the scaled size of the image. The initial features on the representative sampling of the radiograph are taken in order to construct the fuzzy rule.

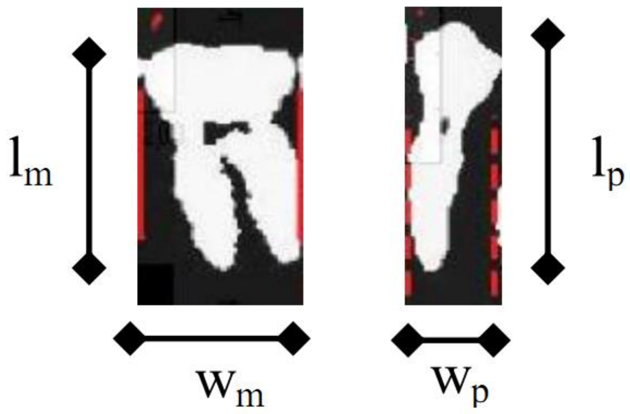


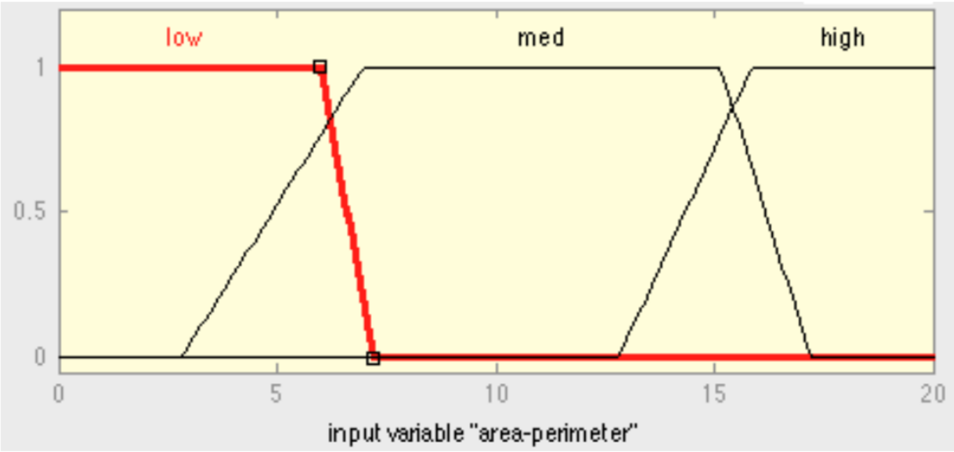
Fig. 4.5 Features extraction of length and width of an individual tooth. The use of ratio length/width enables the system to classify the teeth regardless the variance of the input image size.

4.2.3 Classification using Fuzzy Inference System

Fuzzy inference system is constructed based on the sampling and its interpretation result on the extracted features. After studying the pattern of the ratio of tooth, it is decided that molar and premolar teeth can be identified based on the ratio of size and pixel area, while premolar, canine, and incisor are not clearly distinguishable based on the size. Therefore the generated fuzzy inference system firstly classifies the tooth into molar and premolar. In the later part, the output will be refined that it can label canine. The fuzzy inference system is constructed as shown in fig. 4.6.

R_{ap} : ratio area/perimeter ; R_{lw} : ratio length/width
A: area ; P: perimeter

R_{lw} is low & A is low & P is low → molar is low and premolar is low
R_{lw} is high → molar is med and premolar is high
R_{ap} is low → premolar is low
R_{lw} is med → premolar is low
R_{lw} is low → premolar is high
A is low & P is low → molar is low and premolar is high
A is med & P is med → molar is med and premolar is med
A is high & P is high → molar is high and premolar is low



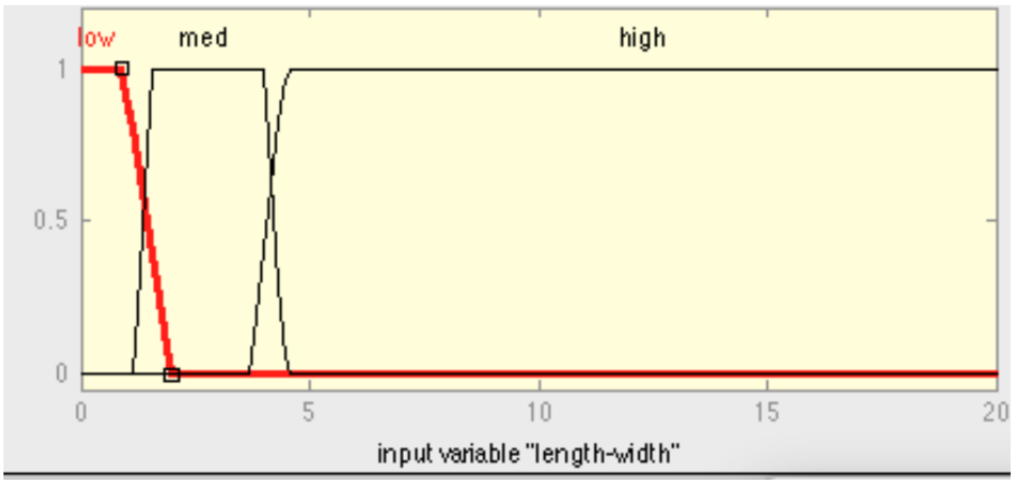


Fig. 4.6 From top-bottom: (1) fuzzy inference rule, (2) fuzzy membership plots for ratio area/perimeter, ratio length/width, and plots for molar and premolar.

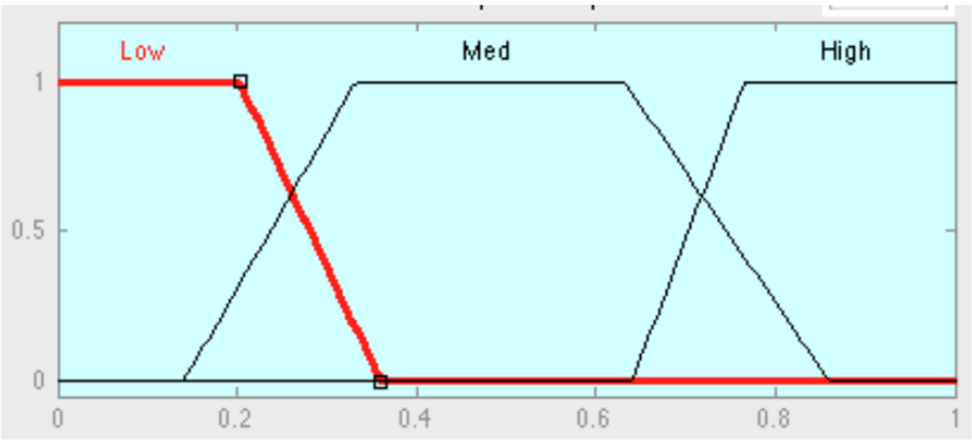


Fig. 4.6 (cont.) From top-bottom: (1) fuzzy inference rule, (2) fuzzy membership plots for ratio area/perimeter, ratio length/width, and plots for molar and premolar.

The reasons behind the choice of length, width, area/perimeter ratio, and length/width ratio parameters, because the study done in [9] proves the feasibility of the parameters of length and width to the ability to classify a tooth. Apart from the referred study, the value was decided based on the preliminary experiment to adjust the specific data characteristics.

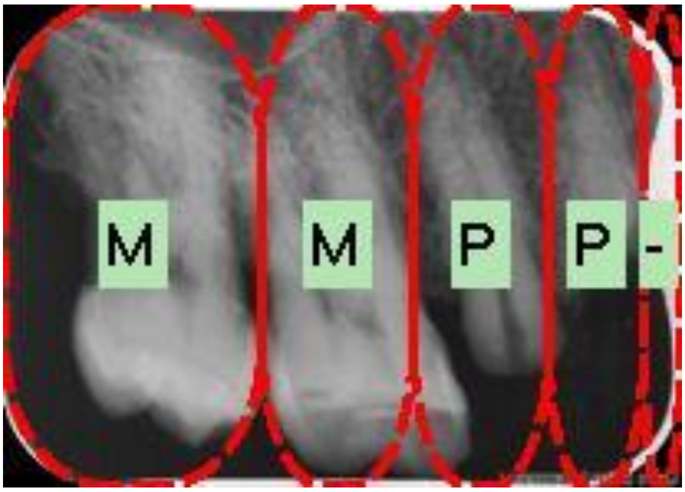


Fig. 4.7 Example of classification result. P and M denotes premolar and molar respectively.

The interpreted result from the fuzzy inference system gives output for one isolated individual tooth by giving a label M for molar and P for premolar. These labels are subject for further analysis in the last step before delivering output to the user.

The last step of this algorithm is to reevaluate the output label in order to adjust the label into the landscape of periapical radiograph. The algorithm is executed is systematically as follows,

1. If the |molar - premolar| > 0.15 , then label the tooth with the single biggest value only (either molar or premolar).
2. Else label the tooth with both value (molar and premolar) & let the user decide.

After the implementation of this algorithm, the final output can be obtained. The label of each individual tooth is overlaid on the original input image. The output example can be seen in fig. 4.7.

4.3 Experiment Classification on 78 Periapical Radiographs

In order to show the accuracy of classification an evaluation on experiments on 78 radiographs (223 teeth in total) is performed.

4.3.1 Classification Accuracy Results

The accuracy of classification is evaluated based on experiments on 78 radiographs. The validation is done by comparing the automatic classification results with manual classification, which is assumed to be 100% correct. An example of classification result is shown in fig. 4.8. The input radiograph and computing environment is as shown in table 4.1.

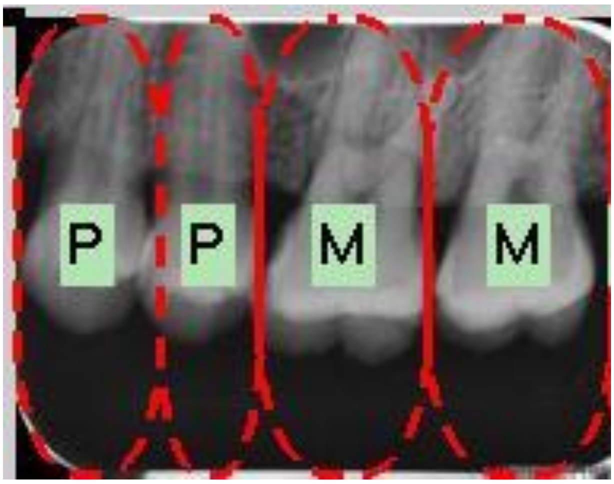


Fig. 4.8 Example of automatic classification result that is accurate to all teeth.

Table 4.1. Radiograph and computing environment for experiment

<table>
<tr><th colspan="2">Type</th><th>Specification</th></tr>
<tr><td colspan="2">Processor</td><td>Intel Core 2 Duo 2.53 GHz</td></tr>
<tr><td colspan="2">Memory</td><td>2 GB RAM</td></tr>
<tr><td colspan="2">Programming language</td><td>Matlab 7.9.0.529</td></tr>
<tr><td colspan="2"></td><td></td></tr>
<tr><td rowspan="2">Radiograph image</td><td>type</td><td>JPG</td></tr>
<tr><td>size</td><td>Varies around 150 x 200 pixels</td></tr>
</table>

The classification accuracies of each category of tooth (the data consists of canine, premolar, and molar) are presented in table 4.2. From 78 periapical radiographs used, there are 223 teeth (roughly 1 radiograph consists around 3 teeth). The dominant tooth in periapical image in the data is either molar or premolar tooth. It is shown that the classification accuracies for molar and premolar tooth are 84.29 % and 82.22 %

respectively. In overall, from 223 teeth, the classification accuracy is 82.51%.

Table 4.2. Classification Results

Dental type	**Number of teeth**	**Correctly detected**	**% Accurately Classified**
Molar	121	102	84.29
Premolar	90	74	82.22
Canine	12	8	66.66
Incisor	0	0	N/A
TOTAL	223	184	82.51

While table 4.2 presents the result based on the number of teeth data, table 4.3 presents the experiment result based on average of classification rate per input radiograph. Given an input of radiograph, the system classifies each tooth correctly with 84.29% in average. Molar tooth has higher classification accuracy rate than premolar tooth given an input radiograph.

Table 4.3. Statistical data based on classification rate per radiograph

	Dental type		**Total (%)**
	Molar (%)	**Premolar (%)**	
Average correctness/radiograph	84.95	80.39	84.29
Standard deviation	28.82	34.75	22.71
Q1	66.66	50.00	66.66
Q2	100	100	100
Q3	100	100	100

In terms of applicability of the algorithm for radiograph, from 78 radiographs, there are 48 radiographs that has 100% classification rate and there are 66 radiographs that has classification rate more than 60%.

Since periapical radiograph consists only either upper or lower jaw, classification result based on upper and lower jaw is presented in table 4.4. The classification result of lower teeth is higher than that of upper teeth. This is caused by the appearance of molar tooth in upper jaw does not show clear root compared with its lower counterpart.

Table 4.4. Classification result in upper and lower jaw

		Upper teeth	Lower teeth
Total teeth		114	109
Correctly classified	**#**	92	92
	%	**80.70**	**84.40**
Average classification rate / radiograph (%)		**82.88**	**85.56**
Standard Deviation		21.51	23.93
Q1		66.66	75
Q2		100	100
Q3		100	100

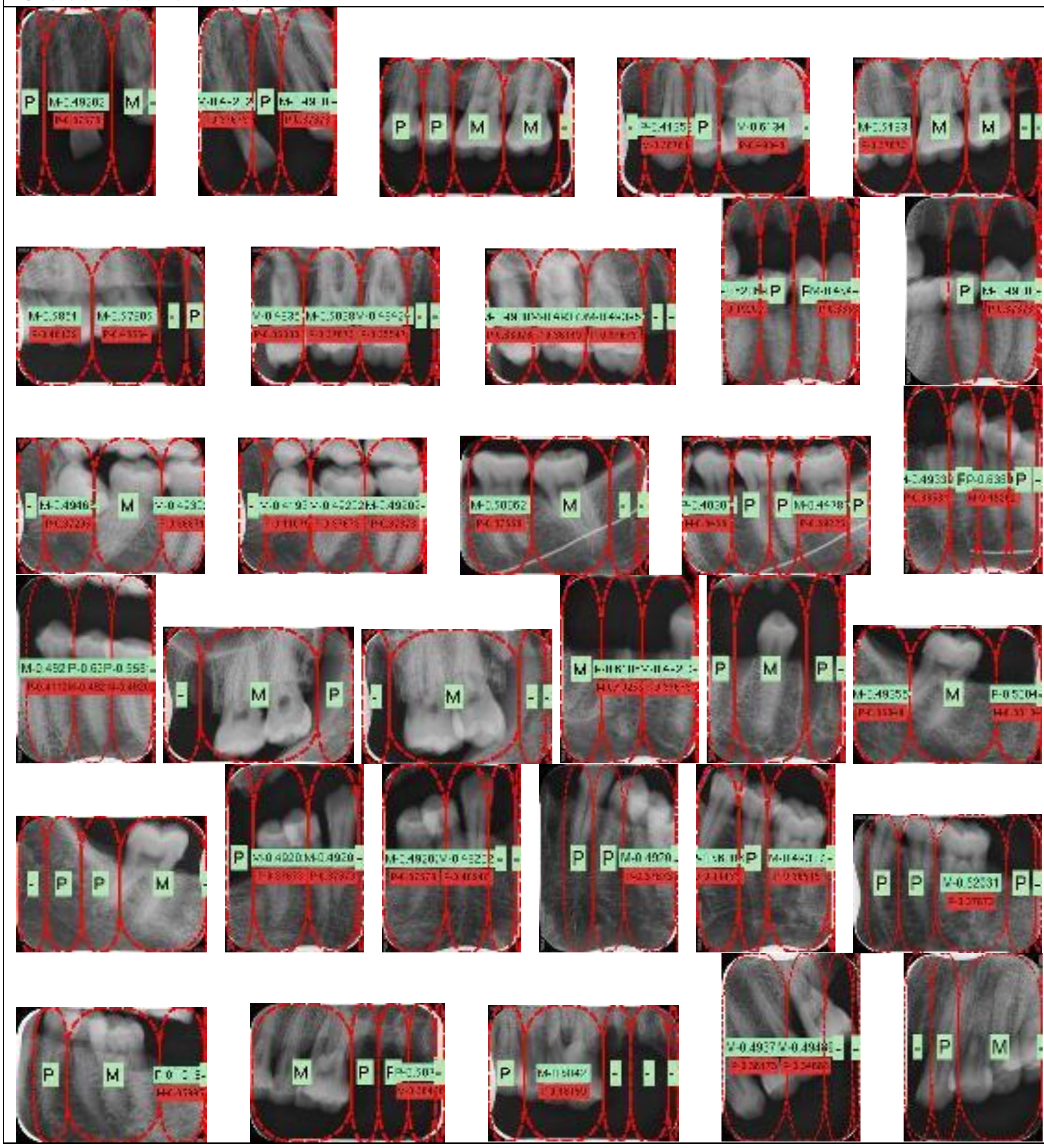
4.3.2 Results Analysis and Interpretation

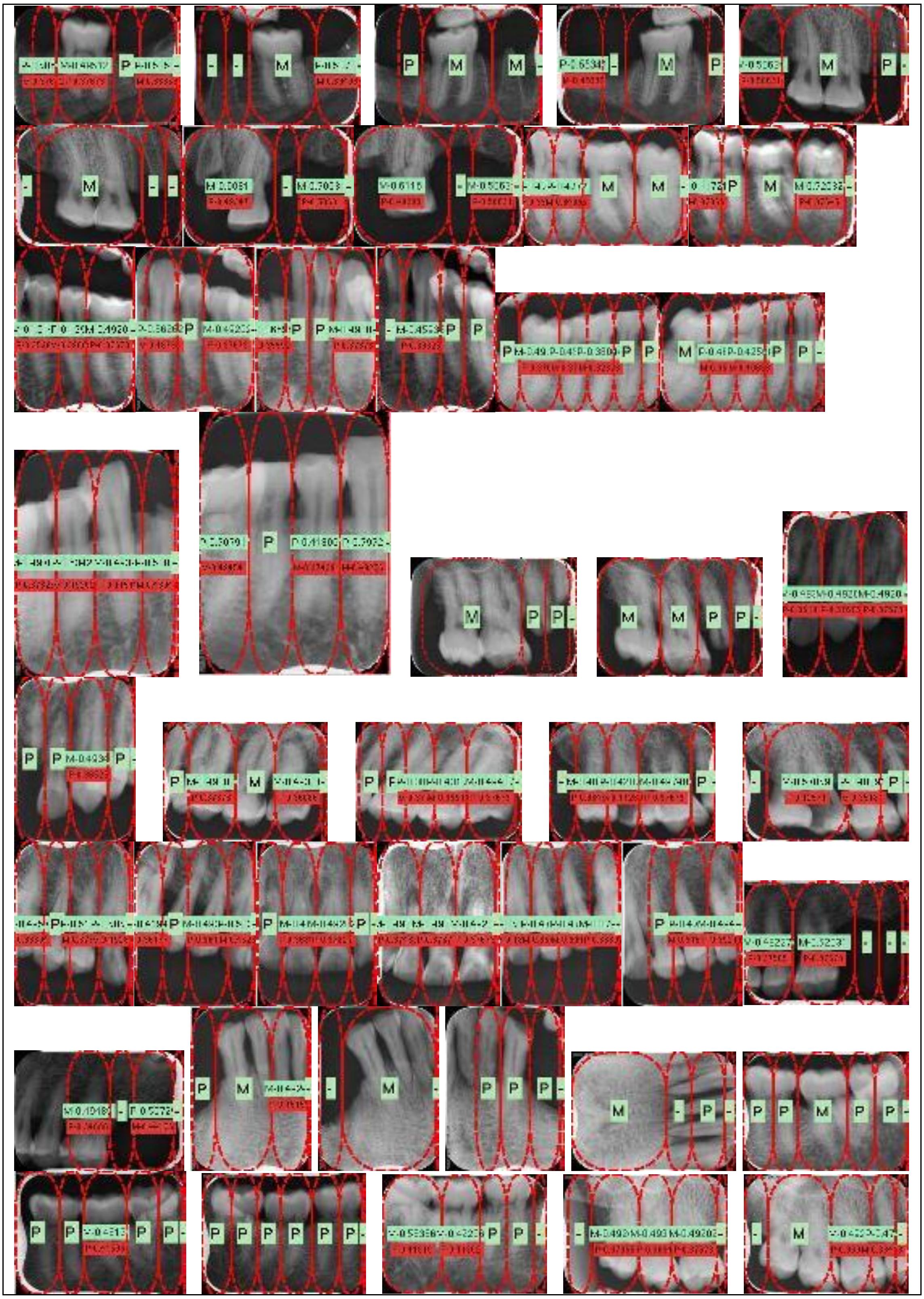
Discussion on Misclassification Results and Limitations

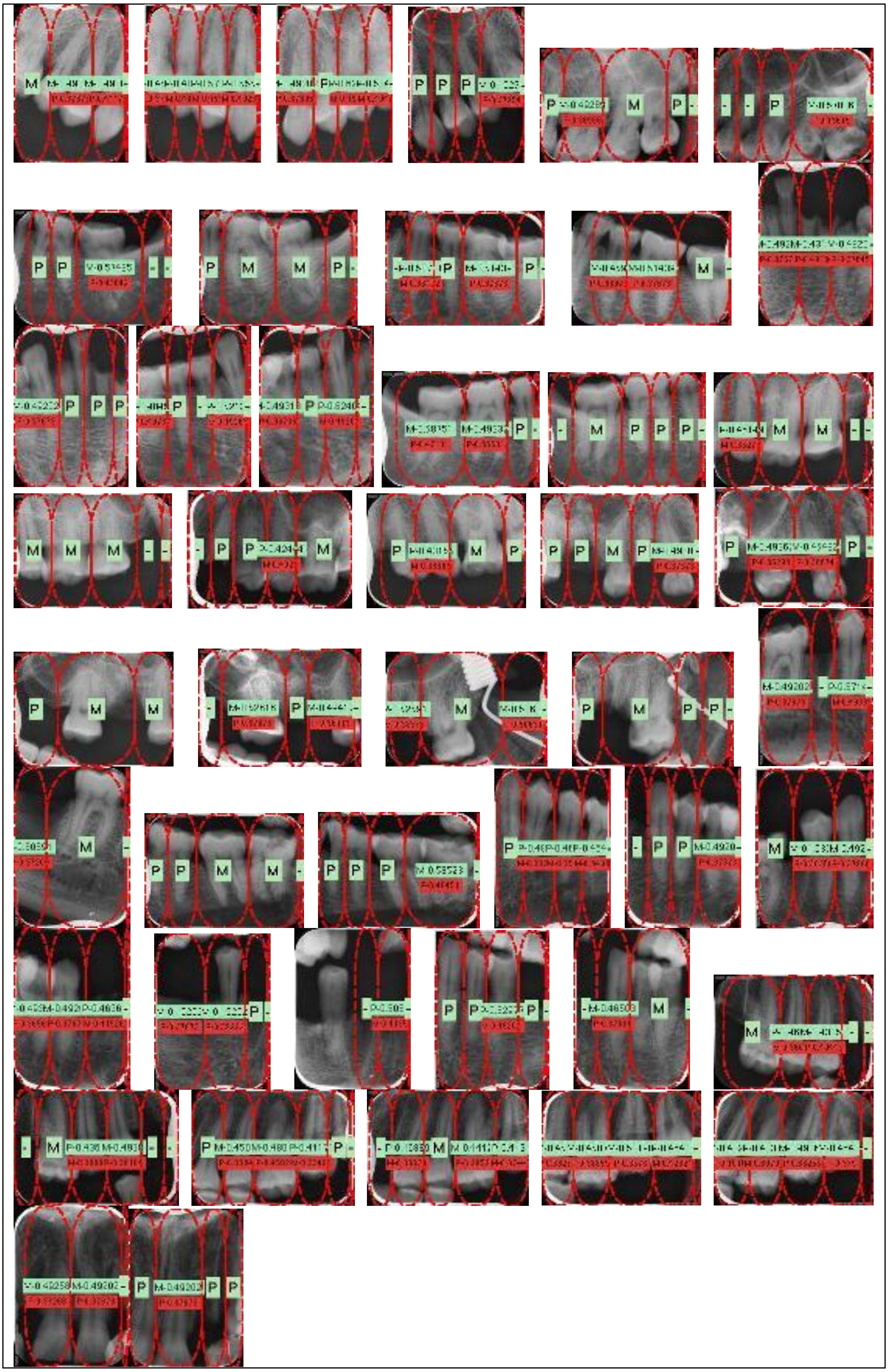
Misclassification happens because there are certain cases of molar tooth that appears like premolar tooth because the root of the molar does not appear clearly. This problem usually is caused by the angle when taking the radiograph. This also tends to happen in upper molar tooth since it has three roots that makes its appearance does not look clear on the radiograph. As the consequence, it leads to the misclassification in the results.

Misclassification also happens due to deformation of the tooth. In order to cope with this problem, the classification result on ambiguous tooth is classified with multiple fuzzy attribute (the number represents degree of membership to molar or premolar). By doing this, the system avoids speculative classification and assists the user to make manual judgment on the corresponding tooth. The compilation of the classification results are shown in Table 4.5.

Table 4.5. Classification results example

Classification results






4.4 Chapter Summary

The proposed method yields the average accuracy result 82.51% from the experiment on 78 periapical radiographs. This method works by isolating each individual tooth by using integral projection, extracting the features of ratios of length/width of the each individual tooth, and classifying each of them using fuzzy inference system. The use of ratio enables the system to cope with various size of periapical radiograph which is commonly happened due to the inconsistent angle and distance when the forensics or dentist taking the radiograph.

Direct matching comparison without classification might be possible, however exhaustive search is need to be done and this process will limit the identification capability to quickly identify the victim's identity as the database/dental records grow. Classification is needed to aid the users (forensics and dentists) during the use of the system. It is expected that the availability of the classification will enable to help the confidence of the users of the accuracy of the system as well as to provide assistive value while extracting features.

The statistical analysis also suggests that the standard deviation of classification is 22.71 %, which can be interpreted that the proposed system can be categorized as having stable classification result. Given a radiograph, consists of three teeth, the system can classify two teeth correctly. Inside the classification results themselves, the system classifies uncertain tooth using multiple fuzzy attributes and does not make speculative classification, which may mislead the end-user. As the result, the system still performs its duty to assist experts during the difficult cases. The experiment results also show that the result is analyzed into three categories, (1) the total teeth and their average classification accuracy, (2) classification rate per radiograph with assessment to molar and premolar classification accuracy, (3) Classification accuracy for teeth in upper jaw and lower jaw.

The two points confirmed in this result are (1) avoiding the speculative result provides higher accuracy while the system provides assistive result in case of ambiguous input. By the ability of the proposed system of avoiding speculative classification, the error rate can be reduced while the output of ambiguous input are still provided in assistive manner to the user by providing the estimation value similarity of molar or premolar teeth. (2) The study in periapical image is done, which is more representative to the possible generated radiograph after disaster. In addition to that, the classification system on periapical image complements the existing research in dental based identification system.

This proposal is built to classify each individual tooth on the periapical radiograph in order to realize automatic dental based identification system which is under development at this moment. It complements the existing classification system on bitewing image by providing a classification system and study on periapical radiograph classification. Moreover, the study on classification system itself may provide insight on feature extraction of the tooth and the features itself are subject to be manipulated, indexed, and searched into and from radiograph database.

The concept of classification using dimensional size as done in this study might be modified for other use, and implemented in other radiograph image, such as dental panoramic radiograph which is commonly available in the dentists and become a personal record in the civilian database.

The ultimate goal of this work is to provide dentist an automatic tool to assist dentist when making a record of a patient and also assist forensics when they are doing identification process. This automatic classification system is crucial in assisting both forensics and dentist so that the laborious work can be reduced and improve the quality of overall work.

Chapter 5

Implementation for Dental Based Personal Identification System and Its Potentials

This chapter explains about the implementation aspects of fuzzy guided segmentation and labeling. The implementation to dental based personal identification system is tested within a simulated retrieval scenario and the result is presented. The second part explains the perspective and possibility to use the proposed segmentation and labeling for taking a main role in deep level understanding system that is being developed in Hirota Laboratory, Tokyo Institute of Technology.

5.1 Implementation on Dental Based Personal Identification System

Dental based personal identification system is the most apparent application that can directly uses the proposals in this thesis. The research and development of this system has been being done in the faculty of computer science and faculty of dentistry, University of Indonesia since 2008. The expected outcome of this implementation is the personal identification system that can computer-aid the forensics and dentists during their works identifying the victims of massive or huge disasters.

For the prove of implementation, an algorithm employing template matching method is implemented and tested by the authors as shown in Fig. 5.1.

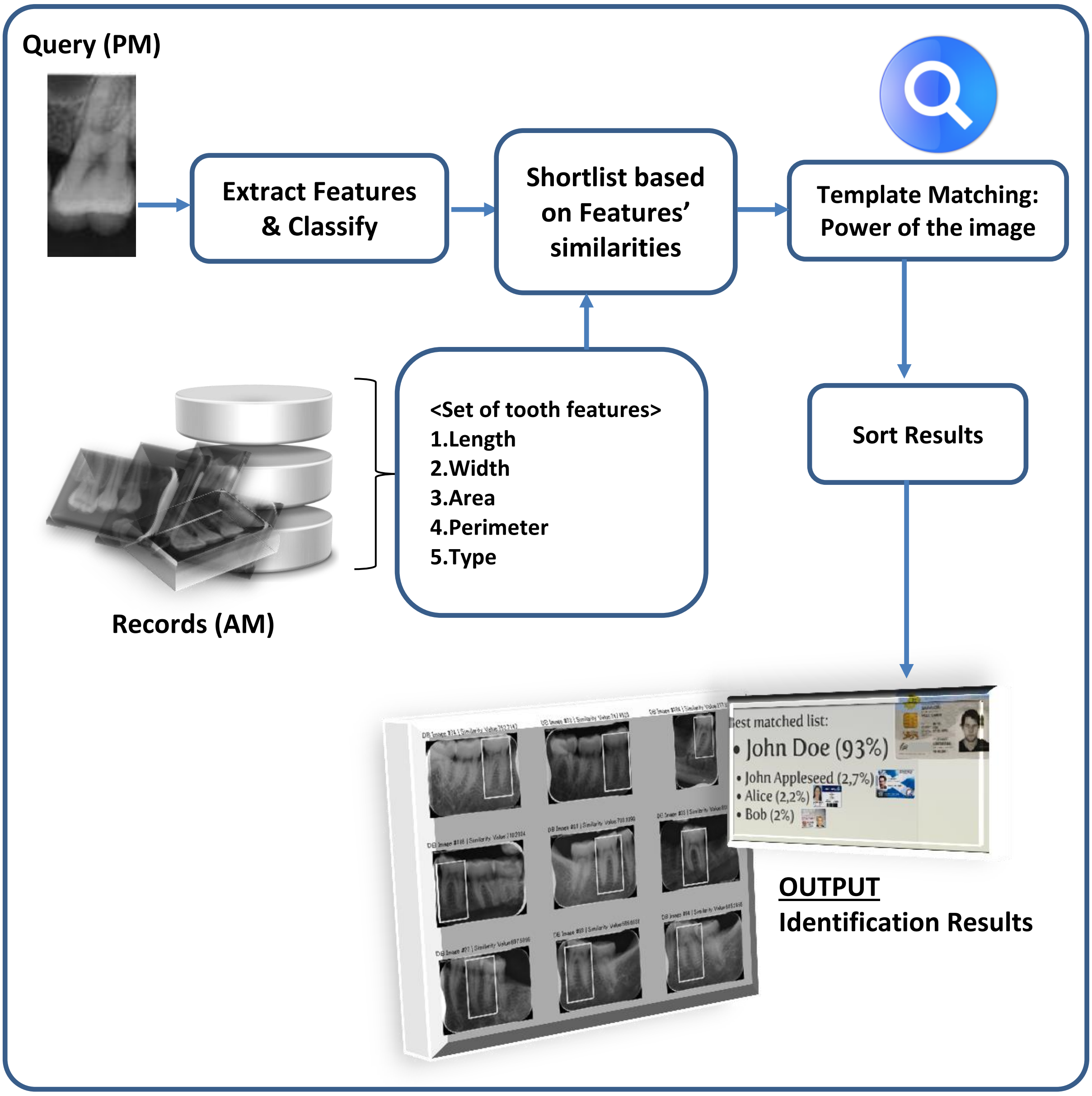


Fig. 5.1. The flowchart of the matching based on the proposed features

The algorithm works by shortlisting the possibilities of the dental records based on the similarity parameters of length, width, area, perimeter, and type of the tooth. From the shortlist, then the template matching algorithm is performed so that the search space has been greatly reduced since the matching process does not need to be done on every records available in the database, instead only to those in the shortlist. In addition to that, the identification process is only done once and does not need to be iterative as in [53]. Therefore, the complexity of the algorithm is also kept into O(n^2).

To give the visual understanding, Fig. 5.2 shows the screenshot of the output of the identification system given a query input. To assists the user, the white squared inside each image of the search result indicates area of similarity.

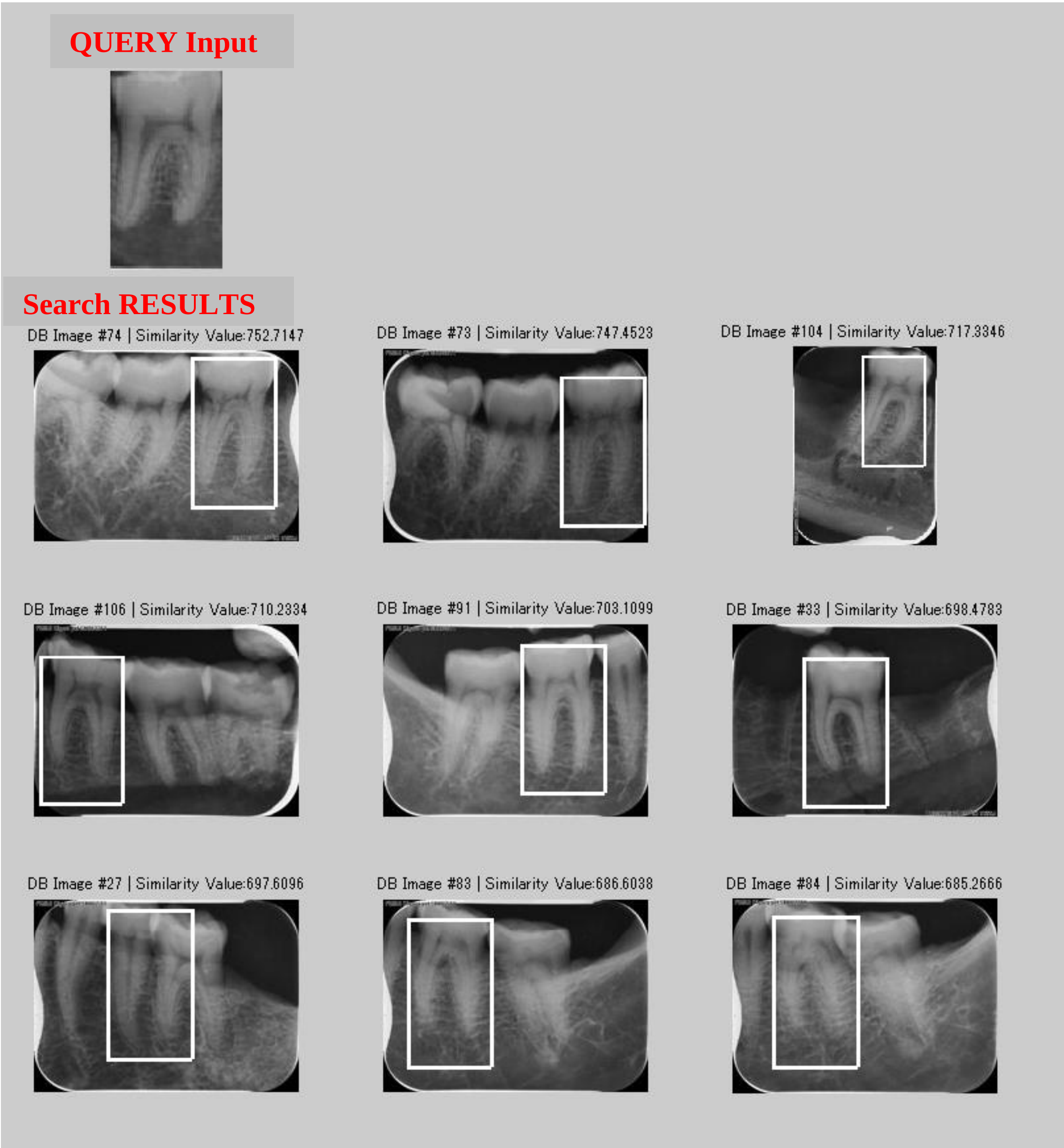


Fig. 5.2. Example of a query and its identification results; the white squared inside each image of the search result indicates area of similarity

In order to assess performance objective, a retrieval scenario from 10 queries of cropped periapical radiograph with single tooth is performed. As the results, eight of 10 queries are successfully identified and retrieved at the 1st rank of the search results, while the other two queries fail to find the their matches. The performance curve of the identification is shown in Fig. 5.3. Considering researches and suggestions done in [86, 87, 88, 89], this experiment shows the applicability and sufficiency of fuzzy guided segmentation and labeling for their use in dental based identification system in the limited data.

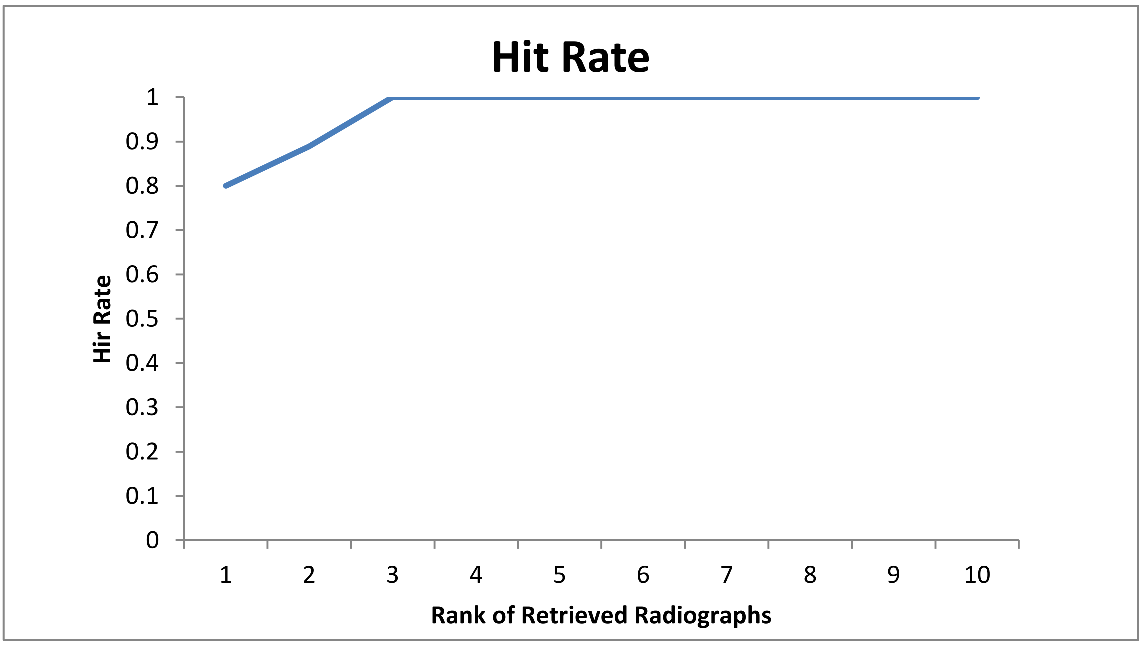


Fig. 5.3. Identification performance curve

5.2 Applicable Perspective on Deep-level Situation Understanding

Dental classification using multiple probabilistic values as proposed to classify tooth inside a radiograph has its potential to be applied to the area of deep level situation understanding. Deep level situation understanding is applied to casual communication between robots and humans [90]. Since robots co-exist with humans increasingly in environment (hospitals, restaurants, offices, manufacturing, homes, etc.), the robot ability to comprehend human intention casually in human-to-human like manner becomes important. . Casual communication may hide real intentions, but human can understand to some extent by taking into account spoken-unspoken messages, emotion, intention, atmosphere, universal-customized knowledge, situation inference, and careful attention (as opposed to only understand the surface level understanding from gesture, speech, and voice). This relationship is shown in Fig. 5.4.

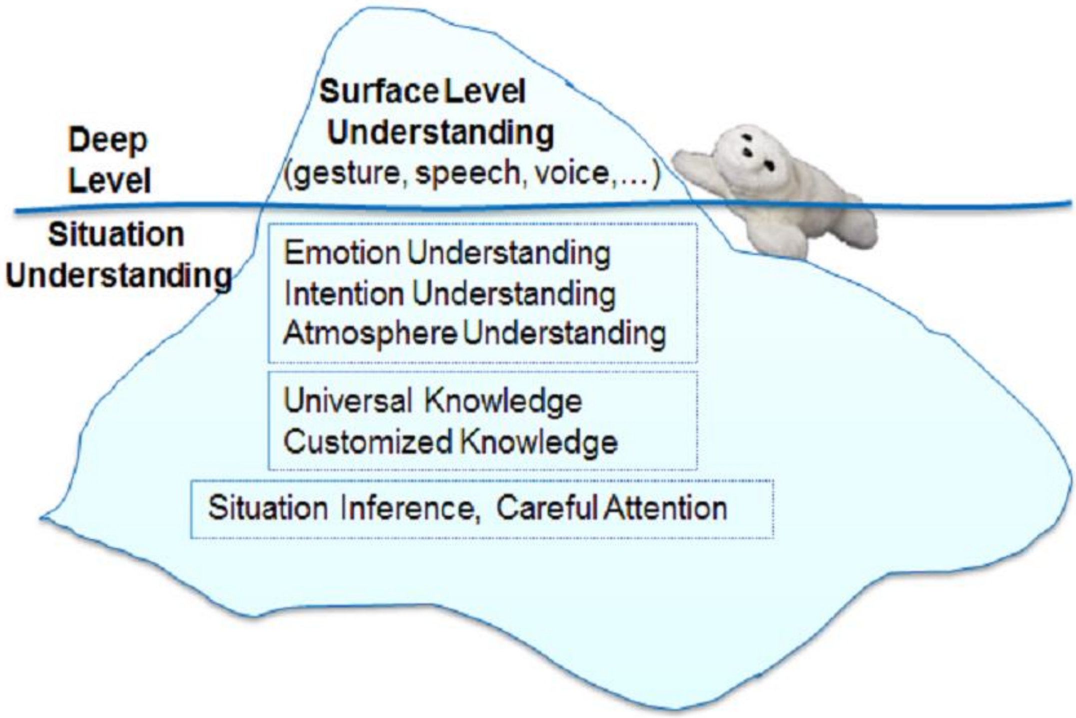


Fig. 5.4. The relationship of the surface level and deep level situation understanding

For instances, when people need for help, one may ask “are you busy?” instead of “could you help me?” In the stationery store, a visitor may ask “do you have a fountain pen?” and the expected response might be a guide to specific location of fountain pens but neither “yes” nor “no” to end the conversation. In this setting, the currently proposed network are shown in Fig. 5.5.

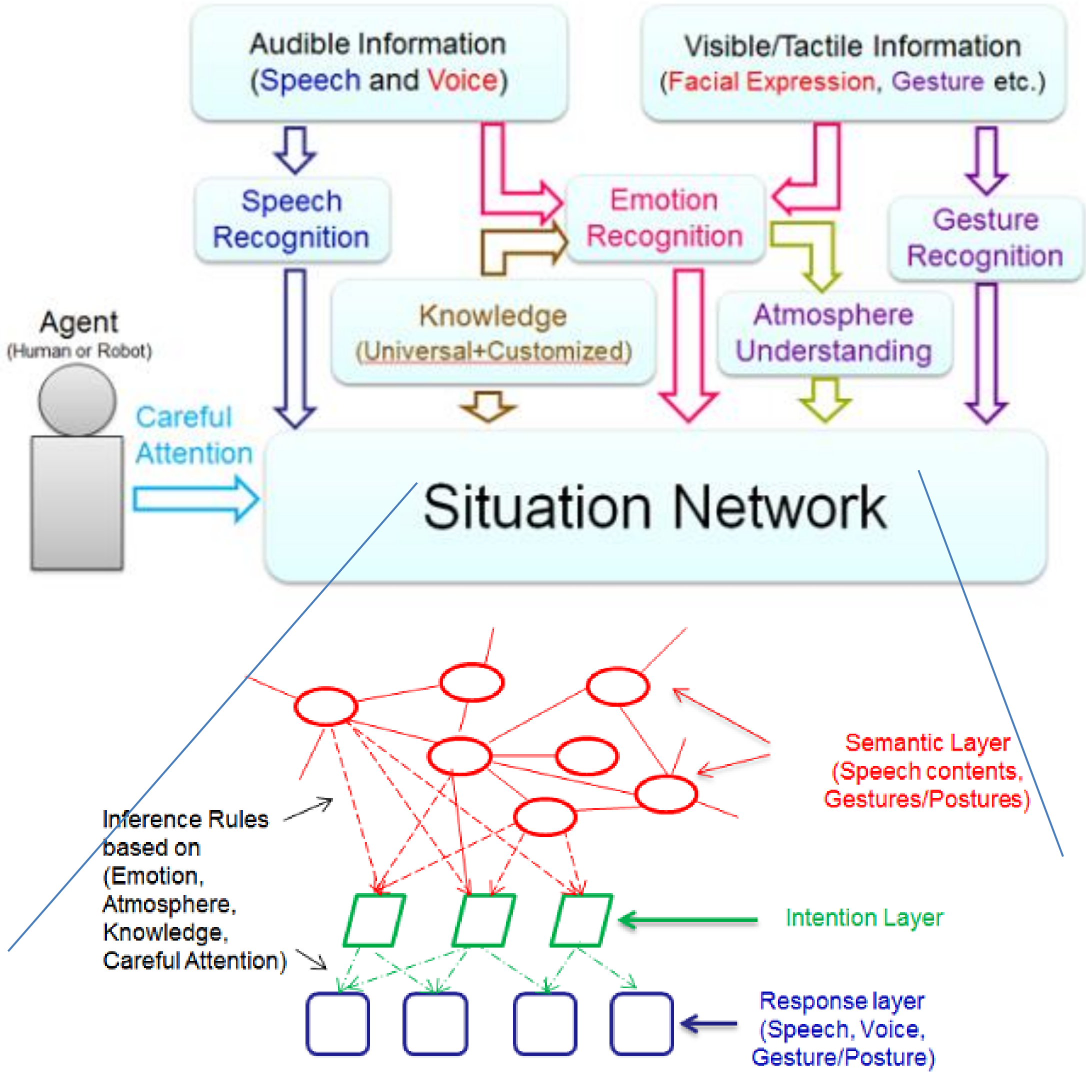


Fig. 5.5. The framework for deep level understanding and its situation network

Referring to Fig 5.5, there is one possible implementation of the fuzzy guided classification with multiple probabilistic values in the intention layer. The implementation may help the proposed framework to avoid misinterpretation of the deep level situation understanding. Since the purpose of multiple probabilistic values is to avoid speculative decision, the system can respond e.g. by asking the visitor to repeat again and therefore avoiding misinterpretation that makes the use of robot becomes inconvenient.

Chapter 6

Conclusions and Future Perspective

6.1 Conclusions

Fostering Scientific Contribution Toward Identification System

To foster the development of automatic identification system, specifically dental based personal identification system, fuzzy guided segmentation and classification methods are proposed. The results of the segmentation and classification show the capacity of the proposed methods to take part in as a module inside identification system..

Fuzzy Logic based Multi Agent System Approach for Radiograph Segmentation

The research is conducted firstly to cope with the challenge to do radiograph segmentation, and as the result, a method called fuzzy logic bassed multi agent system approach is proposed. This study shows the feasibility of the proposal to yield acceptable segmentation result after several iterations needed by the agents to properly segment the image, which two areas, teeth and background, are separated to support the necessary steps in the dental classification.

Multiscale Image Aggregation for Dental Radiograph Segmentation

In order to improve significantly the previous segmentation method, a pixel based segmentation method that does not require iteration to reach convergence in segmentation is proposed. Multiscale image aggregation employs three scaled down size radiographs in addition to the original size one. The result shows improvement both in accuracy of segmentation and the stability of the segmentation performance where it does not need to do iteration as the one done by the multi agent system approach. The statistical T-test is employed and T-test proves statistical significance of the method. The experiment results on 122 radiographs suggest 77.70% segmentation accuracy. In addition, the produced segmentation results are used for the next module to classify tooth type in the dental classification module.

Multiple Fuzzy Attribute for Dental Classification on Periapical

In this part, multiple fuzzy attribute is proposed to isolate each tooth and classify it. Besides, in this method, the features of each tooth are extracted (length, width, area/perimeter ratio, and length/width ratio). The experiment results on 223 teeth produce 82.51% classification accuracy.

Simulated Retrieval Scenario to Show Identification Capabilities

In the simulated retrieval scenario, the shortlisting of features from the fuzzy guided segmentation and labeling cut down the search space and keep the search result in $O(n^2)$. Even with its application with simple algorithm like template matching, the proposed system proves can give perfect answer for eight out of 10 queries.

6.2 Future Perspective

In spite of the specific domain problem addressed in this thesis, the future perspective of the research is broad in the sense that the proposal can be remodeled to cope with the other problem domains. To be more specific, several concrete applications that can be constructed using the modules of fuzzy segmentation and labeling are mentioned i.e., dental based personal identification system, multimodal identity archiving system, multimodal general identification system, and problem-domain based algorithmic enhancements.

Dental Based Personal Identification System

Dental based personal identification system is the most apparent application that can directly uses the proposals in this thesis. The research and development of this system has been being done in the faculty of computer science and faculty of dentistry, University of Indonesia since 2008. The expected outcome of this system is the real personal identification system that can computer-aid the forensics and dentists during their works identifying the victims of massive or huge disasters.

Dental Work Archiving and Identification System Development

Since the scope of this research does not cover the dental work for the segmentation and identification purposes due to the limitation of the data, however, this research is worth doing in as the next step to enhance the identification capabilities significantly of the proposed system. This is because of the information of dental work and series of teeth provide even more describing features for identification purpose. In addition to that, the existence of dental work information may foster more fruitful cooperation between forensics and dentists in the case of identification of huge victims.

Multimodal Identity Archiving System

Multimodal identity archiving system is an archival system intended to document the personal identity data. The personal data such as biometric (iris, fingerprint, eye, palm, palmvein, etc.), dental, social network account, etc. can be used to represent one identity well. The availability of such data can be useful for both government (to enforce law and security in a country) and citizen (to easily access a unified and centralized personal data for various purposes such as bank account, health record, etc.). There is one research proposal in 2012 about the development of a system called SMaRTIS: Profile-Tracking Based Identification System Using Encoded Multimodal Biometric Data. This proposal research is a collaboration work between King Saud University/Salman Bin Abdulaziz University and Tokyo Institute of Technology. The research done in this thesis can contribute to the development of one modality, dental based archiving system.

Multimodal General Identification System

Multimodal general identification system is the extension of multimodal identity archiving system. Once the stored personal data available, the identification module extension can provide the capability of multimodal identity archiving system to identify people based on the model of query-retrieval system. The scheme of this work is also a part of the previously mentioned SMaRTIS system and the current research in this thesis can take part in the identification system based on the dental data.

Problem-domain Based Algorithmic Enhancements of The Methods.

Fuzzy segmentation and labeling proposed in this research is specifically intended to work on the dental radiograph image. In spite of its specific purpose, it is feasible to further develop and enhance the methods to work on the other problems mainly in medical images, such as MRI data, or even extend it further to other domain in the image-related problem/research area. This is caused by the nature that segmentation and classification system is required in most of the image understanding prurposes.

Bibliography

[1] M. Petju, et al.: Importance of Dental Records for Victim Identification Following the Indian Ocean Tsunami Disaster in Thailand, Elsevier Journal of The Royal Institute of Public Health, 2007, Vol. 121, pp. 251-257, 2007

[2] O. Nomir, et al.: Hierarchichal Contour Matching for Dental X-Ray Radiographs, Elsevier Pattern Recognition, Vol. 41, pp. 130-138, 2007

[3] M. Abdel-Mottaleb, et al.: Challenges of Developing an Automated Dental Identification System, pp. 411-414, IEEE, 2004

[4] A. K. Jain and H. Chen, “Matching of Dental X-Ray Images for Human Identification,” Pattern Recognition, Elsevier, Vol. 37, No. 7, pp. 1519-1532, 2004.

[5] Y.H. Lai, et al.: Effective Segmentation for Dental X-Ray Images Using Texture-Based Fuzzy Inference System, LNCS 5259, pp. 936-947, Springer-Verlag Berlin Heidelberg, 2008

[6] M. L. Tangel, et al., “Fuzzy Logic based Emotional Multi Agent System Approach for Dental X-Ray Image Segmentation,” International Symposium on Intelligent System Conference 2010, Tokyo Metropolitan University, Japan, 2010.

[7] M. L. Tangel, et al., “Multiscale Image Analysis for Radiograph Segmentation,” World Congress of International Fuzzy System Association 2011, Surabaya-Bali, Indonesia.

[8] M. Tangel, C. Fatichah, M. R. Widyanto, F. Dong, and K. Hirota, “Multiscale image aggregation for dental radiograph segmentation, journal of advanced computational intelligence and intelligent informatics,” 16 (3), pp. 388 – 396, 2012.

[9] P.L. Lin, et al.: An Effective Classification and Numbering System for Dental Bitewing Radiographs using Teeth Region and Contour Information, Elsevier Pattern Recognition, 2009

[10] F.Aeini and F. Mahmoudi, "Classification and numbering of posterior teeth in bitewing dental image," ICACTE Vol. 6, pp.66-72, 2010,

[11] M. Mahoor and M. Mottaleb, "Classification and numbering of teeth in dental bitewing images," Pattern Recognition-Elsevier, Vol. 38, No. 4, pp. 577-586, 2005

[12] L. G. Shapiro and G. C. Stockman, "Computer Vision," pp. 279-324, Prentice-Hall, 2001.

[13] H. Gao and O. Chae, "Individual Tooth Segmentation from CT Images Using Level Set Method With Shape and Intensity Prior," Pattern Recognition, Elsevier, Vol. 43, No. 7, pp. 2406-2417, 2010.

[14] G.W. Corder and D.I. Foreman, "Nonparametric Statistics for Non-Statisticians," pp. 39-52, Wiley, 2009.

[15] J. Zhang and S. Kamata, "Adaptive Local Contrast Enhancement for the Visualization of High Dynamic Range Images," Pattern Recognition, IEEE, pp. 1-4, ICPR 2008.

[16] http://radonc.ucsf.edu/research_group/jpouliot/Tutorial/HU/Lesson7.htm, Access time: January 2011.

[17] P. Soille, "Morphological Image Analysis: Principles and Applications," pp. 173-174, Springer-Verlag, 1999.

[18] N. Otsu, "A Threshold Selection Method from Gray-Level Histogram," IEEE Trans. on SMC, Vol. 9, No. 1, pp. 62-66, 1979.

[19] LNAI: 4687 N. Benamrane and S. Nasane: Medical Image Segmentation by a Multi-Agent System Approach, pp. 49-60, Springer-Verlag Berlin Heidelberg, MATES 2007, 2007

[20] C. Huang, et al.: Computer-assisted Orientation of Dental Periapical Radiographs,

pp. 649-653, American Academy of Otolaryngology, 2007

[21] H. Chen, et al.: Dental Biometrics: Alignment and Matching of Dental Radiographs, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 27, pp. 1319-1326, 2005

[22] D.E.M. Nassar, et al.: A Neural Network System for Matching Dental Radiographs, Elsevier Pattern Recognition, Vol. 40, pp. 65-79, 2007

[23] Autonomous Agents and Multi-Agent Systems: Explorations in Learning, Self-Organization and Adaptive Computation: Jiming Liu, pp. 164-179, World Scientific, 2001

[24] M.S. El-Nasr, et al.: FLAME – Fuzzy Logic Adaptive Model of Emotions, Autonomous Agents and Multi-Agent Systems, 3, pp. 219-257, Kluwer Academic Publishers, 2000

[25] L. P.M. Bagher: Intelligent Agent System Simulation using Fear Emotion, World Academy of Science, Engineering and Technology, 48, pp. 334-338, World Academy of Science, Engineering and Technology, 2008

[26] P. L. Lin, Y. H. Lai, and P.W. Huang, "Classification and numbering system for dental bitewing radiographs using teeth region and contour information," Pattern Recognition-Elsevier, Vol.43, No. 4, pp. 1380-1392, 2010

[27] D. E. M. Nassar, "Automated Dental Identification: A Micro-Macro Decision-Making Approach," Ph.D. Dissertation, College of Engineering and Mineral Resources, West Virginia University, 2005

[28] J. Huang, S. Zhang, D. Metaxas, "Efficient MR Image Reconstruction for Compressed MR Imaging," Medical Image Analysis, Vol. 15, pp. 670 – 679, 2011.

[29] S. Y. Ababneh, J. W. Prescott, M. N. Gurcan, "Automatic Graph-cut Based Segmentation of Bones from Knee Magnetic Resonance Images for Osteoarthritis Research," Medical Image Analysis, Vol. 15, pp. 438 – 448, 2011.

[30] C. Petitjean, J. N. Dacher, "A Review of Segmentation Methods in Short Axis

Cardiac MR Images," Medical Image Analysis, Vol. 15, pp. 169 – 184. 2011.

[31] O. Friman, et. Al., "Probabilistic 4D Blood Flow Tracking and Uncertainty Estimation," Medical Image Analysis, Vol. 15, pp. 720 – 728. 2011.

[32] F. Kesthkar, W. Gueaieb, "Segmentation of Dental Radiographs using a Swarm Intelligence Approach," Conf. on Electrical Comp. Eng. (2006) pp. 328–331

[33] E.H. Said, D.E.M. Nassar, and G. Fahmy, H.H. Ammar, "Teeth segmentation in digitized dental X-ray films using mathematical morphology," IEEE Transaction Information Forensic Security 1 pp. 178–189, 2006.

[34] S. Li, T. Fevens, A. Krzyzak, C. Jin, S. Li, "Semi-automatic computer aided lesion detection in dental X-rays using variational level set," Pattern Recognition 40, pp. 2861–2873, 2007.

[35] H.D. Cheng, M. Xue, X.J. Shi, "Contrast enhancement based on a novel homogeneity measurement," Pattern Recognition 36, 2687–2697, 2003.

[36] S. Nasr-Isfahani, A. Mirsafian, A. Masoudi-Nejad, "A New Approach for Touching Cells Segmentation," IEEE International Conference on BioMedical Engineering and Informatics, pp. 816-820, 2008.

[37] Xiaodong Yang, Houqiang Li, and Xiaobo Zhou, "Nuclei Segmentation Using Marker-Controlled Watershed, Tracking Using Mean-Shift, and Kalman Filter in Time-Lapse Microscopy," IEEE Transactions on Circuits And Systems—I: Regular Papers, Vol. 53, No. 11, pp. 2405-2414, November 2006

[38] F. Cloppet and A. Boucher, "Segmentation of overlapping/aggregating nuclei cells in biological images," 19th International Conference on Pattern Recognition, ICPR, 2008.

[39] S. Shah, A. Abaza, A. Ross and H. Ammar, "Automatic Teeth Segmentation Using Active Contour Without Edges" Proc. of the Biometric Consortium Conference (BCC), Baltimore, MD, Sept. 19-21, 2006.

[40] M. L. Tangel, C. Fatichah, M.R. Widyanto, F. Dong, and K. Hirota, "Dental

Radiograph Segmentation using Emotional Multi-Agent System Approach", In Proceedings of the second Multidisciplinary International Student Workshop, Tokyo, Japan, 2010

[41] M. Cavalcanti, A. Ruprecht, W. Johnson, S. Thomas, J. Jakobsen, S. Paulo, "Oral and maxillofacial radiology," Oral Surg. Oral Med. Oral Pathol., 88, pp. 353–357, 1999.

[42] Eric Whaites, "Essentials of Dental Radiography and Radiology, 4e," Churchill Livingstone; 4 edition, pp. 75-100, February 19, 2007.

[43] B. G. Brogdon, M.D., "Forensic Radiology," CRC Press, Boca Raton, 1998.

[44] M. Mahoor and M. Mottaleb, "Automatic Classification of Teeth in Bitewing Dental Images," Image Processing, ICIP 04, International Conference Vol. 5, 2004

[45] N. Al-sherif, G. Guo, and H. Ammar, "Automatic Classification of Teeth in Bitewing Dental Images Using OLPP," IEEE International Symposium on Multimedia, pp. 92-95, 2012.

[46] L. F. Cost and R.M. Cesar Jr., "Shape Analysis and Classification Theory and Practice," CRC Press, 2000.

[47] Martin L. Tangel, Chastine Fatichah, Fei Yan, Janet P. Betancourt, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Dental Classification for Periapical Radiograph based on Multiple Fuzzy Attribute", 2013 IFSA World Congress and NAFIPS Annual Meeting, Edmonton, Canada, 2013

[48] American Dental Association, http://www.ada.org/ access time: November 2011

[49] M. Adoram and M.S. Lew, "Image Retrieval using Shape," IEEE Conference on Multimedia Computing Systems, Vol. 2, pp. 597-602, 1999

[50] D. Heesch and S. Ruger, "Combining Features for Content-Based Sketch Retrieval – A Comparative Evaluation of Retrieval Performance," Proc. Of 24th BCSIRSG European Colloquium on IR Research Glasgow (LCNS 2291), UK, March 2002.

[51] R. Hu, J. Collomosse, "A Performance Evaluation of Gradient Field HOG

Descriptor for Sketch based Image Retrieval," Computer Vision and Image Understanding, available online in 2013.

[52] C. Zhao, W. Shi, Y. Deng, "A new Hausdorff distance for image matching," Pattern Recognition Letters, 26, pp. 581–586, 2005

[53] Omaima Nomira, Mohamed Abdel-Mottalebb, "Hierarchical contour matching for dental X-ray radiographs," Pattern Recognition, Volume 41, Issue 1, pp. 130–138, January 2008,

[54] G. Fahmy, et. al., "Toward an Automated Dental Identification System (ADIS)," J. Electron, Imaging vol . 14 pp. 1-13, 2005

[55] J. Zhou, M. Mottaleb, "A Content-Based System for Human Identification based on Bitewing Dental X-Ray Images," Pattern Recognition Vol. 38, pp. 2132 – 2142, 2005.

[56] O. Nomir, M. Mottaleb, "A System for Human Identification from X-Ray Dental Radiographs," Pattern Recognition Vol. 38, pp. 1295– 1305, 2005.

[57] A. Jain, L. Hong, and S. Pankanti, "Biometric Identification," Communication of the ACM, Vol. 43, No. 2, pp. 91-98, Feb. 2000

[58] J.D. Zhou and M. Mottaleb, "Automatic Human Identification based on Dental X-Ray Images," Proceedings of the SPIE Conference on Defense and Security – Biometric Technology for Human Identification (OR30), Orlando, FL, April 2004

[59] R. O. Duda and P. E. Hart,. "Pattern Classification and Scene Analysis," John Wiley & Sons, New York 2000,

[60] O. Nomir, M. Abdel-Mottaleb, "Fusion of matching algorithms for human identification using dental X-ray radiographs," IEEE Trans. Inf. Forensic Secur. 3 pp. 223–233, 2008.

[61] R.C. Gonzalez, R.E. Woods, "Digital Image Processing," second ed., Prentice Hall, 2002

[62] Lowe, David G., "Object recognition from local scale-invariant features,"

Proceedings of the International Conference on Computer Vision 2. pp. 1150–1157, 1999.

[63] Nourdin Al-sherif, Ayman Abaza, and Hany Ammar, “Human Identification Based on Tooth Contour Guided Sift Descriptor”, Proceedings of the IASTED International Conference December 14 - 16, 2011 Dallas, USA Signal and Image Processing (SIP 2011).

[64] D. Nassar, A. Abaza,Xin Li, and H. Ammar, “Automatic Construction of Dental Charts for Postmortem Identification,” IEEE Transactions on Information Forensics and Security, vol. 3, no. 2, pp. 234–246, 2008

[65] P. H. Lin, Y. H. Lai, and P. W. Huang, "Dental biometrics: Human identification based on teeth and dental works in bitewing radiographs," Pattern Recognition 45 pp. 934–946, 2012

[66] T. Chomdej, W. Pankaow, S. Choychumroon, "Intelligent dental identification system (IDIS) in forensic medicine," Forensic Science International 158 pp. 27–38, 2006

[67] V. Pinchi, et. al., "Dental identification by comparison of antemortem and postmortem dental radiographs: Influence of operator qualifications and cognitive bias," Forensic Science International 222, pp. 252–255, 2012

[68] B. Ermenc , K. Rener, "Possibilities for dental identification in the case of mass disaster in Slovenia," Forensic Science International 103, pp. S67–S75, 1999.

[69] G. Fahmy, D.M. Nassar, E. Haj-Said, H. Chen, O. Nomir, J.D. Zhou, R. Howell, H.H. Ammar, M. Abdel-Mottaleb, A.K. Jain, "Towards an automated dental identification system (ADIS)," Proceedings of National Conference on Digital Government Research, DGO, Seattle, WA, USA, pp. 789–796, 2004.

[70] G. Fahmy, D. Nassar, E. Haj-Said, H. Chen, O. Nomir, J. Zhou, R. Howell, H. Ammar, M. Abdel-Mottaleb, A. Jain, "Toward an automated dental identification system (ADIS)," J. Electron. Imaging, 14 (4), 2005.

[71] D. Nassar, E. Haj Said, A. Abaza, S. Chekuri, J. Zhou, M. Mahoor, O. Nomir, H. Chen, G. Fahmy, H. Ammar, M. Abdel-Mottaled, A. Jain, "Automated dental identification system ADIS," Proceedings of National Conference on Digital Government Research, DGO, Atlanta, GA, USA, May 2005.

[72] F. Samadzadegan, F. Bashizadeh, M. Hahn, P. Ramzi, "Automatic registration of dental radiograms," Geo-Imagery Bridging Continents, Istanbul, Turkey, 12–23 July 2004.

[73] M. Abdel-Mottaleb, O. Nomir, D. Nassar, G. Fahmy, H. Ammar, "Challenges of developing an automated dental identification system," IEEE Mid-West Symposium for Circuits and Systems, Cairo, Egypt, 27–29 December 2003.

[74] A.K. Jain, H. Chen, S. Minut, "Dental biometrics: human identification using dental radiographs," Proceedings of the Fourth International Conference on AVBPA, Guildford, UK, pp. 429–437, 2003.

[75] D. Nassar, and Hany Ammar, "A Neural Network System For Matching Dental Radiographs", Pattern Recognition, vol. 40, pp. 65-79, Jan 2007.

[76] S. Chekuri, D. Nassar, A. Abaza, A. Bahu, U. Qureshi, and H. Ammar "webADIS: A Flexible web-based Environment for the Automated Dental Identification System", Proc. of 2nd International Computer Engineering Conference (ICENCO), Cairo, Egypt, December 2006.

[77] O. Nomir and M. Abdel-Mottaleb, "Hierarchical Dental X-Ray Radiographs Matching", Proc. of the International Conference on Image Processing (ICIP), Atlanta, GA, October 8-11, 2006.

[78] Surendra Ramteke, Rahul Patil, And Nilima Patil, "A State of Art Automated Dental Identification System (ADIS)," Advances In Computational Research, Volume 4, Issue 1, pp.95-98, 2012.

[79] Diaa Eldin M. Nassar and Hany H. Ammar, "A Prototype Automated Dental Identification System (ADIS)," Lane Department of Computer Science and

Electrical Engineering, West Virgnia University, March 2003.

[80] Diaa Eldin M. Nassar and Hany H. Ammar, "A Prototype Automated Dental Identification System (ADIS)," Lane Department of Computer Science and Electrical Engineering, West Virgnia University, March 2003.

[81] C. P. Pereira and J. C.Santos, "How to do identify single cases according to the quality assurance from IOFOS. The positive identification of an unidentified body by dental parameters: A case of homicide," Journal of Forensic and Legal Medicine Vol. 20, pp. 169-173, 2013

[82] S. Singh, D. Bhargava, A. Deshpande, "Dental orthopantomogram biometrics system for human identification," Journal of Forensic and Legal Medicine pp. 1-3, 2013

[83] B. A. Eastwood, J. Fletcher, and W. Laird, "The Value of Dental Restorations in Post-mortem Identification," Journal of the Forensic Science Society, Vol. 24, Issue 6, pp. 569–576, November 1984.

[84] S.A. Sholl, G.H. Moody, "Evaluation of dental radiographic identification: an experimental study," Forensic Science International 115, pp. 165-169, 2001

[85] David Sweet, "Forensic dental identification," Forensic Science International 201 pp.3–4, 2010

[86] http://www.csee.wvu.edu/adis/ access time: September 2011

[87] A.K. Jain, H. Chen, "Registration of dental atlas to radiographs for human identification," Proc. of SPIE Conf. on Biom. Technol. Hum. Identification 5779 pp. 292–298, 2005.

[88] http://www.socialresearchmethods.net/kb/stat_t.php access time: April 2013.

[89] N1 – P. Stimson & C. Mertz, Forensic Dentistry, CRC Press 1997

[90] Y. Tang, et. al., "Deep Level Situation Understanding and Its Application to Casual Communication between Robots and Humans," the 10th International Conference on Informatics in Control, Automation and Robotics (ICINCO), 2013.

Related Publications

Journal Papers

[J3] **Martin L. Tangel**, Chastine Fatichah, Fei Yan, Janet P. Betancourt, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Fuzzy Indexing for Dental based Personal Identification System", Journal of Computer in Biology and Medicine, Elsevier (in preparation).

[J2] **Martin L. Tangel**, Chastine Fatichah, Fei Yan, Janet P. Betancourt, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Dental Classification and Numbering for Periapical Radiograph based on Multiple Fuzzy Attribute", International Journal of Computer Aided and Engineering, Inderscience (in preparation).

[J1] **Martin L. Tangel**, Chastine Fatichah, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Multiscale Image Aggregation for Dental Radiograph Segmentation", *Journal of Advance Computational Intelligence and Intelligent Informatics (JACIII),* Vol. 16 No. 3, 2012.

International Conference Papers

[C3] **Martin L. Tangel**, Chastine Fatichah, Fei Yan, Janet P. Betancourt, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Dental Classification for Periapical Radiograph based on Multiple Fuzzy Attribute", *2013 IFSA World Congress and NAFIPS Annual Meeting*, Edmonton, Canada, 2013 – **(Accepted)**.

[C2] **Martin L. Tangel**, Chastine Fatichah, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Multiscale Image Analysis for Dental Radiograph Segmentation", *Proceedings of The 2011 IFSA World Congress and the 2011 AFSS (IFSA-AFSS 2011*), Surabaya, 2011 – ***Best Young Researcher Award***.

[C1] **Martin L. Tangel**, Chastine Fatichah, M. Rahmat Widyanto, Fangyan Dong, Kaoru Hirota, "Fuzzy Logic based Emotional Multi Agent System Approach for Dental X-Ray Image Segmentation," *Proceedings of The 2010 International Symposium on Intelligent Systems (iFAN 2010)*, Tokyo, 2010

Related Publications

Domestic Conference Papers

[D1] **M. L. Tangel**, C. Fatichah, M.R. Widyanto, F. Dong, and K. Hirota, "Dental Radiograph Segmentation using Emotional Multi-Agent System Approach", In Proceedings of the 2nd Multidisciplinary International Student Workshop, Tokyo, Japan, 2010.

Awards

[A2] **Best Young Researcher Award**
2011 International Fuzzy System Association (IFSA) World Congress and Asian Fuzzy Systems Society (AFSS) International Conference, Surabaya and Bali, Indonesia, June 2011.

[A1] **Gold Prize, Best Poster Award, Master Thesis Presentation**
Department of Computational Intelligence and Systems Science, Tokyo Institute of Technology, Japan, February 2011.