"EDGE DETECTION IN DENTAL RADIOGRAPHS USING GENERALIZED TYPE-2 FUZZY LOGIC SYSTEM"

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CERTIFICATE

This is to certify that the Dissertation-II titled "**Edge Detection in Dental Radiographs using Generalized Type -2 Fuzzy Logic System**". That is being submitted by "**Aayushi Agrawal**" in partial fulfillment of the requirements for the award of Master of Technology, is a record of bonafide work done under my guidance. The content of this report, in full or in parts, have neither taken from any other source nor have been submitted to any other Institute or university forward of any degree or diploma and the same is certified.

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Examiner I **Examiner II**

ABSTRACT

Dental image processing is use in case of human recognition. Proceeding a pace ahead in the area where image processing of dental radiograph for effective detection and diagnosis of dental diseases required. Edge detection plays an important role on dental radiograph for better detection of diseases. Taking consideration this problem edge detection of dental radiograph takes place. For this, different edge detection techniques are discussed in this research. The techniques are sobel edge detector , T1FLS and IT2FLS. Results are compared on the basis of total edge detected pixels and total time consumed by algorithm to detect edges from an image. The technology of the computer and new applied science of fuzzy logic are growingly, penetrating and intersecting. Fuzzy logic, established on the fundamental estimate that is fuzzy sets every component in the sets can presume a logic from 0 to 1 and not only 0 or 1 as in classical set possibility. Fuzzy Logic allows for easy path to reach at a distinct decision based on imprecise , vague, noisy, ambiguous, or lacking input data.

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DECLARATION

I, Aayushi Agrawal, student of Master of Technology under Department of Electronics and Communication Engineering of Lovely Professional University, Punjab, hereby declare that all the information furnished in this dissertation-II report is based on my own intensive research and is genuine. This dissertation-II, to the best of my knowledge, does not contain any work which is not done by me.

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LIST OF ABBREVIATIONS

MFs	Membership Functions
T1FLS	Type 1 Fuzzy Logic System
IT2FLS	Interval Type 2 Fuzzy Logic System
GT2FLS	General Type 2 Fuzzy Logic System
FOU	Footprint Of Uncertainty
FIS	Fuzzy Inference System

1

INTRODUCTION

In dental x-ray imaging, edge detection acts a very helpful function in detecting and diagnosis of the dental diseases. Since, dental radiograms are poor and complicate in some of the diseases extraction such as tooth decay, cavities[1], tooth abscess, impact tooth etc. Brightness of x-ray image are not good enough because of sequins occurs due to the presence of water on teeth.

Edges can be the outcome of varies in color, light absorption, texture and shadow these varies can be employed to decide the depth, orientation, size and surface property of digital image [2]. In evaluating an image digitally, edge detection necessitates filtering unrelated data to choose the edge levels. The recognition of indirect varies may be shuffled up with noise and that is depends on the picture element threshold of vary that determines an edge. Recognition of these unbroken edges is actual hard and interval taking particularly while an image is degraded by noise. Edges can be specified as a group of immediate pixel location where a sudden vary in intensity values takes place . Edges be the boundaries among objects and background. An edge detector can be used for feature extraction, image segmentation and object identifications [3].

The edge detection procedure is critical pace in the examination of medical images. Conventional edge detectors are centered on derivatives of an image concentration purpose. They have high performance speed and are widely implemented. However, they fail to detect edges in complex medical images and those with acquisition artifacts. Therefore, it necessitates a comprehensive modification to enhance their performance. To overcome the problems of conventional edge detectors, Fuzzy Logic technique came into existence. Fuzzy logic is soft computation procedure designed for modeling partial information or ambiguous information The usage of type-1 fuzzy logic in actual computer structures is wide, especially in user productions and operating applications. Fuzzy logic is field of soft computation which alters a computer organization to argue with uncertainness. A fuzzy inference system (FIS) comprises a set of rules determined above fuzzy sets. Fuzzy sets simplify the theory of a conventional set by granting the degree of membership to be several value with in 0 and 1 (Zadeh, 1965)[4].

Fuzzy skilled organizations have been employed by various achievements to complications of conclusion, controller, diagnosis and sorting, only since they can handle the difficult knowledgeable thought elaborate in these regions of presentation. This uncertainness extends to rules whose antecedents(input Mfs) or consequents (output Mfs) are uncertain, that understands into uncertain input MFs or output MFs (Karnik & Mendel 1998). Type-1 fuzzy organizations similar the ones remarked beyond, whose MFs are type-1 fuzzy sets are impotent to immediately manage such uncertainties[3][4]

Nowadays, the effectiveness of type-2 fuzzy logic is what it accepts us one further pace towards the destination of ‘Computing with Words’ or the purpose of computers to act human sensing. This study focused on the impression of a fuzzy set whereas the membership degree of a fuzzy sets are evaluated with linguistic relations such as small, medium and large.[5][6] At this phase, the explore was of extremely numerical, theoretic nature and actually was around constructing more or less of the foundations to more recent work.

1.1 Basic Human Teeth Structure

Human teeth structure[7] in Fig.(1) shows, mainly consist of three tissues they are

i. *Hard tissues:* It is also known as calcified tissues having a hard intercellular matrix and also highly mineralized. Cementum , dentine and enamel are the hard tissues in human teeth structure.

ii. *Soft tissues:* It is present to protect and cover the root of the teeth. Tooth pulp is soft tissues found in teeth.

iii. *Supporting tissues:* It is present around the teeth and helpful in providing the necessary supports to hold teeth in use.

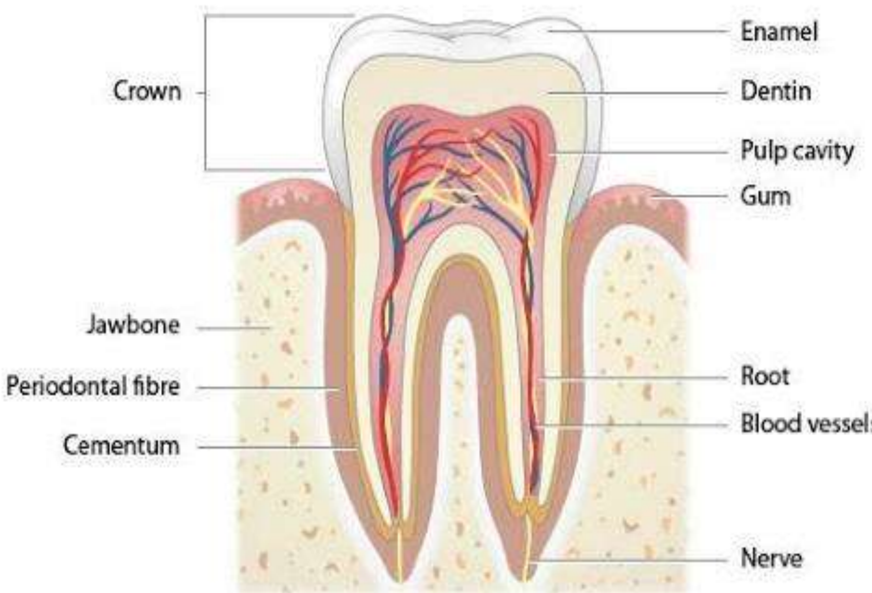


Fig. 1.1: Basic structure of human

1.2 Dental Diseases

The major significant function of teeth is to increase appearance and individual's integration in modern society. It is also helpful to make ready the food digestive. Sometimes when humans are not aware the importance of teeth and not brushing their teeth daily properly and many more causes leads to some dental diseases[7] are mentioned in Table.1 along its prevention and treatments.

The mouth is occupied place, with thousands of bacteria continuously on the move. While some microorganisms are innocuous, others can affect the all teeth and gums. Dangerous bacteria are confined in a monochrome gummy film known as plaque, the origin of gum disease. If not distant, plaque forms up on teeth and eventually affect the gums and reasons bleeding. Left unchecked, connective tissue and bone are damaged, and teeth regularly turn out to be free and have to be detached.

A latest survey of 1,000 people over 35 completed by Harris Interactive Inc. established that 60 percent of grown person measured knew minute, if everything, about gum infection, the available treatments, symptoms and most prominently the effects. And about 39 percent do not reach dentist commonly. Yet, gum infection is the important source of adult tooth damage[8].

Table 1.1 Common Dental Diseases along its causes, prevention and possible treatment outcome

S.No	Dental Diseases	Causes	Prevention	Possible treatment outcome	Images
1.	Tooth Decay	Improper teeth cleaning. Over eating and drinking of sugar.	Washing mouth after eating. Less consumption of sugar.	Remineralization. Fluoride treatments.	 (a)
2.	Chipped Tooth	Due to some accidents. Cavities which make weaken.	Uses of mouth guard. Avoid eating the hardest food.	Tooth Filling. Covered with crown (made up ceramics).	 (b)
3.	Stained Teeth (Discoloration)	Chewing a tobacco or smoking. Improper teeth brushing.	Avoid chewing tobacco or smoking Brush teeth twice in a day.	Tooth Bonding. Advance whitening.	 (c)
4.	Impacted Teeth	Improper eruption of tooth Insufficient space in jaw	Continuously updating the dental X-ray.	Tooth Extraction	 (d)
5.	Sensitivity (Cold)	Due to some predefined problems they are Cavities, Cracked, exposed roots etc.	Avoid drinking or eating acidic food or drinks.	Apply protection layer (Fluoride layer). Brush with fluoride gel.	 (e)

6.	Hyperdontia	Actual cause is unknown but many experts believe that it is due to genetic problem.	Not available.	Surgical Extraction. Orthodontic treatment.	 (f)
7.	Crooked Teeth	Sucking of thumb. Usage of baby bottle at large extent. Teeth grinding.	Avoid thumb sucking. Avoid usage of baby bottle a lot.	Mouth Guard. Therapy.	 (g)
8.	Diastema	Different shape and size of teeth. Tongue thrusting.	Placement of permanent retainer	Frenectomy. Dental crowns. Invisalign.	 (h)
9.	Periodontal Diseases	Smoking. Diabetes. Hormonal changes in women	Avoid smoking. Repeatedly checkup and cleaning of teeth.	Flap surgery. Bone and tissues grafting. Deep cleaning.	 (i)
10.	Bruxism	Stress. Sleep disorders.	Usage of Bite splint at night.	Biofeedback exercises. Physical therapy. Plastic tooth guard. Relaxation techniques.	 (j)
11.	Dental Abscess	Smoking. Diabetes. Gum disorders.	Brushing of teeth after every meals. Avoidance of smoking.	Root canal treatment. Drainage of pus.	 (k)

12.	Dental Trauma	Hit by hard surface. Rigorous sports activities.	Usage of mouth guard.	Tooth filling.	 (l)
13.	Oral Cancer	Smoking. Tobacco.	Avoidance of smoking and Tobacco.	Radiation therapy	 (m)
14.	Cracked Tooth	Eating hard food. Weakened tooth. Clenching teeth at night.	Avoid eating hard food. Avoid doing clenching.	Bonding. Placing crown.	 (n)

1.3 Type 1 Fuzzy Logic

Fuzzy logic is established upon the philosophy of fuzzy sets, which is a simplification of a conventional sets theory. Proverb that the model of fuzzy sets is the simplification of the conventional set theory meaning the lattest is a peculiar event of fuzzy sets theory. Fuzzy Logic is methodology to calculating founded on ‘degree of true statement’ instead of the traditional ‘True or False’(1 or 0) reasoning upon that the recent computer is established . When the argument is in unsure and in this event, use of the fuzzy set technique [9].

The general structure of a T1FLS comprises of various theoretical constituents: a "rule base", that holds collection of fuzzy rules that is a "data base" ("dictionary"), that describes the MFs employed in fuzzy rules "reasoning mechanism", that implements the illation process on the rules and agreed realities to develop a rational decision. The overall, can approximate that the fuzzy inference structure enforces a nonlinear function to its contribution place till outcome place. This function is achieved by collection fuzzy rules (if-then), every of that defines the limited performance of the function.

1.3.1 Fuzzy Set Theory

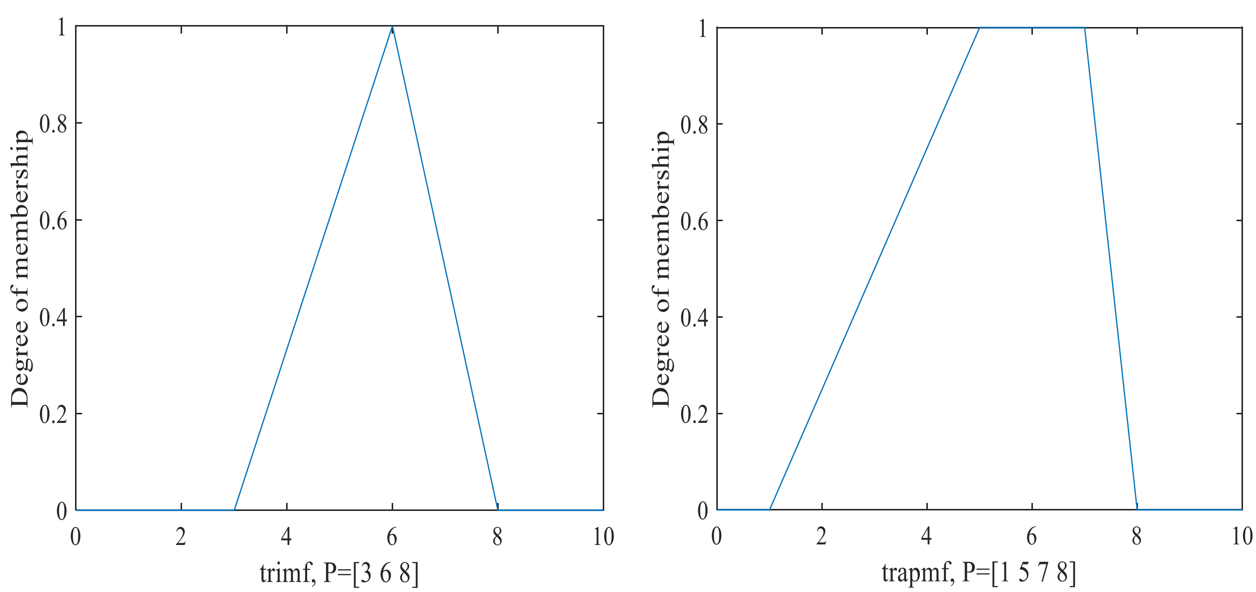
A Fuzzy set is specified as if 'U' is a universe of discourse(UOD) and 'a' is a particular component of 'U', then a fuzzy set 'S' describes on 'U' will be spelled as a aggregation of governed matches in equation number (1.1)

$$S = \{ (a , \mu_S(a)) \} , \text{ where } a \in U \tag{1.1}$$

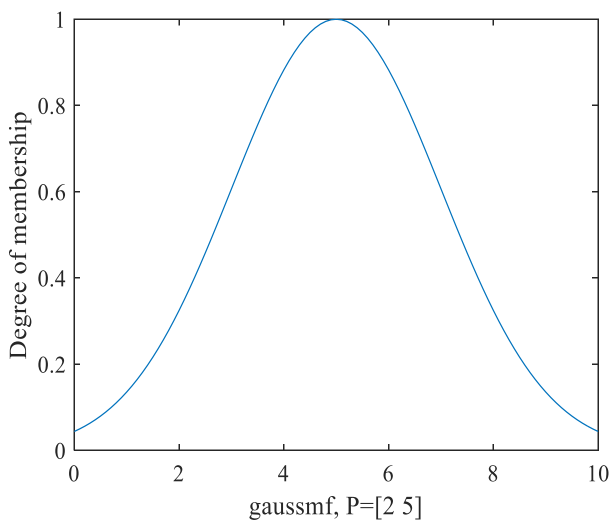
where $\mu_S(a)$ is called "membership function" (or MF) towards the fuzzy set 'S'. The MF represents every component of 'a' to a membership degree (or membership measure) within 0 and 1. Understandably, that defines a fuzzy set as a modest addition to the explanation of classic set where the feature purpose is allowed to be whatever values within 0 and 1. The values of the MFs $\mu_S(a)$ is bounded to 0 or 1,thus 'S' is summary to a traditional set and $\mu_S(a)$ is the representative role of 'S'[10]

1.3.2 Fuzzy Membership Functions

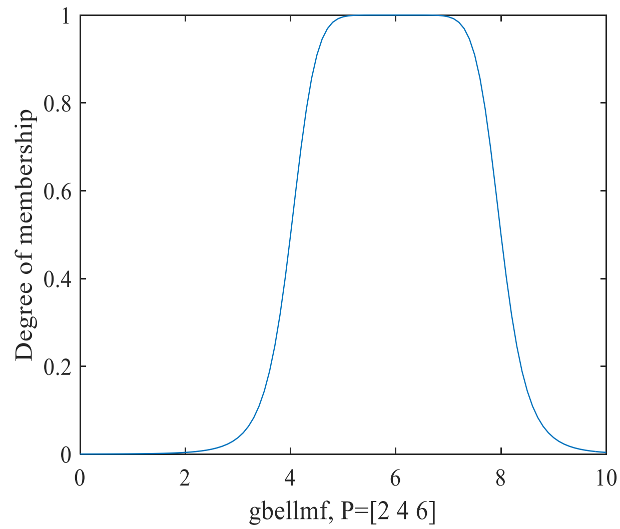
Since remarked earlier, a fuzzy set is entirely described by the situation MF. Because almost fuzzy sets in role must its own universe of discourse 'U' comprising the real axis 'T', it may be unpractical to figure out completely the pairs describing a MFs.



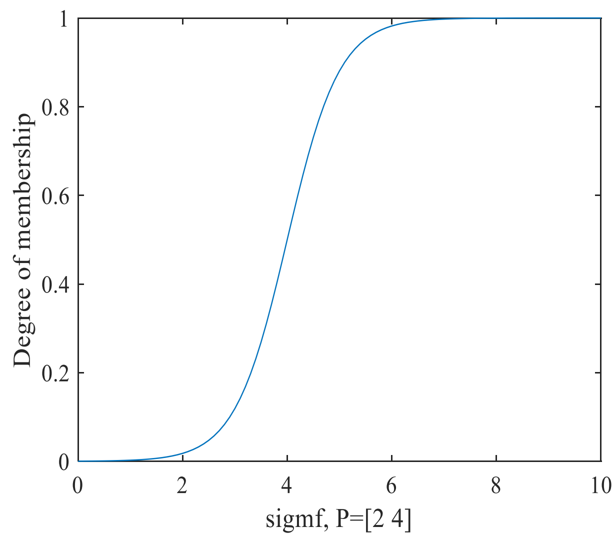
(a) (b)



(c)



(d)



(e)

Fig 1.2 : Fuzzy Membership Functions (a) Triangular MF (b) Trapezoidal MF (c) Gaussian MF (d) Generalized bell MF (e) Sigmoidal MF

1.3.3 Fuzzy Rules

The conventional methods for structure examination are as such unprepared for covering with humanitarian organizations, whose functionality is toughly determined by human judicial decision, opinion and feelings. This is the expression of what may to be known as the "principle of incompatibility": "As the complication of a system raises, our power to make exact and yet important statements around its behavior contracts until a threshold values is arrived at beyond their precision and implication become nearly mutually exclusive features "

1.3.4 Fuzzy If-Then Rules

A "fuzzy if-then rule" (also defined as fuzzy implication, fuzzy rule base or "fuzzy conditional statement") accepts the kind

$$\text{if r is R then s is S} \tag{1.2}$$

in equation (1.2) where ‘R’ and ‘S’ are linguistic variables describes by the fuzzy sets upon universes of discourse ‘r’ and ‘s’, respectively. Frequently "r is R" is known as "antecedent" or "premise", and "s is S" is known as the "consequence".

1.3.5 Fuzzy System

Fuzzy system contains of a preparation of the function where a passed input set and output applying fuzzy logic, which comprises of following five steps :

Step 1: Fuzzification of linguistics variables, fixing the control purposes and standards.

Step 2: Application of fuzzy operators (And, Or, Not) and in the IF input contribution of the rule. Find the output and input associations and select a minimal number of variables for input to the FIS.

Step 3: Significance from input to the output (THEN contribution of the rule) for the wanted system outcome reaction for a devoted FIS input considerations.

Step 4: Aggregation of consequents across the rules by producing fuzzy logic MFs that express the significance (standards) of input/output positions employed in the rule applied in the system.

Step 5: Defuzzification to obtain a crisp result.From step 1 to 5 to be followed for implementation of any fuzzy logic system commonly. Input to fuzzy logic system is fuzzy and after Defuzzification.

1.3.6 Defuzzification

This is the last stage in fuzzy arrangement where the fuzzy outcome involves to be altered to a non fuzzy form. The fuzzy rule base comprises for illustrate, employs such step to provide a crisp control logic.

1.4 Interval Type 2 Fuzzy Logic System (IT2FLS)

IT2FLS structures, where the input and output MFs are type-2 fuzzy sets. These sets are fuzzy, where membership classes itself are type-1 fuzzy sets; so it is most beneficial in considerations wherever it is challenging to decide an strict membership function degree for fuzzy set. The elaborated fuzzy logic (type-2 fuzzy logic) is capable to deal uncertainnesses since it can prototypical and reduce their consequences.

1.4.1 Type-2 Fuzzy Sets

A type-2 fuzzy sets are described by a fuzzy MFs , that is the membership degree for every component of these sets are a fuzzy set within [0,1], different from type-1 fuzzy set wherever the membership degree is a hard number within [0,1]. That sets may be applied in positions anywhere there is uncertainness around the membership degrees itself , e.g., an uncertainness in the figure of MFs or within about of its constraints. Contemplate the conversion from conventional sets to ambiguous sets. When cannot decide the membership of the component in set 0 or 1, use of fuzzy sets of type-1. Likewise, once the condition is so uncertain that must suffering defining the membership degree yet as a crisp number within [0,1],

1.4.2 Footprint of uncertainty(FOU)

Vagueness in the primary memberships of the type-2 fuzzy set, B, comprises of a limited section that is known as “footprint of uncertainty” (FOU). Arithmetically, it is the combination (maximum) of each primary membership functions.

1.4.3 Upper and lower membership functions

An “upper MFs and a “lower MFs” are two type-1 MFs that are limits for the FOU of a type-2 fuzzy set B. The upper MFs is related to the upper limit of FOU(B). The lower MFs is related to the lower limit of FOU(B).

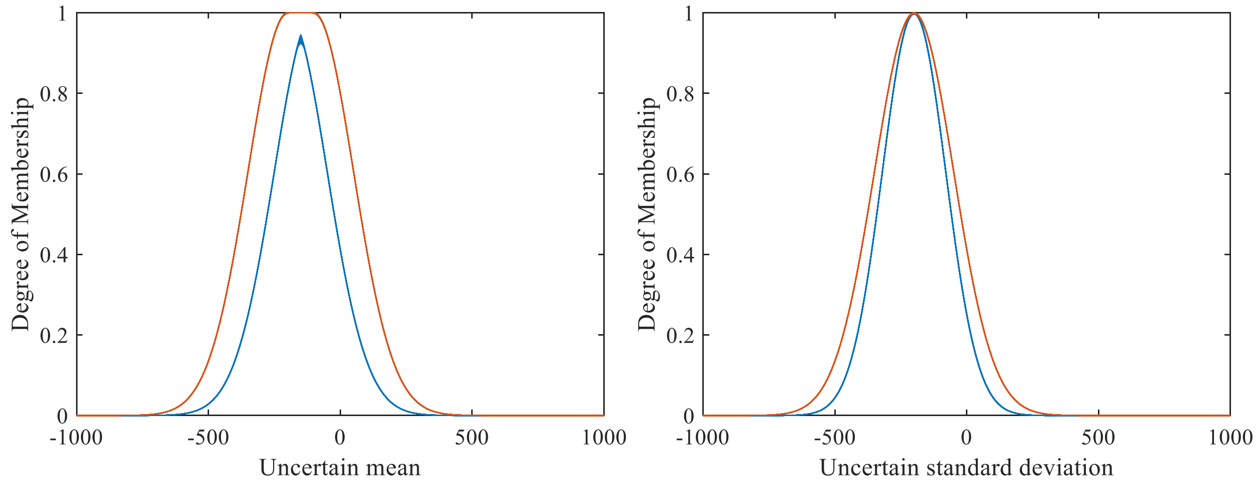
1.4.4 IT2FLS Membership Function

Gaussian MFs with mean ‘m’ and a standard deviation ‘σ’ that can accept values in [σ1,σ2] is shown in equation (1.3)[11]

$$\mu(x)=\exp\{-½[(x-m)/\sigma]^2\};\quad \sigma \in [\sigma 1,\sigma 2] \tag{1.3}$$

Gaussian MFs with a fixed standard deviation ‘σ’, but an uncertain mean, accepting values in [m1, m2] is shown in equation (1.4)

$$\mu(x)=\exp\{-½[(x-m)/\sigma]^2\};\quad m \in [m1,m2] \tag{1.4}$$



(a) (b)

Fig 1.3 IT2FLS Membership Function (a) Uncertain Mean (b) Uncertain Standard Deviation

1.5 Generalized Type-2 Fuzzy Logic

A generalized type-2 fuzzy set (GT2FS) is categorized by a type-2 MFs $\mu A\ (x,)$, where $x \epsilon X$, u $\epsilon\ Jx \subseteq [0,1]$ and $0 \leq \mu A\ (x,u) \leq 1$, and can be represented by

$$A = \ (x,), \quad x, \ | \forall x \in X, \quad \forall u \in Jx \subseteq \ 0,1 \qquad (1.5)$$

Where 'Jx' is called the primary membership of 'x' in . At every value of $x = x'$, the two-dimensional plane, where axes are 'u' and μ x′,u , is called a vertical slice of 'A' . A secondary MFs is a vertical slice of μ x,u . It is μ x = x′,u , for $x' \in X$ and $\forall u \ \in Jx' \subseteq \ 0,1$, and it is defined in equation (1.6)

$$\mu \ = x', \equiv \mu A \ \ x'u \qquad Jx' \subseteq \ 0,1 \qquad (1.6)$$

1.5.1 α-Planes Representation

An α-plane for 'A' GT2FLS, in this case 'Ã', is referred by 'Ãα', and it is the union(max) of each primary membership functions of 'Ã', where secondary membership grades are greater or equal to α (0 ≤ α ≤ 1)[12] . The equation of the alpha plane is presented by equation (1.7)

$$\tilde{A}\alpha = \ \ x, ,\tilde{A}\ x,u \geq \alpha | \forall x \in X, \forall u \in JX \subseteq 0,1 \qquad (1.7)$$

1.5.2 Generalized Type 2 Fuzzy Logic Membership Function

Three-dimensional graphical demonstration for the type-2 set for that a principal membership function be determined. The secondary membership function representing to every field detail is supposed to rise from the lower MFs to the principal MFs , and reduction from the principal MFs to the upper MFs. This function darks the region among the principal MFs and the upper and lower MFs in this way that the concentration of sheltering enhances from the brightest at the lower MFs to the sullenest at the principal membership function and after that reductions once more to the brightest at the upper MF[12]

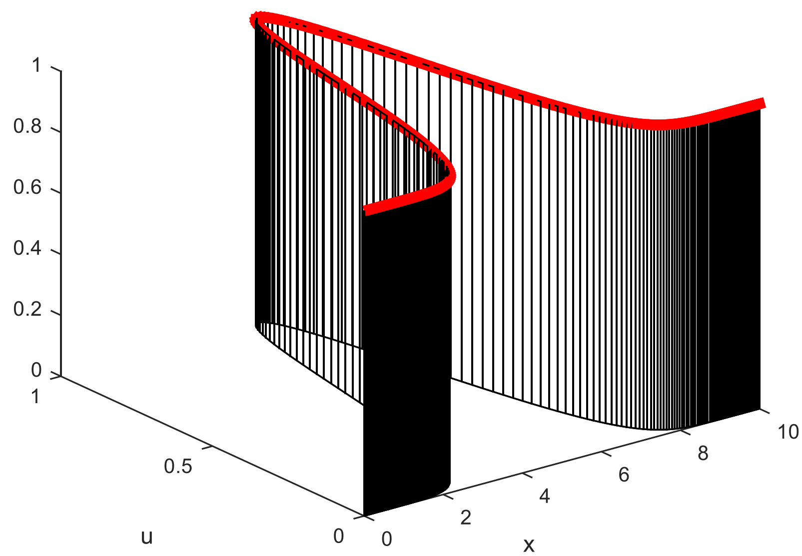


Fig 1.4 GT2FLS Membership Function

2

SCOPE & OBJECTIVE OF THE STUDY

2.1 Scope of study

Edge plays a significant role in medical image processing applications. It allows to provide an outline of the object. When an edge is detected, the unnecessary details are removed, while only the important structural information is retained. The edge detection method using fuzzy has less computational complexity, take less time for edge detection and it is very robust to noise and give better result than other methods that are penetrating to noise. Thus the scope of edge detection method using fuzzy logic in dental radiographs is as follows :

- The procedure of mining features, gathering & analyzing the valuable image data for medical diagnostics of teeth that is the major requirement of today's health science . In this area of dental image processing, maximum of the research prepared is advantageous for pathological science specialists for the determination of human identification.
- Proceeding a step forward in this field of dental medicine the identification of dental diseases from digital dental x-rays with edge detected image is being favorable and supportive for equally doctor as well as patient.

2.2 Objective of study

In instance of medical x-ray images human participation and perceptual experience is of major significance. It is a challenging job to infer the dental diseases in several contrast conditions. Nowadays, digital dental x-ray images in which improvement is prepared automatically are obtainable but the arrangement are actual expensive. These algorithms will provide alternative solution to this trouble. It contains X-ray imaging & processing for recognizing the accurate position & depth of destruction in affected tooth. Therefore, edge detection of x-ray images plays an important role. Thus, the main goal of this research are as follows :

- To introduce the best edge detection technique for dental radiographs.
- To provide edge detection algorithm which is helpful for detection of various dental diseases for better diagnosis.
- To provide a method that has less computational complexity, take less time for edge detection.
- To provide an algorithm for edge detection that can give improved visual presence of edges that is not conceivable in situation of sobel and prewitt operator.

3

LITERATURE REVIEW

3.1 Dr. N. Senthilkumaran, "Edge Detection for Dental X-ray Image Segmentation using Neural Network approach"(2016)

Key points—Neural network method is used for detection of edges in dental x-ray images where inputs to the network are pixels of original image after minimizing the output error, output pixels are replaced in the edge detected image. Artificial Neural Network (ANN) is used because in this iterative training and learning takes place from input to output mapping. This algorithm is helpful in finding problems such as tooth decay, bone damage used for supporting the teeth and dental injures. This method may be extended for the diagnosis of major problems related to teeth[13].

3.2 N.P.Ansingkar and M.G.Dhopeshwarkar, "Study and Analysis of Edge Detection Techniques for Segmentation using Dental Radiograph"(2015)

Key points— In this paper, firstly x-ray image required pre-processing for enhancement using Gaussian Low Pass Filter then various edge detection techniques are applied and at last comparison of results takes place, which shows that canny operator provide best results among sobel and perwitt[14].

3.3 Kanika Lakhani, Bhawna Minochaa and Neeraj Gugnani, "Analyzing edge detection techniques for feature extraction in dental radiographs"(2016)

Key points— As discussed in the findings above that the smoother and sharper edges can now be made available for feature extraction for problem identification. Future work comprises the employment of above process on a larger sample space and extending the work to feature extraction for the recognition of problems. Comparable structures shall be collected composed to practice collections and based on these clusters, pattern matching algorithm shall be implemented for the diagnosis purpose[15].

3.4 Martin L., Tangel , Chastine , Fatichah Fei Yan, Janet P. Betancourt , M. Rahmat, Widyanto , Fangyan Dong, Kaoru and Hirota, "Dental Classification for Periapical Radiograph based on Multiple Fuzzy Attribute" (2013).

Key points— Fuzzy logic approach for the detection of edges from dental x-ray segment. Fuzzy inference system(FIS) is used which is having three main steps that are fuzzification, knowledge base and defuzzification. Extraction of edges are depend upon degree of whiteness and blackness of 8 neighbors gray level pixels that is done by powerful rules applied to it. The results are compared with Roberts method and clearly visible that more precise edges are detected by Fuzzy logic approach. Higher level of fuzzy logic approaches might be used for better detection of edges[16].

3.5 Dr. N. Senthilkumaran, "Fuzzy Logic Approach to Edge Detection for Dental X-ray Image Segmentation" (2012)

Key points— Fuzzy logic constitutes a beneficial numerical model to handle with uncertainty of entropy. Fuzzy image working is the gathering of all methods that realize, characterize and route the images, where sections and characteristics as fuzzy logic sets. The demonstration and dispensation be contingent on the particular fuzzy procedure and in the hard to be figured out [17].

3.6 Muhamad Rizal Mohamed razali, Rozita Hassan, Nazatul Sabariah Ahmad and Zulkifly Mohd Zaki &Waidah Ismail, "Sobel And Canny Edges Segmentations For The Dental Age Assessment"(2014)

Key points— Sobel and canny edge detector are widely used for detection of edges as they are simply calculating the gradients of image for edge detection. Here it is useful in detecting edges for dental age assessment. Comparison of sobel and canny edge detector occurs and results that sobel is better than canny for dental images then soft algorithms are used where inputs are dealing with approximation model[18].

3.7 A J Solanki , “Threshold Selection in ISEF based Identification of Dental Caries in Decayed Tooth” (2016)

Key points— The edge detection by ISEF is helpful in detecting dental caries in tooth decay form dental x-ray images. After that it also gives the decision for the treatment like root canal treatment or filling. Results are giving the idea where the caries effected area is present and also verified by doctor[19].

3.8 K. Padma Vasavi , N. Udaya Kumar, M. Madhvi Latha and E. V. Krishna Rao, “An Edge Detection Scheme for Endodontic Working Length Measurement in Root Canal Treatment for Succedaneous Teeth” (2015)

Key points— The root canal treatment , finding the length of root is very important parameter and that is done by use of edge detection in dental x-ray. The implementation of algorithm for the solution of above mentioned problem takes place by the use of MMST where laplacain pyramid is used to decompose the image into number of levels, directional decomposition of image is done by the use directional filters banks. Statistical thresholding is done for detection of edges in an image. And results conclude that clearly and precise detection of root canal length for further diagnosis. Root length might be measured more accurately by soft algorithms where output is depended upon applied rules and membership function[20].

3.9 P. M. Mahant, N.P. Desai, K .R .Jain and M. G. Mahant, “Optimal Edge Detection Method for Diagnosis of Abscess in Dental Radiograph” (2015)

Key points— Identification of dental abscess is also major problem by the use of dental x-ray images only. For this optimal edge detection required solves the same problem which states that firstly image require removal of noise from it after that edge detection is applied for extraction of abscess. Results of this edge detected images are shown to the dentist and well appreciated by them[21].

3.10 Gayathri Vand Hema P Menon, “Challenges in Edge Extraction of Dental X-Ray Images Using Image Processing Algorithms – A Review” (2014)

Key points— The effects found in applying dissimilar edge mining approaches on uneven dental images require to been argued. The traditional edge removal methods observed in this paper appears to be insufficient for effectively attaining the edge structures from dental images. Therefore, the learning indicates a compulsion for better-quality edge mining process above dental x-ray[22].

3.11 Dr. N. Senthilkumaran, "Genetic Algorithm Approach to Edge Detection for Dental X-ray Image Segmentation"(2012)

Key points— Genetic Algorithms(GA) provides flexible edge detection in very shady images. Since, it is also applied in dental X-ray images, for identifying the diseases like tooth decay, impact tooth and so on. Mainly GA consists of three stages, they are selection, crossover and mutation for processing of any application. Comparison of results takes place with Roberts operator and found that GA gives better results comparatively[23].

3.12 Ionel-Bujorel Pavaloiu , Nicolae Goga , Andrei Vasilateanu, Iuliana Marin, Andrei Ungar, Ion Patrascu and Catalin Ilie, "Neural Network Based Edge Detection for CBCT Segmentation" (2015)

Key points—NN architecture and procedure able to extract edges from CBCT dental data, an important step in the segmentation process. The proposed NN uses gradient, standard deviation, maximum value, distance between the max valued pixels, polar coordinates and order as inputs for a 3x3 block surrounding the candidate edge pixel. The results are a proof of the validity of NN as a tool for edge detection in the medical domain and look interesting for an extremely complicated problem, because of the noise and low contrast for the images. The quality is modest compared with (used as an automatic procedure), but the process is extremely fast once the NN is trained[24].

3.13 L. Lin, W. Huang, Y.S. Cho, and H. Kou, "An automatic and effective tooth isolation method for dental radiographs", (2013)

Key points—The problem of finding missing teeth to be solved using this procedure of edge detection. In jaw, where the teeth is missing, values of standard deviation , euler number and area becomes zero. Additionally, for proper alignment of teeth, its measurement are very important. Traditionally, gear tooth micrometer and vernier caliper are used but results are not in fraction, then minute changes in measurement leads to improper alignment of teeth[25].

3.14 Jufriadif Na`am, Johan Harlan, Sarifuddin Madenda and Eri Prasetio Wibowo, "The Algorithm of Image Edge Detection on Panoramic Dental X-Ray Using Multiple Morphological Gradient (mMG) Method",(2016)

Key points— The algorithm of Multiple Morphological Gradient (mMG) is applied in [5] for clearly visibility of boundaries of object in panoramic radiograms. Some position of dental caries are also defined, which says that it is divided into two groups, that are smooth surface and gap of teeth. The result of this algorithm is very useful for the identification of cavities and verification of the same is done by two dentist. Furthermore, this algorithm should be applied for the detection of more number of dental diseases[26].

3.15 Olivia Mendoza, Patricia Melin, Guillermo Licea "A New Method for Edge Detection in Image Processing using Interval Type-2 Fuzzy Logic"(2007)

Key points—In this paper, first of all sobel operator is employed to calculate the gradients in both x and y directions. Then edges are calculated expending type-1 and type-2 fuzzy logic with the gradients calculated by sobel operator.Four inputs are given to T1FLS and T2FLS in which two inputs are gradients in both x and y directions and two responses are filters which calculated when employing two masks for the convolution to the unique image .Histogram parameter has been used to make the evaluation among T1FLS and T2FLS . And histogram shows that T2FLS gives improve result than T1FLS[27].

4

RESEARCH METHODOLOGY

In previous chapters discussion about the topic and review on edge detection techniques takes place. And in scope and objective of study, demonstration of how edge detection using implemented algorithm is helpful for doctors and patients occurs. Additionally, in this chapter methodology behind algorithm provided as well as problems to be solved like whereas the edges are not visibly well-defined, that are, edges are cracked, imprecise, or blurry etc., and in that situation edge detection turns to be very challenging.

4.1 Edge Detection using Sobel Operator

In this technique, an image is distributed into two areas. If the pixels are consuming large conflict in the gray degree their locality area, then that pixels are categorized in a edge section and if the pixels are small conflict of gray degree , their locality area, then the pixels are categorized in a smooth area.

4.1.1 Algorithm of edge detection using Sobel Operator

Step 1: The gradient of an image is intended for every pixel location

Step 2: Obtain the x-direction derivative:

Step 3: Obtain the y-direction derivative:

Step 4: Obtain the Gradient

Step 5: Combine both x and y-direction gradient

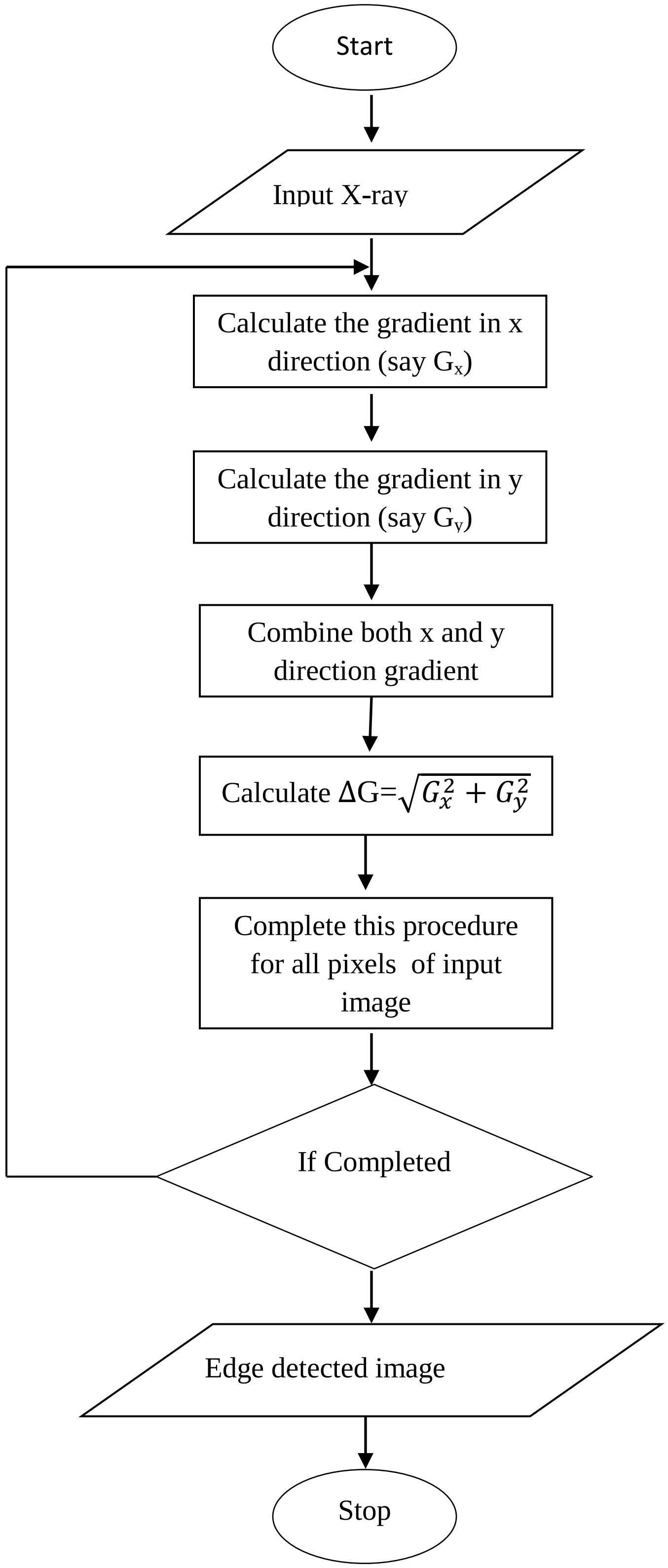


Fig.4.1: Algorithm of sobel edge detector

4.2 Edge detection using Tpye 1 Fuzzy Logic

T1FLS, successfully employed to lots of engineering issues, the major benefits of fuzzy systems have the power to show knowledge by applying linguistic fuzzy principles, that can be realized and plan by humans. Moreover, the T1FLS are modified to deal with impreciseness, uncertainty and ambiguity in linguistic expressions. Edge detection using T1FLS is an another technique to detect edges which considers image be a fuzzy. In majority of images where edges aren't distinctly determined, that is to say edges are discontinued, unclear, or blurred and in that situation edge detection gets more hard.

4.2.1 Sobel Operator

This operator comprises the match of 3×3 masks for convolution as formulate in equation (4.1) where the Sobelx and Sobely are sobel operators across x-axis and y-axis . The mask for convolution is very smaller than that of input image. For the result , a mask moves throughout an image , changing the pixels to b squared at once

$$\mathrm{Sobel}_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \qquad \mathrm{Sobel}_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & 1 \end{bmatrix} \tag{4.1}$$

Equation (4.2) and (4.3) defines 'I' as input image , 'Gx' ,'Gy' shows that images of every level comprises of x-axis , y-axis derivative estimation and * defines the convolution operator.

$$Gx = \mathrm{Sobel}_x * I \tag{4.2}$$

$$Gy = \mathrm{Sobel}_y * I \tag{4.3}$$

A convolution mask is commonly far lesser than the concrete image. As a outcome, the mask is slip above the image, influencing a square of pixels.

4.2.2 Inputs for Type-1 FIS

For the T1FLS, mainly four inputs be needed , out of them two are the gradients related to horizontal and vertical axis, computed to that we called as variable DH and DV respectively which is equal to Gx and Gy respectively which are mentioned and that another two inputs be the filters

$$hHP = \begin{bmatrix} -1/16 & -1/8 & -1/16 \\ -1/8 & 3/8 & -1/8 \\ -1/16 & -1/8 & -1/16 \end{bmatrix} \qquad hMF = (1/25) * \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \tag{4.4}$$

Then the inputs for T1FLS are: DH=Gx, DV=Gy, HP= hHP*I and D= hMF*I where '*' is the convolution operator in equation (4.4).

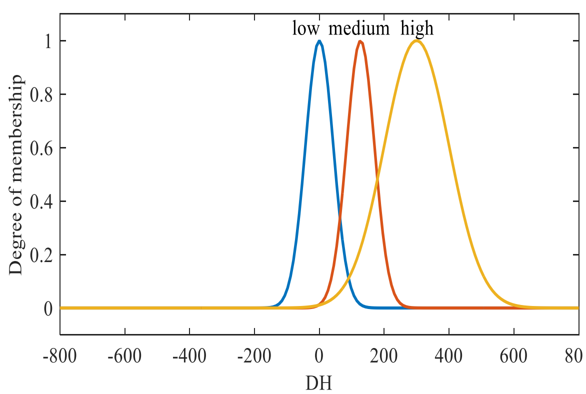
4.2.3 Fuzzy variables

For entirely the fuzzy linguistic variables, the MFs are Gaussian. Agreeing to the carried out tests, the values in '**DH'** , '**DV'**,and '**HP'** ranges from -800 to 800, then the grades in x-axis corrected in where the MFs are LOW (43,0),MEDIUM (43,127) and HIGH (43,255).

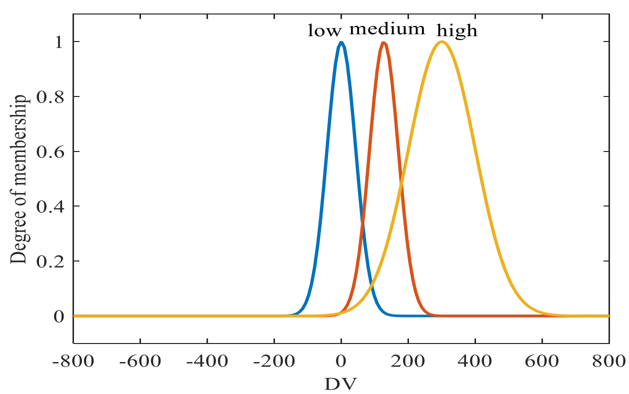
In the event of variable **D**, the tests held values in the range from 0 to 255, and therefore the range in x-axis is attuned. The outcome variable **Edges** which are also handles the range between 0 and 255

4.2.4 Input and Output MFs

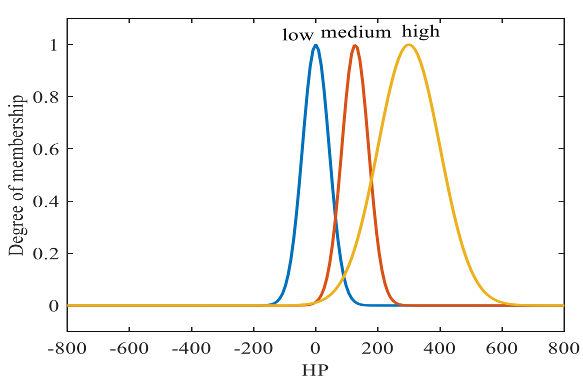
Following are the membership functions defined for input and output of fuzzy variables that is DH,DV,HP,D and Edges



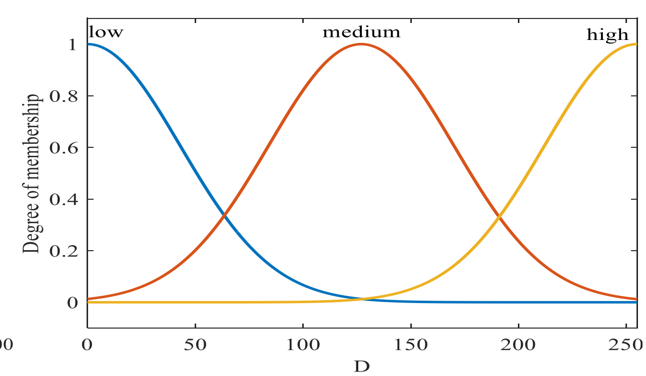
(a)



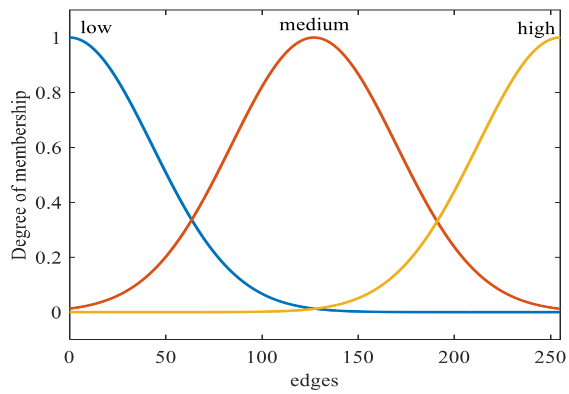
(b)



(c)



(d)



(e)

Fig. 4.2: Input and output MFs of edge detection using T1FLS From (a) to (d) input MFs and (e)

4.2.5 Fuzzy Inference Rules

Following are the rules which used for valuate the input variables for both T1FLS and IT2FLS , hence at the end image shows the edge pixels of input image in two color approaches black and where the background was approaches white.

Rule 1 : If (DH is Low) and (DV is Low) then (EDGES is Low).

Rule 2 : If (DH is Medium) and (DV is Medium) then (EDGES is High)

Rule 3 : If (DH is High) and (DV is High) then (EDGES is High)

Rule 4 : If (DH is Medium) and (HP is Low) then (EDGES is High).

Rule 5 : If (DV is Medium) and (HP is Low) then (EDGES is High).

Rule 6 : If (D is Low) and (DV is Medium) then (EDGES is Low).

Rule 7 : If (D is Low) and (DH is Medium) then (EDGES is Low).

4.2.6 Algorithm of edge detection using T1FLS

Step 1: Input an image.

Step 2: Obtain the gradient alongside magnitude and way for image gradient.

Step 3: The sobel detector is used to extract the parameters of image.

Step 4: Then, find the output of the sobel operator and apply fuzzy rules

Step 5: Define input and output membership function for the FIS.

Step 6: Determine the fuzzy rules to obtain the output image

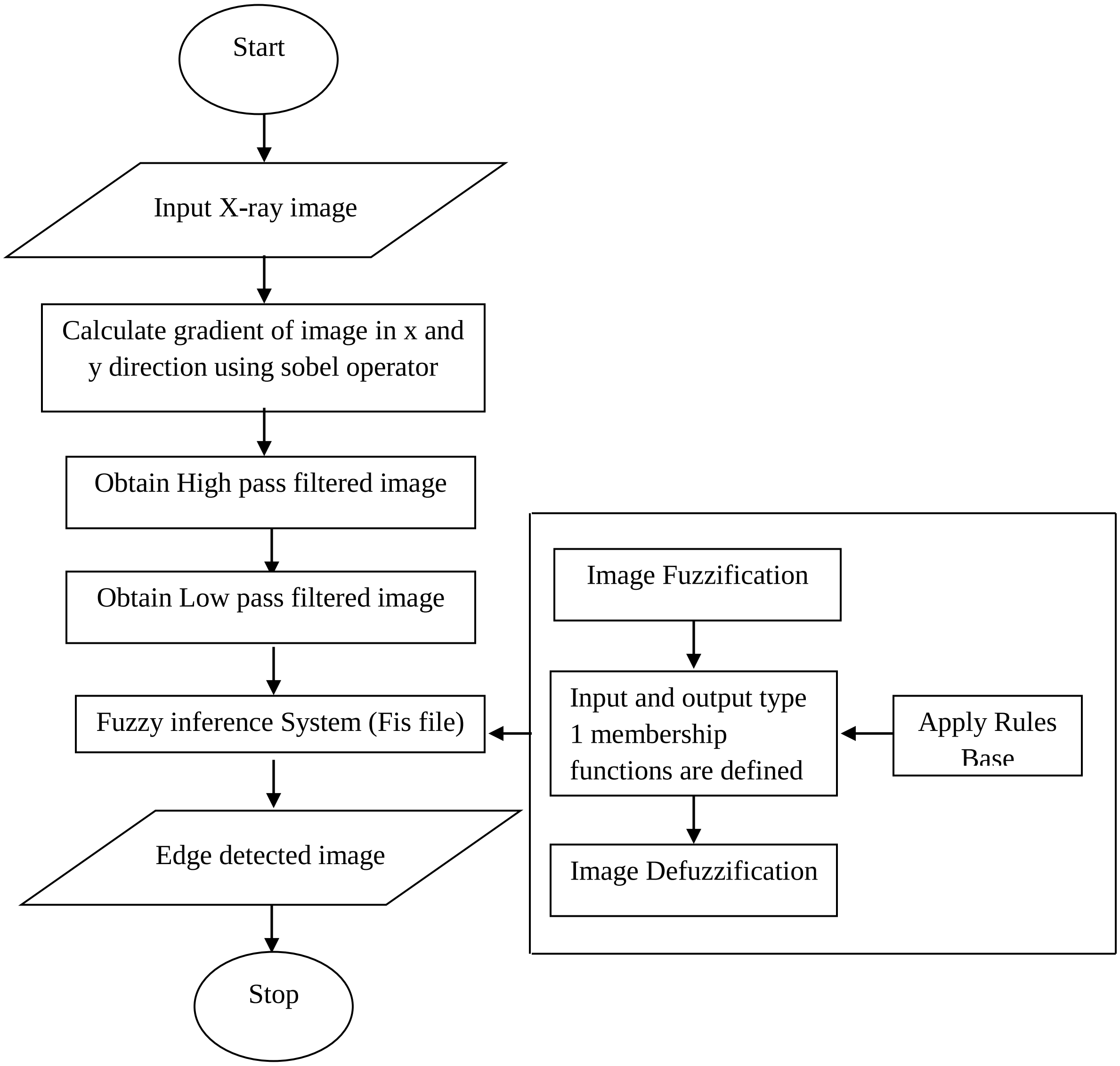


Fig.4.3: Algorithm of TIFLS edge detector

4.3 Edge detection using IT2FLS

In IT2FLS where consequent or antecedent membership functions has been fuzzy type -2 sets . These sets are whose membership function itself are type -1 membership grades ; they are much helpful in conditions where it‟s hard to defines appropriate membership functions towards the fuzzy sets[13]. Edge detection with IT2FLS follows the same process that in T1FLS but only difference is in applied membership function and results outcomes after the comparison . The broad of the footprint of uncertainty (FOU)[10] region selected for every membership functions constituted the one which had improved results later various experiments.

4.3.1 IT2FLS Variables

For different input variables, different means and standard deviation are there. Following are the means and standard deviations which were assigns to inputs and outputs

- For input variable DH

  Upper mean = [-200 200 600]

  Lower mean = [-100 100 500]

  Upper spread = [120 120 210]

  Lower spread = [100 100 210]

- For input variable M

  Upper mean = [-200 200 600]

  Lower mean = [-100 100 500]

  Upper spread = [120 120 120]

  Lower spread = [100 100 100]

- For input variable DV and HP

  Upper mean = [-200 200 600]

  Lower mean = [-100 100 500]

  Upper spread = [120 120 210]

  Lower spread = [100 100 210]

- For output variable EDGES

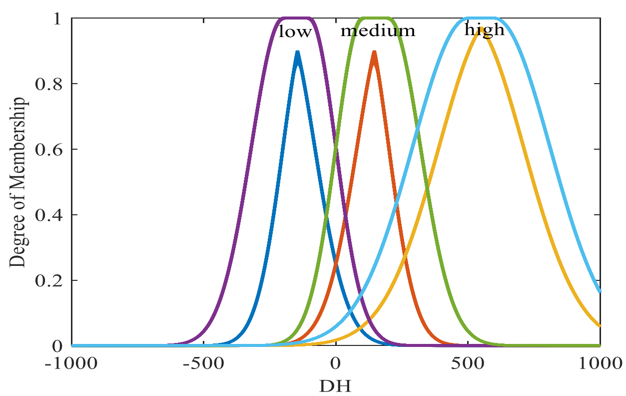
  Upper mean = [-200 200 600]

  Lower mean = [-100 100 500]

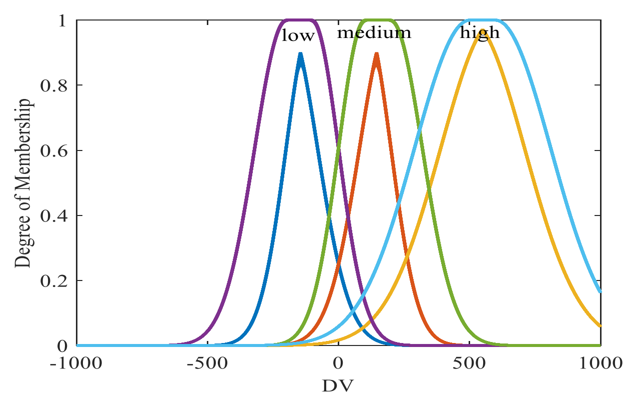
  Upper spread = [120 120 120]

  Lower spread = [100 100 100]

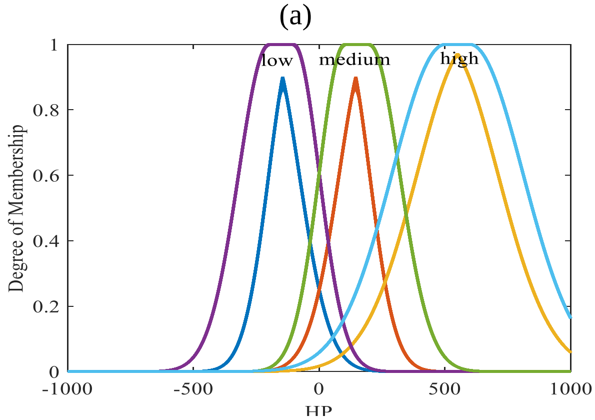
4.3.2 Input and Output Membership



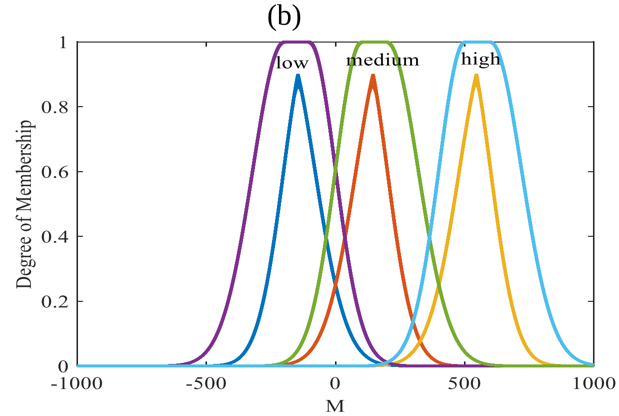
(a)



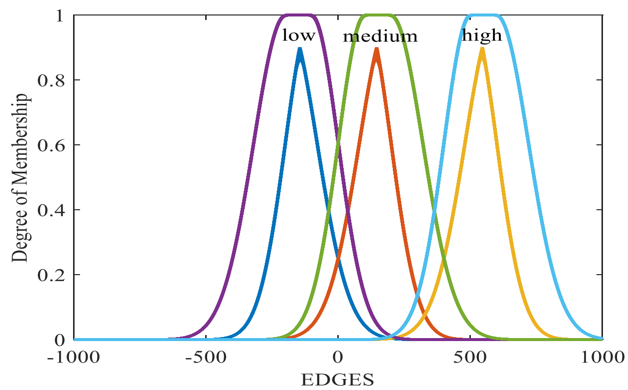
(b)



(c)



(d)



(e)

Fig 4.4 Input and output MFs of edge detection using IT2FLS From (a) to (d) input MFs and (e) Output MF

4.3.3 Algorithm of edge detection using IT2FLS

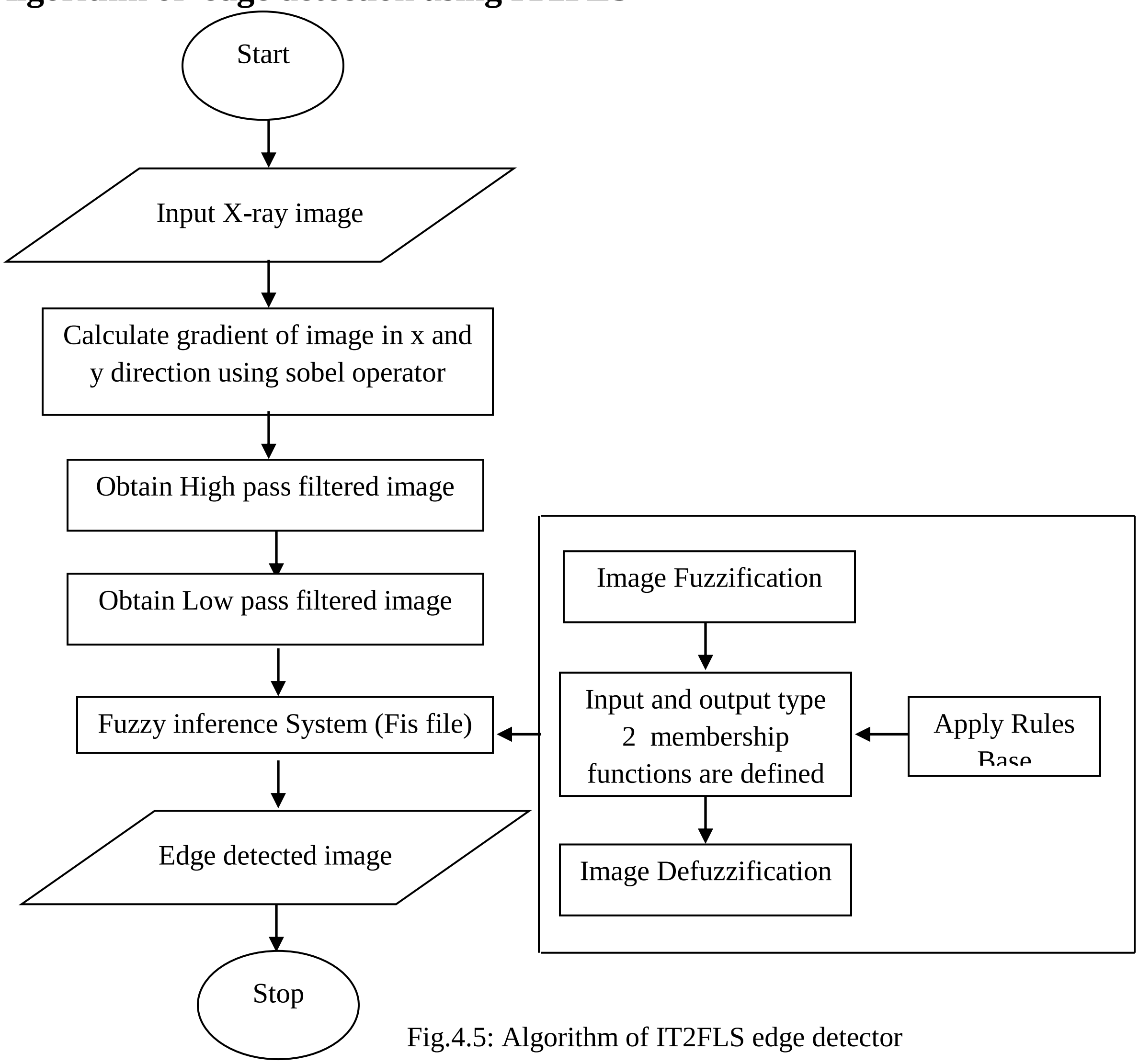


Fig.4.5: Algorithm of IT2FLS edge detector

Step 1 : Take the input image.

Step 2 : Exchange the RGB image to Gray scale image. It is given by Y' = 0.299R' + 0.587G' + 0.114B

Step 3 : Find the gradient along magnitude and direction for image gradient.

Step 4 : Then, obtain the output of the sobel after that applying fuzzy rules

Step 5 : Determine input and output MFs for theIT2FLS.

Step 6 : The input and output membership function applied to FIS.

Step 7 : Determine the fuzzy rules to achieve the output image.

5

PROPOSED & FUTURE WORK PLAN WITH TIMELINES

In proposed work plan , three different methods for edge detection using fuzzy logic has been implemented on dental x-ray images. Comparison has been made among these three methods (sobel edge detector , T1FLS and IT2FLS) on the bases of edge detected pixels and time taken by algorithms to detect the edges from the dental x-ray images. The dental disease to be detected are Crooked teeth, Diastema and Chipped tooth from the edge detected image. These diseases are discussed in chapter 1 of this research along with causes, possible treatment and preventions. The results of applied techniques is helpful in detection and proper diagnosis of mentioned dental diseases.

In the next stage, GT2FLS will be implemented on different images of patients and a comparison has been made among all these methods. Furthermore, implementation will be more focused about to detect more and more dental diseases using edge detection techniques. And to automate the system to give possible diseases detected from the edge detected x-ray images. The proposed work plan with timeline is shown in the table 5.1 and future work plan is shown in the table 5.2.

5.1 Proposed Work Plan

Table 5.1 Proposed work plan with timeline

S. NO	MONTHS / WORK	Jan-July 2017	Aug 2017	Sept 2017	Oct-Nov 2017
1.	Study on edge detection techniques on dental radiographs	☆			
2.	Paper writing on "Review- Edge detection techniques on dental radiographs"	☆			
3.	Implementation of edge detection using sobel		☆		
4.	Implementation of edge detection using T1FLS and IT2FLS.		☆		
5.	Comparison of implemented algorithms			☆	
6.	Paper writing on "Comparative study on edge detection techniques (Sobel, T1FLS and IT2FLS)"			☆	☆

5.2 Future Work Plan

Table 5.2 Future work plan with timeline

S. NO	**MONTHS** / **WORK**	**Jan 2018**	**Feb 2018**	**March 2018**	**April 2018**
1.	Implementation of GT2FLS for edge detection	☆	☆		
2.	Comparison of all type of FLS.			☆	
3.	Report Writing			☆	☆

6

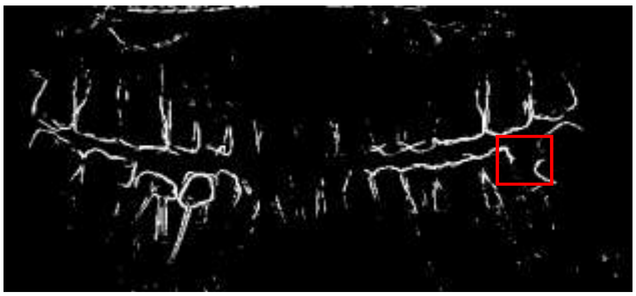
RESULTS
&
DISCUSSION

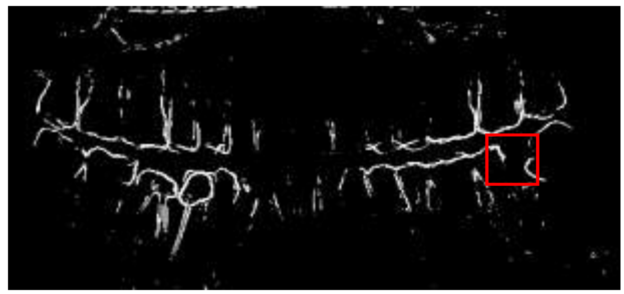
This chapter comprises , the results of all the methods have been shown on the basis of threshold parameter. The edge detection is done by Sobel , T1FLS and IT2FLS. Then comparison has been made among these three methods. In case of sobel edge detection, different values of threshold has been selected and for each value of threshold the implemented method gives different levels of edges. The value of threshold is associated with gradient value of all the pixels to make decision whether each pixel is edge or not. If the figured gradient pixel is lower than a threshold is considered as edge pixel. In the second part results of T1FLS and IT2FLS has been shown and then a comparison has been made between these two methods. In this MATLAB is used to evaluate these algorithms by setting different thresholds.

6.1 Results of Sobel Edge Detector

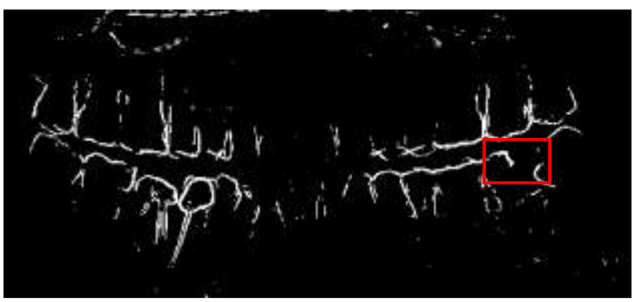
Edges are determined by applying a threshold that on trial and inaccuracy process by the user. The sobel edge detector has been applied on dental x-ray images i.e. patient 1 to 10 image of size 1536x2969. The original image and edge detection at different values of threshold has been shown for all images..

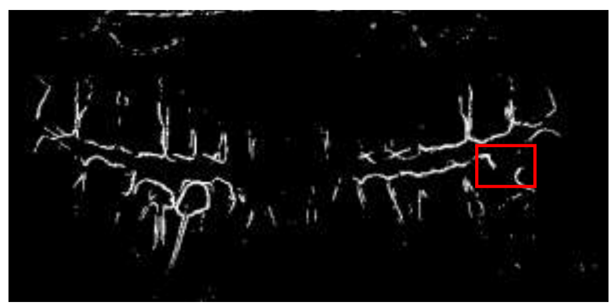
(a) (b)





(c) (d)



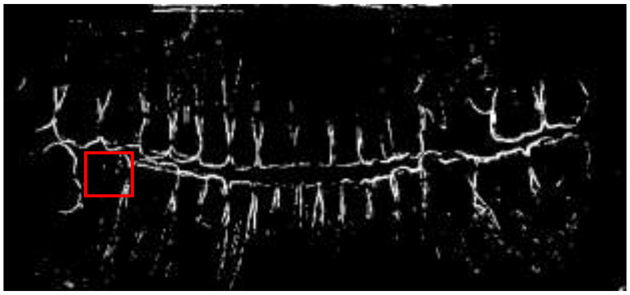


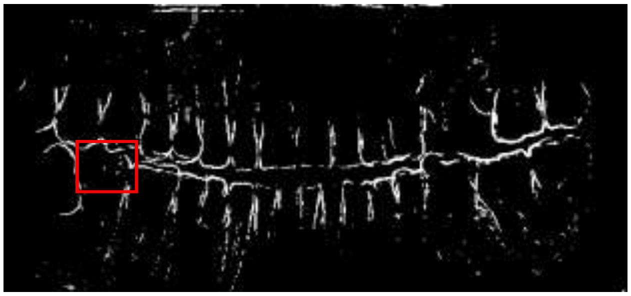
(e) (f)

Fig.6.1 (a) original image for **patient 1** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

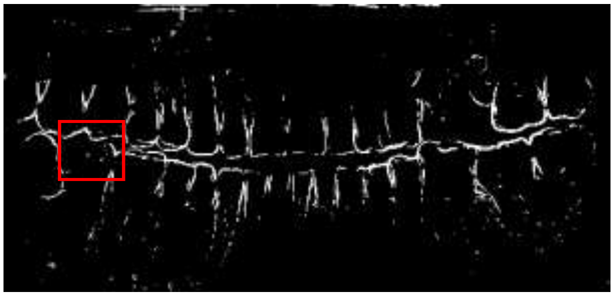
In fig.6.1 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 5072, In figure (d) the number of edges is app. 4565. In figure (e) the number of edges is approximately 4118. In figure (f) the number of edges is approximately 3769. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect chipped tooth for proper diagnosis.

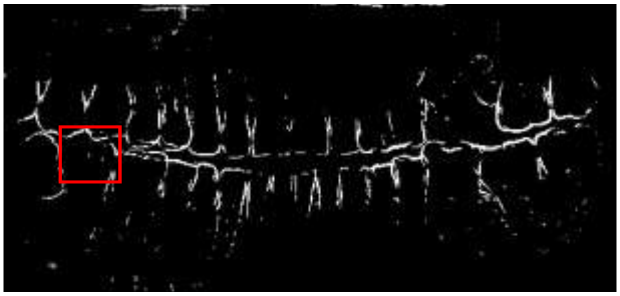
(a) (b)





(c) (d)





(e) (f)

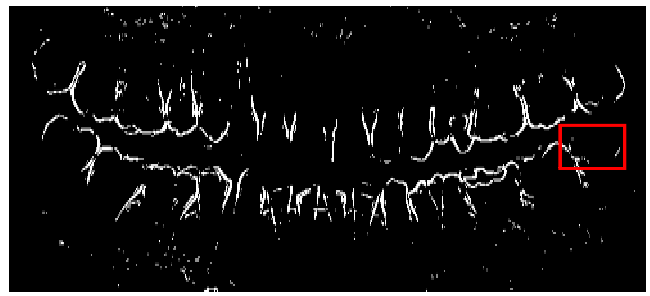
Fig.6.2 (a) original image for **patient 2** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.2 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 5705, In figure (d) the number of edges is app. 5052. In figure (e) the number of edges is approximately .4488 In figure (f) the number of edges is approximately 3998. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect chipped tooth for proper diagnosis.

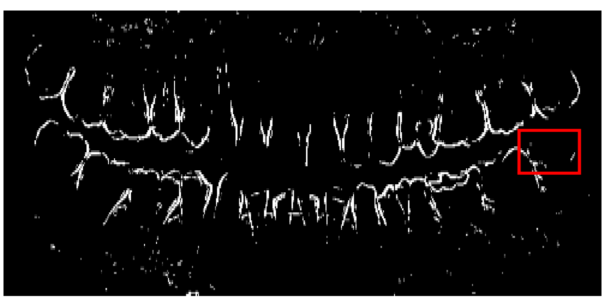
(a)

(b)

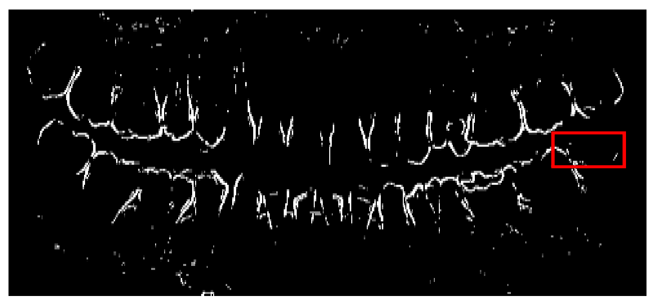
(c)



(d)



(e)



(f)

Fig.6.3 (a) original image for **patient 3** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.3 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 6085, In figure (d) the number of edges is app. 5415. In figure (e) the number of edges is approximately .4853 In figure (f) the number of edges is approximately 4443. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect chipped tooth for proper diagnosis.

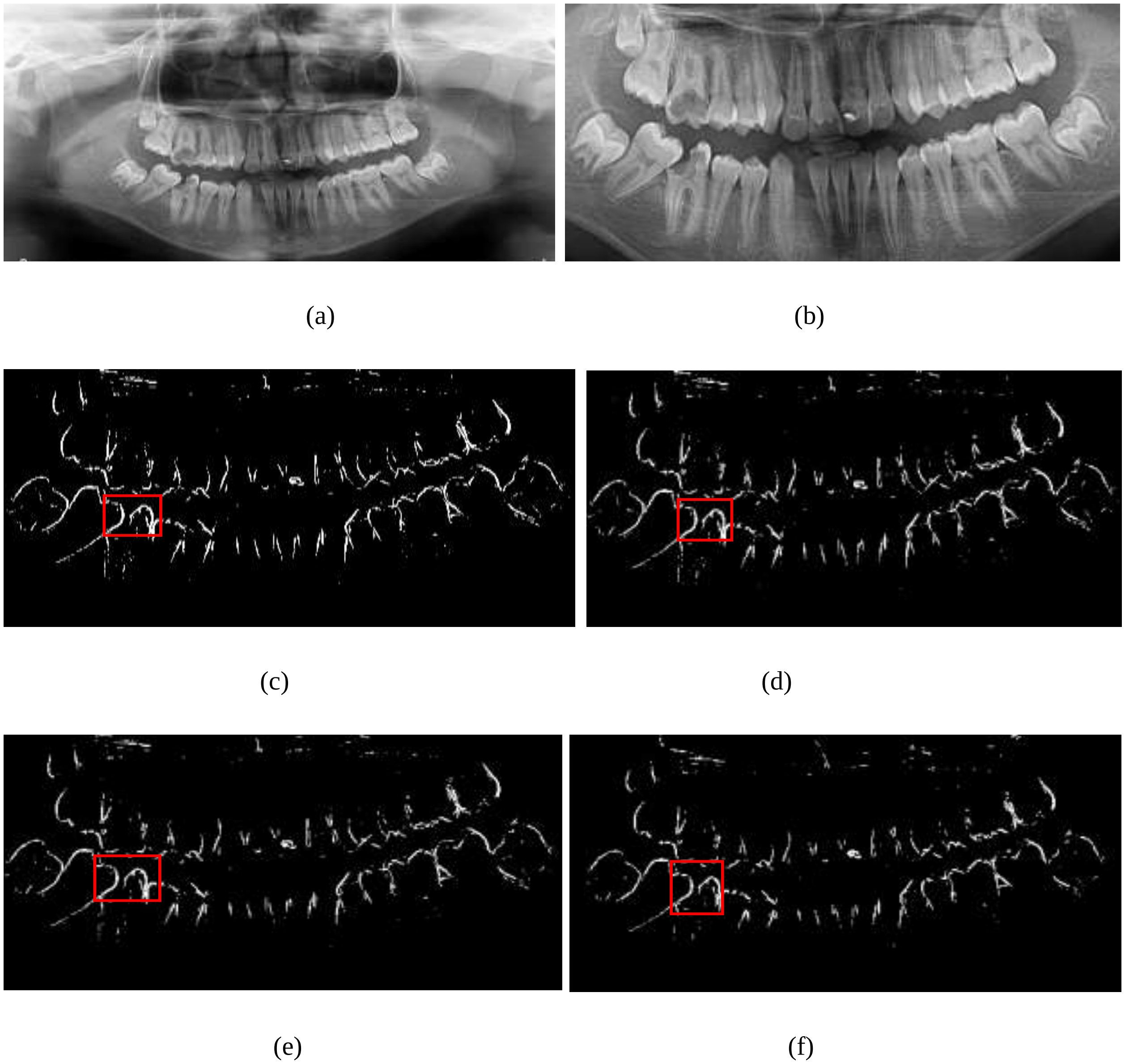


Fig.6.4 (a) original image for **patient 4** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.4 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 4049, In figure (d) the number of edges is app.3552. In figure (e) the number of edges is approximately 3156. In figure (f) the number of edges is approximately 2788. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect chipped tooth for proper diagnosis.

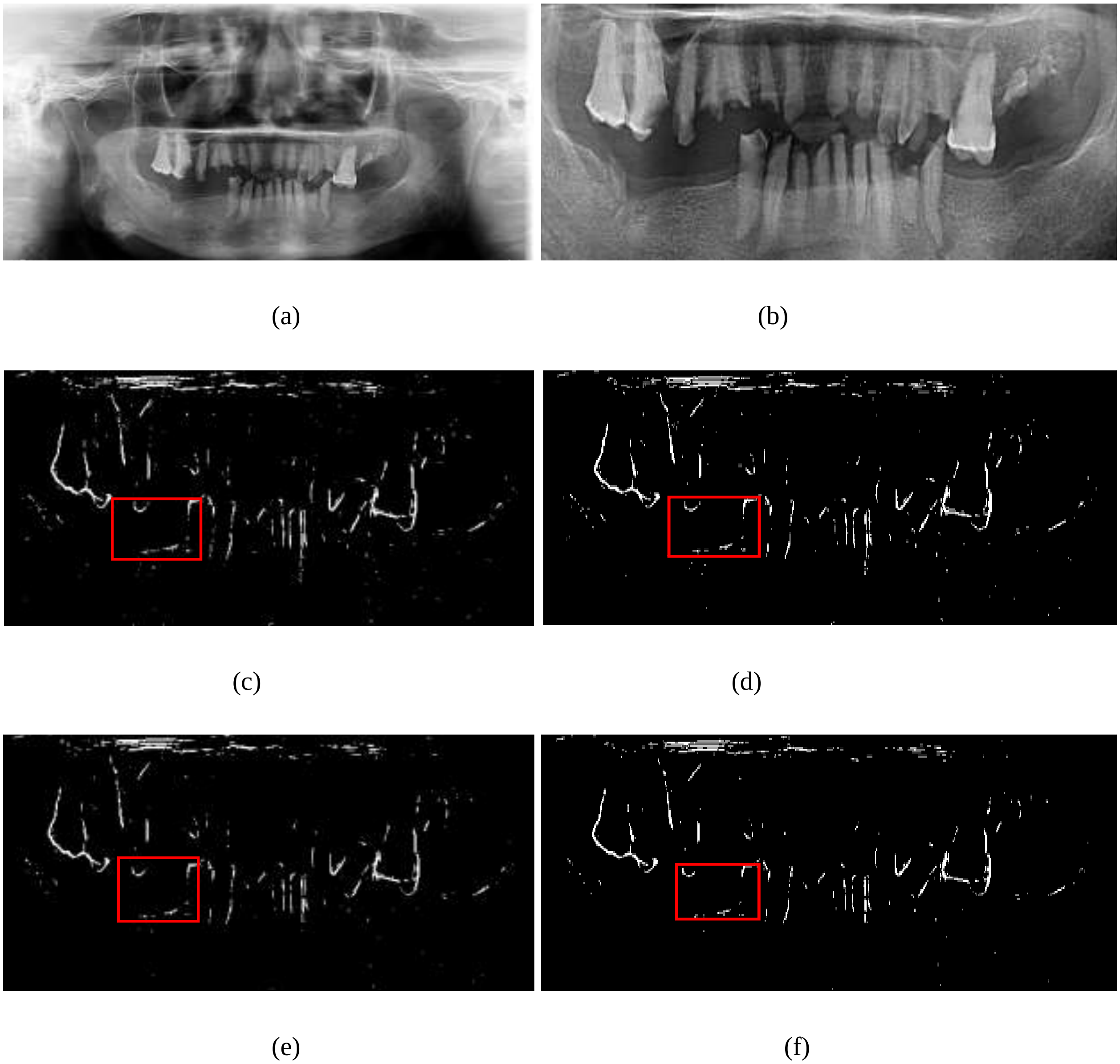
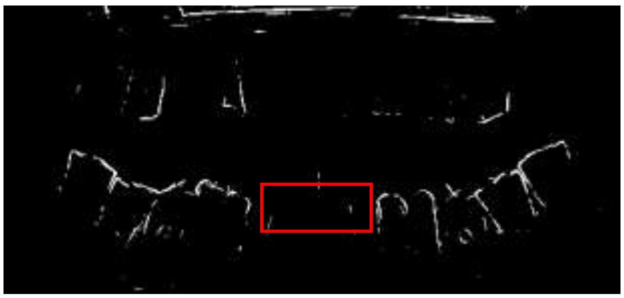


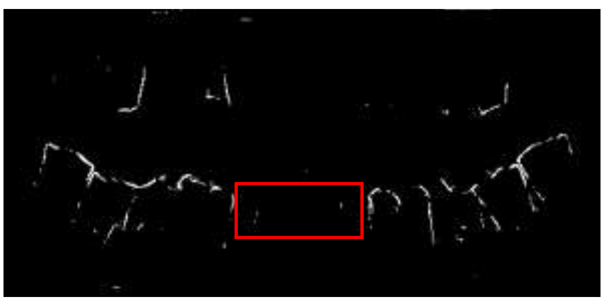
Fig.6.5 (a) original image for **patient 5** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.5 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 3078, In figure (d) the number of edges is app. 2659. In figure (e) the number of edges is approximately 2307. In figure (f) the number of edges is approximately 2015. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect diastema disease for proper diagnosis.

(a) (b)



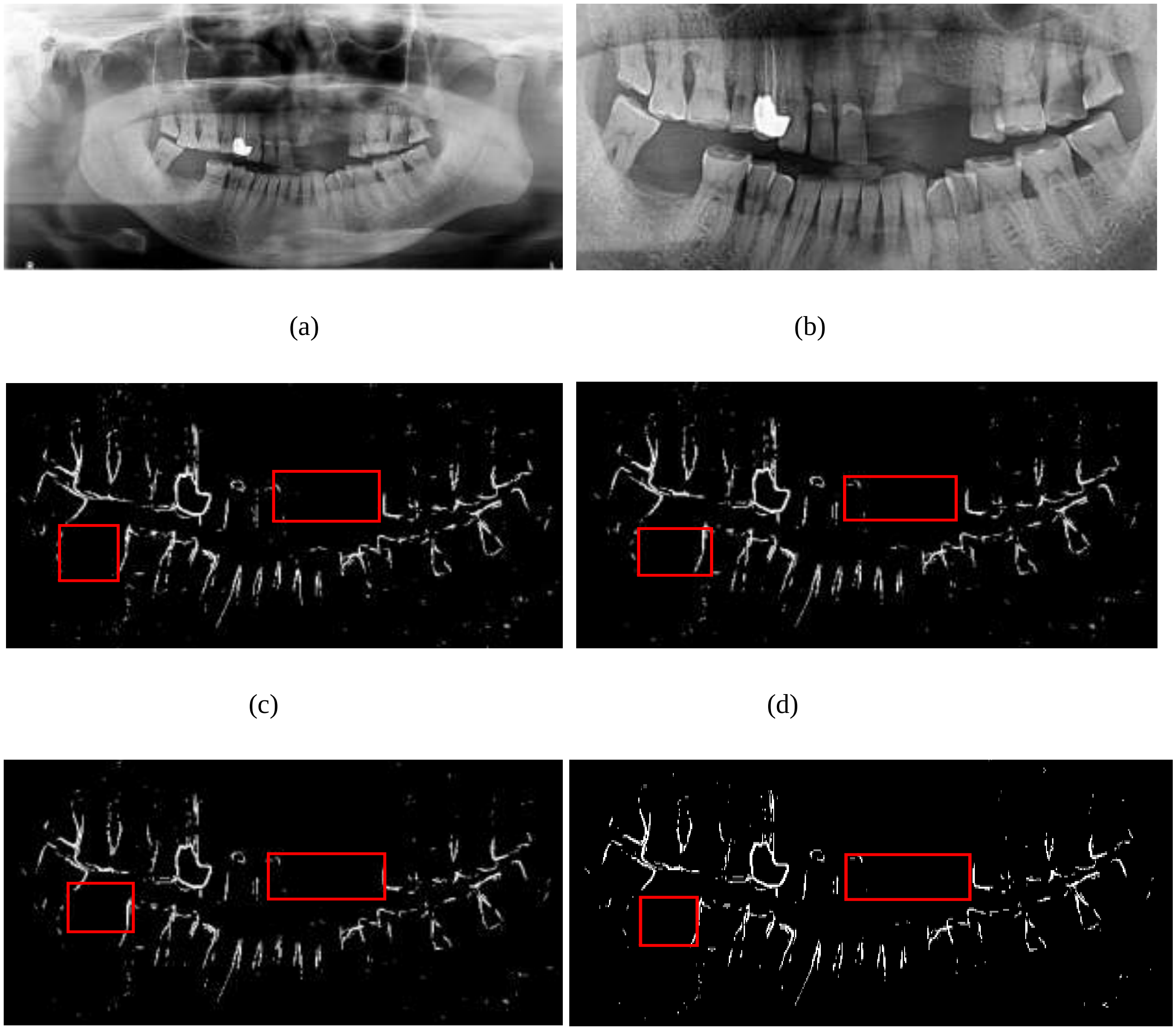
(c) (d)



(e) (f)

Fig.6.6 (a) original image for **patient 6** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.6 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 2030, In figure (d) the number of edges is app. 1749. In figure (e) the number of edges is approximately 1530. In figure (f) the number of edges is approximately 1344. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect diastema disease for proper diagnosis.



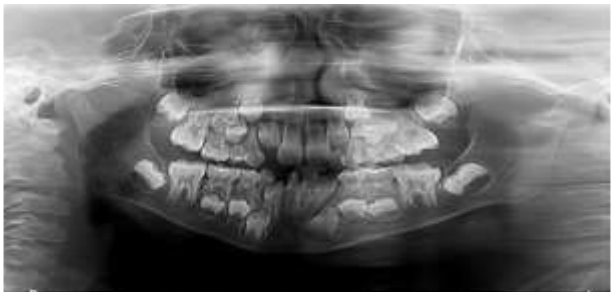
(a) (b)

(c) (d)

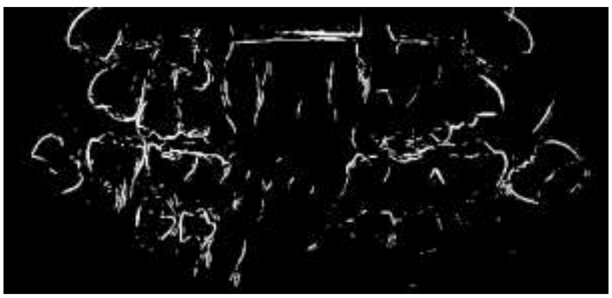
(e) (f)

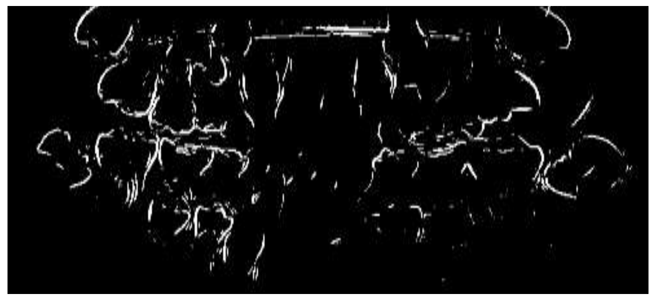
Fig.6.7 (a) original image for **patient 7** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.7 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 4026, In figure (d) the number of edges is app. 3552. In figure (e) the number of edges is approximately 3156. In figure (f) the number of edges is approximately 2816. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect diastema disease for proper diagnosis

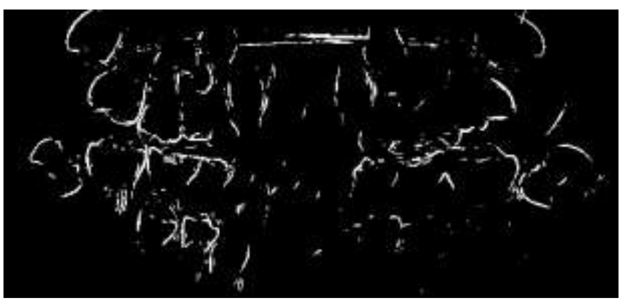


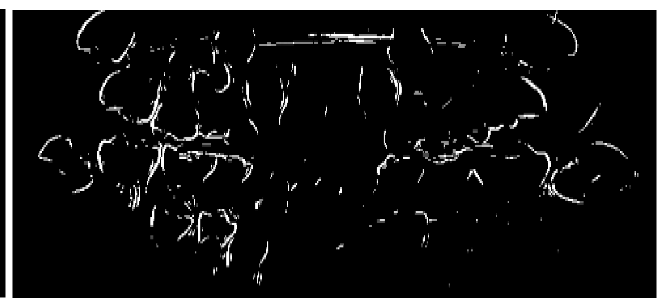
(a) (b)





(c) (d)



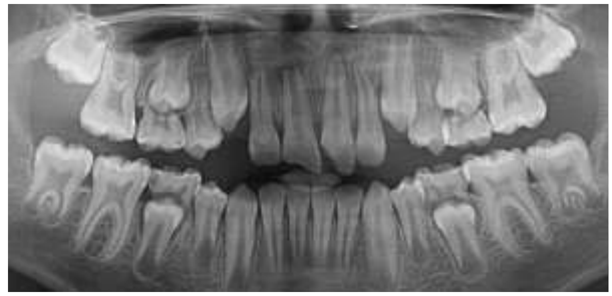


(e) (f)

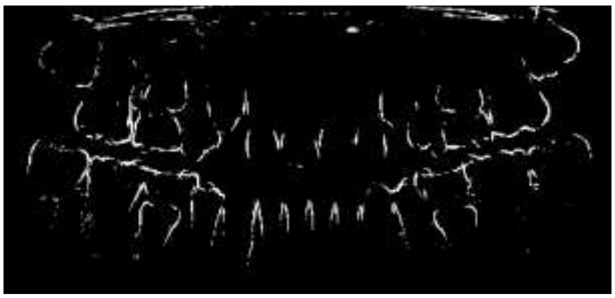
Fig.6.8 (a) original image for **patient 8** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.8 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 5269, In figure (d) the number of edges is app. 4679. In figure (e) the number of edges is approximately. 4140. In figure (f) the number of edges is approximately 3740. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect crooked teeth for proper diagnosis

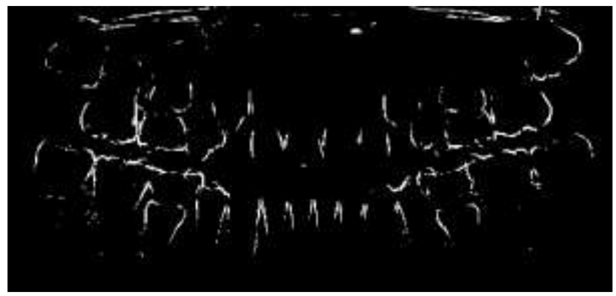
(a)



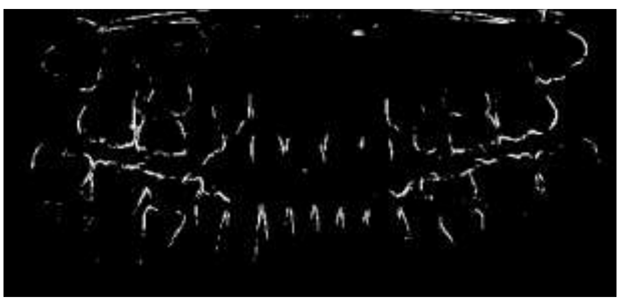
(b)



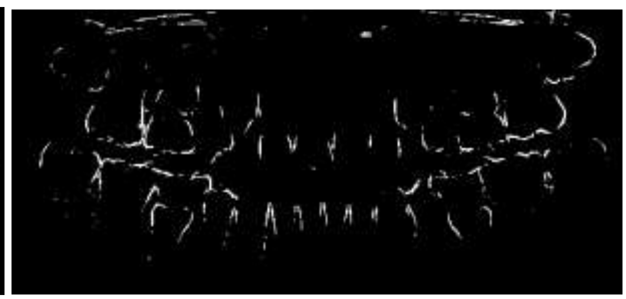
(c)



(d)



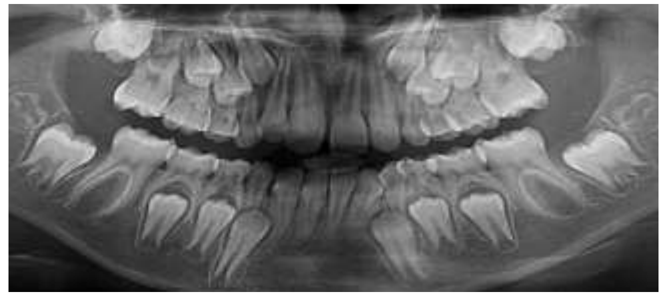
(e)



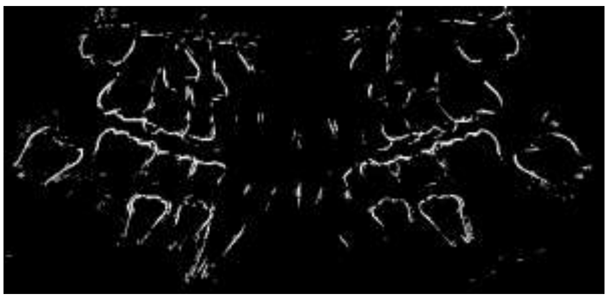
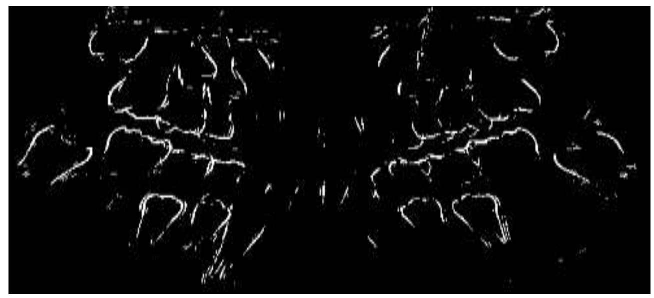
(f)

Fig.6.9 (a) original image for **patient 9** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

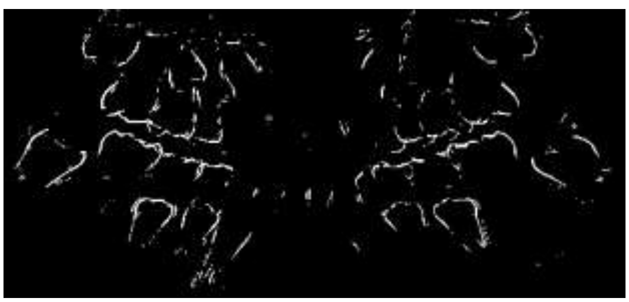
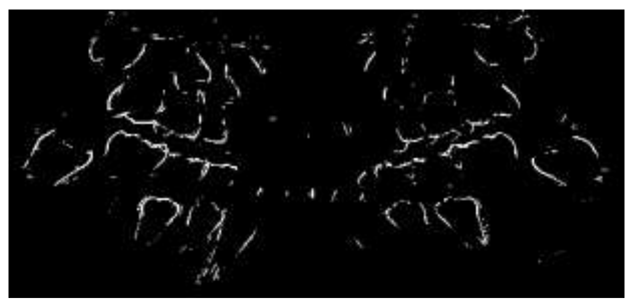
In fig.6.9 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 3814, In figure (d) the number of edges is app. 3311. In figure (e) the number of edges is approximately. 2903. In figure (f) the number of edges is approximately 2561. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect crooked teeth for proper diagnosis

(a) (b)

(c) (d)

(e) (f)

Fig.6.10: (a) original image for **patient 10** (b) Cropped image(c) T=210 (d) T=220 (e) T=230 (f) T=240

In fig.6.10 (a) shows original image in gray scale of size 1536x2969. And figure (b) shows cropped and enhanced image of original image using histogram equalization In figure (c) the pixels which have values 0 i.e. less than 210 has been considered as edges, the number of edges is approximately. 4125, In figure (d) the number of edges is app. 3623. In figure (e) the number of edges is approximately. 3192. In figure (f) the number of edges is approximately 2824. Thus, figure (b) has given more number of edges than other images. So as to compare with other threshold values, this method gives best result at 210 of threshold value. By using this edge detected image trying to detect crooked teeth for proper diagnosis.

Table 6.1 Edge Detected pixels using Sobel edge detection technique.

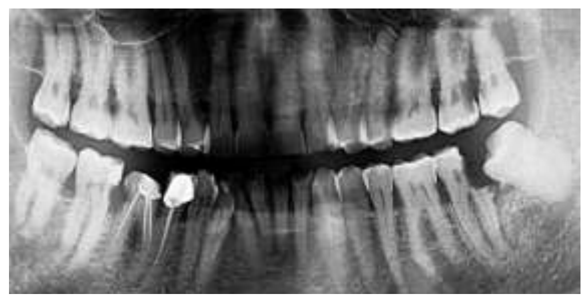
Patient No.	Total edge pixels detected			
	T = 210	T = 220	T = 230	T = 240
P1.	**5072**	4565	4118	3769
P2.	**5705**	5052	4488	3998
P3.	**6085**	5415	4853	4443
P4.	**4049**	3552	3156	2788
P5.	**3078**	2659	2307	2015
P6.	**2030**	1749	1530	1344
P7.	**4026**	3552	3156	2816
P8.	**5269**	4679	4140	3740
P9.	**3814**	3311	2903	2561
P10.	**4125**	3623	3192	2824

From table 6.1 it is clearly visible that, when threshold value is 210 then all pixels values are more in all patients dental radiographic images. As the threshold values are decreasing, total number of edge detected pixels are decreasing , Then possible deduction ie that threshold value is directly proportional to total edge detected pixels in an image. For getting more precise results we need to defined or used less threshold values for proper edge detection in an input image .In table patients from 1 to 10 are taken and analyses of results takes place with respective to different dental images input. Patients with different diseases that are chipped tooth, diastema and crooked teeth wanted to detect by these edge detection technique. By edge detection using sobel gradient in dental radiographs possibly chipped tooth and diastema diseases can be detected at threshold 210 during processing of radiographs, which is helpful to doctors for proper diagnosis of these diseases.

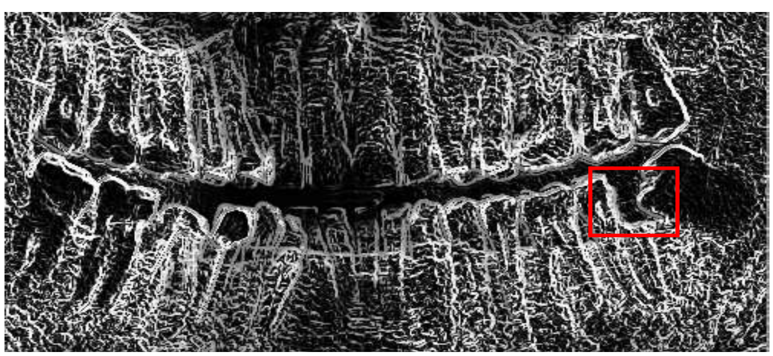
6.2 The result of type-1 fuzzy logic

In T1FLS it is essential to use sobel operators to the input images, after that use a Fuzzy Inference System to produce the route of edges. The Sobel operator employed on the image in gray level computes the gradient of brightness of every pixel, applying the guidance of the larger potential increase of black to white, in addition calculates the amount of change of that direction. The Sobel operator applied on a digital image in gray-scale calculates the gradient of the intensity of brightness of each pixel, providing the position of the larger probably growth of black to white, in adding computes the number of varies of which direction. The Sobel operator completes a 2-D spatial gradient dimension on an image. Classically it is employed to invent the estimate absolute gradient magnitude at every point in an input gray level scale image.

(a)



(b)



(c)

Fig.6.11**:**(a) original image for **patient 1** (b) Cropped image and (c) Edge detected image for detection of chipped tooth

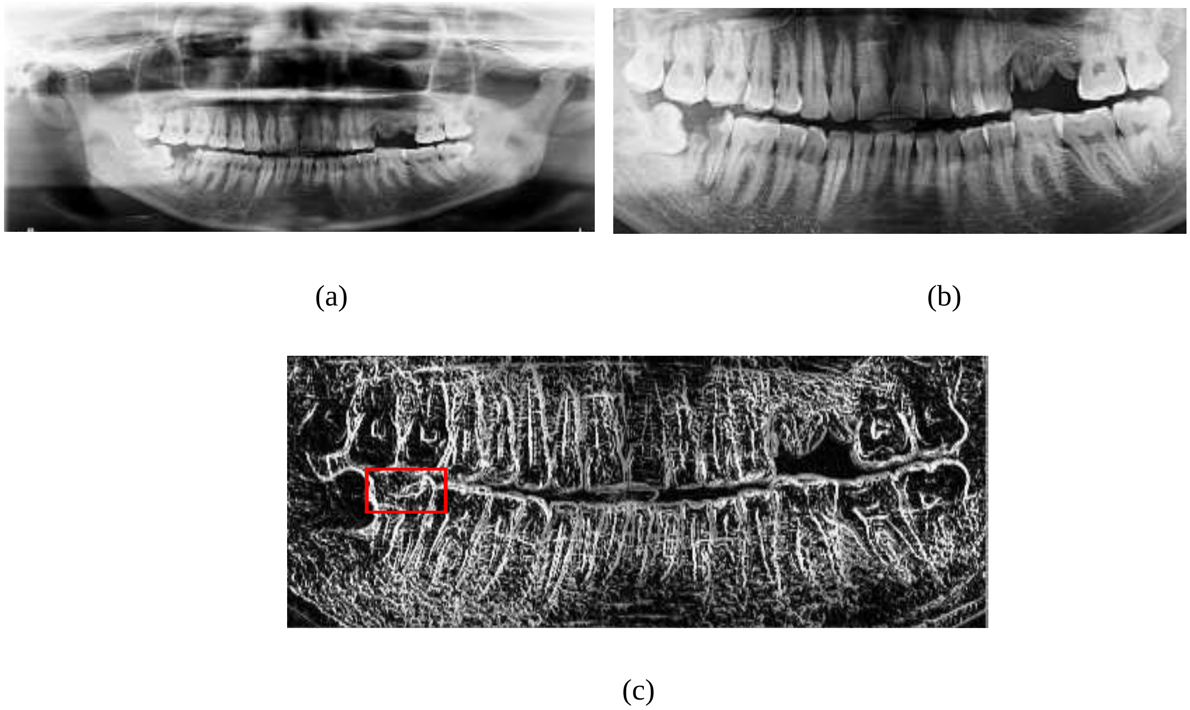


Fig.6.12: (a) original image for **patient 2** (b) Cropped image and (c) Edge detected image for detection of chipped tooth

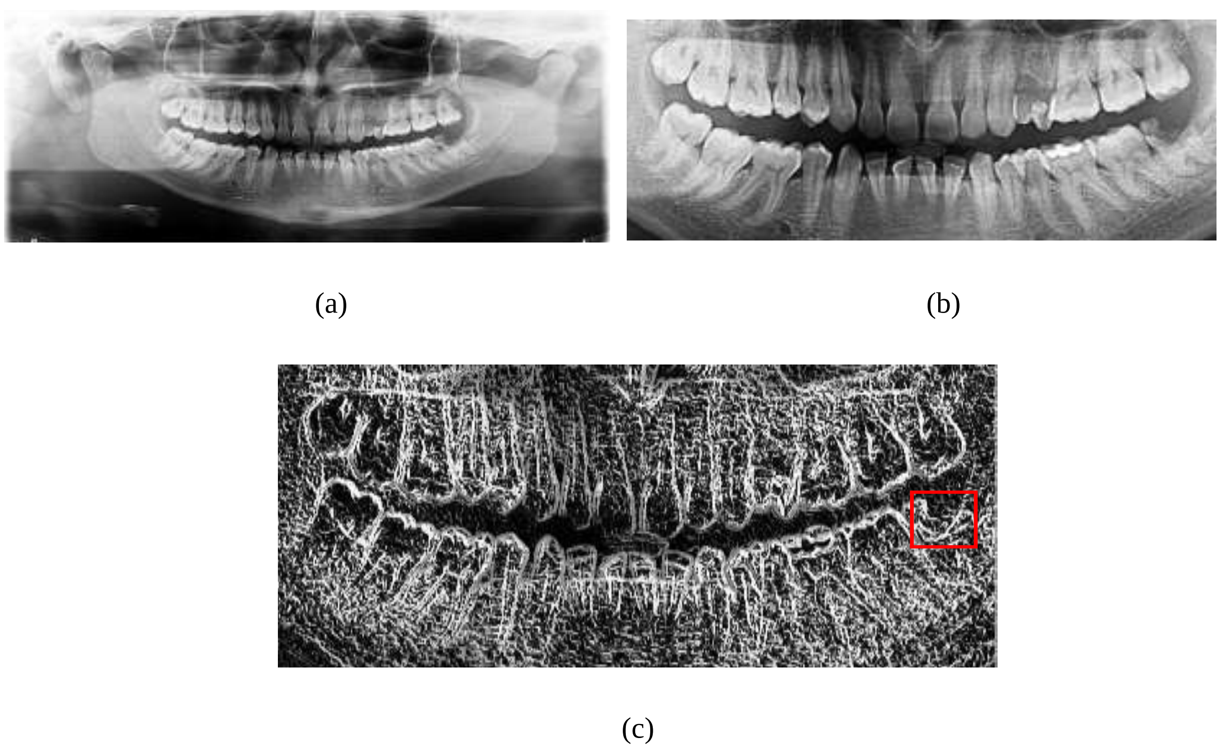
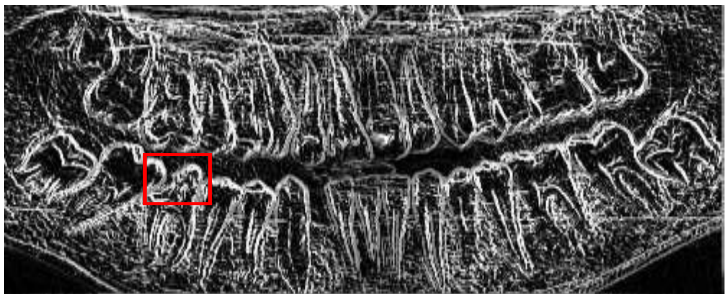


Fig.6.13: (a) original image for **patient 3** (b) Cropped image and (c) Edge detected image for detection of chipped tooth

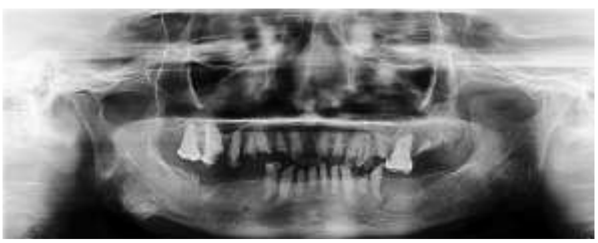
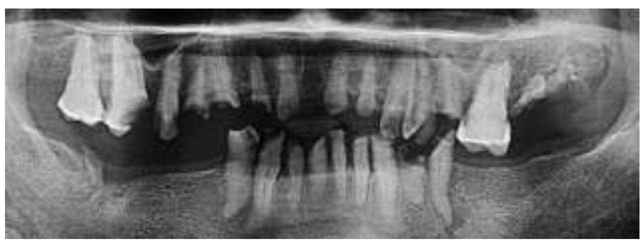
 

(a) (b)

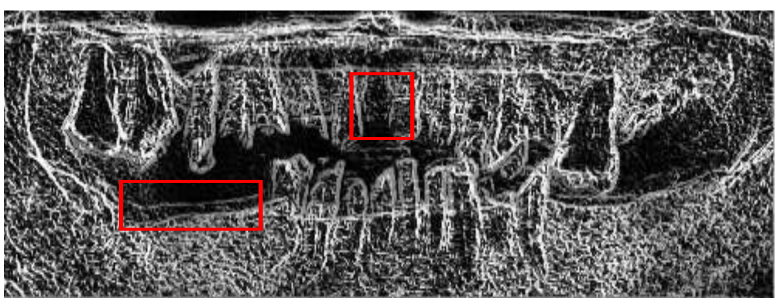


(c)

Fig.6.14 :(a) original image for **patient 4** (b) Cropped image and (c) Edge detected image for detection of chipped tooth

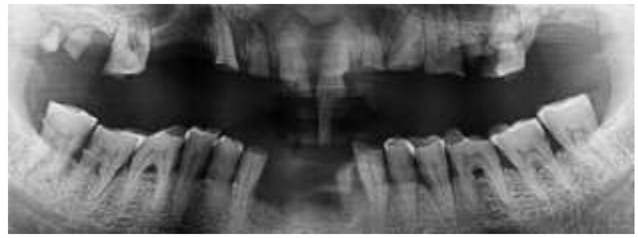
 

(a) (b)

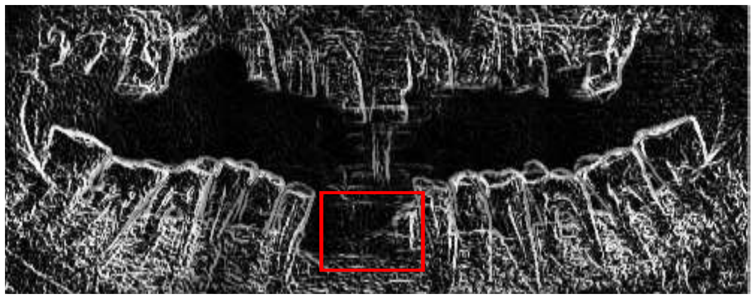


(c)

Fig.6.15: (a) original image for **patient 5** (b) Cropped image and (c) Edge detected image for detection of diastema disease

(a) (b)



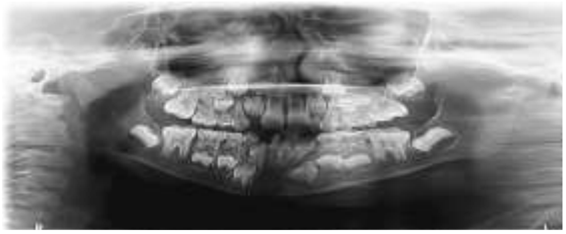
(c)

Fig.6.16 : (a) original image for **patient 6** (b) Cropped image and (c) Edge detected image for detection of diastema disease


(a) (b)

(c)

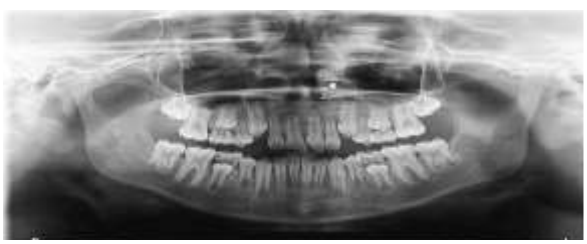
Fig.6.17 : (a) original image for **patient 7** (b) Cropped image and (c) Edge detected image for detection of diastema disease



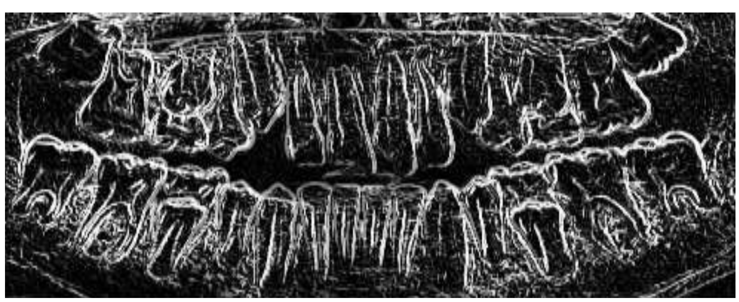

(a) (b)

(c)

Fig.6.18: (a) original image for **patient 8** (b) Cropped image and (c) Edge detected image for detection of Crooked teeth



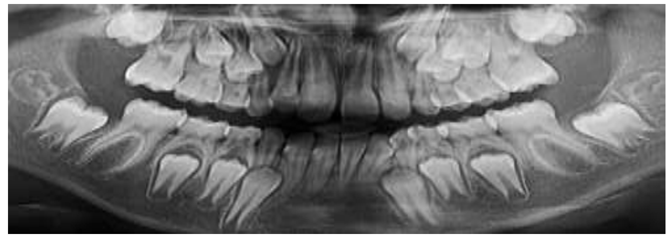

(a) (b)



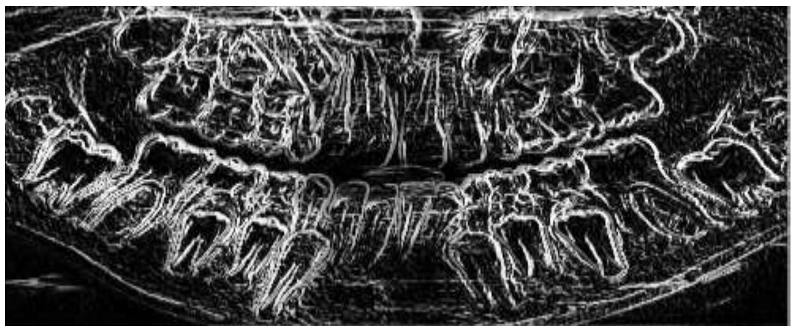
(c)

Fig.6.19:(a) original image for **patient 9** (b) Cropped image and (c) Edge detected image for detection of Crooked teeth

(a)



(b)



(c)

Fig.6.20: (a) original image for **patient 10** (b) Cropped image and (c) Edge detected image for detection of Crooked teeth

In type-1 fuzzy logic it is essential to employ sobel operators to the input images, and then usage a FIS to produce the vector of edges .Computes the intensity of brightness of every pixel, affording the direction of the larger potential growth of black to white, in calculation computes the number of change of that is direction. The Sobel operator executes a 2-D spatial gradient capacity on an image. The type-1 fuzzy logic is implemented on ten patient dental images .The edge image that contains edge pixels are obtained for all the ten images, total number of edges is calculated for all ten images.

Table 6.2 shows edge detected pixels using T1FLS for total patients that is 10 for every patients total edge detected values are different. In this edge detection sobel operator is used because analyses said that sobel operator is best operator among all operator for calculation of gradients. And from table 6.1 and 6.2 we can conclude that edge detected pixels are more in T1FLS and we discussed that by taking consideration lots of parameters of the image edge detection or any other results gets more precise. . The Sobel operator employed on a digital image in gray level computes the gradient of the intensity of brightness of every pixel, providing the direction of the superior possible escalation of black to white, in calculation computes the number of change of that particular direction.

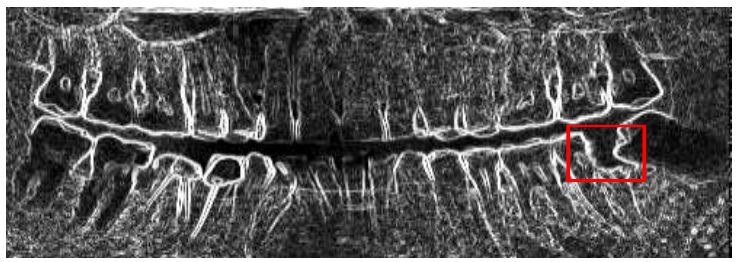
Table. 6.2. Edge Detected pixels using T1FLS edge detection technique.

Patient Number	**Edge detected Pixels**
P1.	25120
P2.	26342
P3.	24567
P4.	25486
P5.	29613
P6.	16017
P7.	25546
P8.	20505
P9.	20493
P10.	20552

6.3 Results of IT2FLS Edge Detector

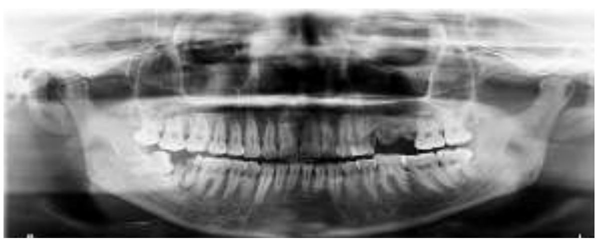
Interval type-2 fuzzy logic is a generalization of traditional type-1 fuzzy logic. The procedure for edge detection using type-2 fuzzy logic is same as that of type-1 fuzzy logic. The only difference is in the way of defining membership function. Edge detection with IT2FLS follows the same process that in T1FLS but only difference is in applied membership function and results outcomes after the comparison . The broad of the footprint of uncertainty (FOU) region selected for every membership functions constituted the one which had improved results later various experiments. These were carried out to load an input image or to employ the filters remarked earlier. As of big quantity of information which evaluated by fuzzy rules.

(a) (b)

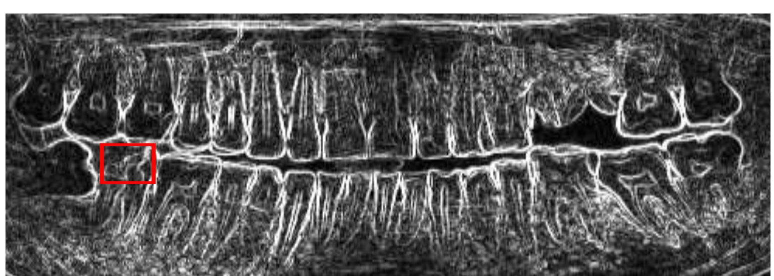


(c)

Fig.6.21 : (a) original image for **patient 1** (b) Cropped image and (c) Edge detected image for detection of Chipped tooth



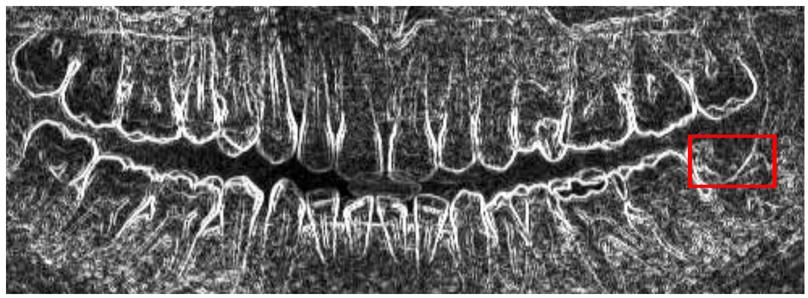
(a) (b)



(c)

Fig.6.22 : (a) original image for **patient 2** (b) Cropped image and (c) Edge detected image for detection of chipped tooth

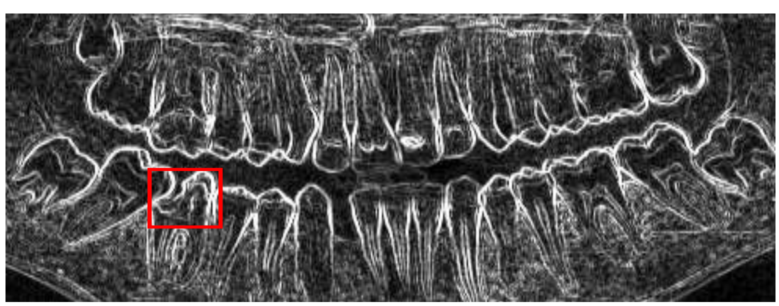

(a) (b)



(c)

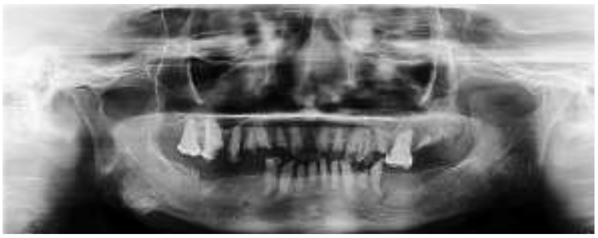
Fig.6.23: (a) original image for **patient 3** (b) Cropped image and (c) Edge detected image for detection of chipped tooth

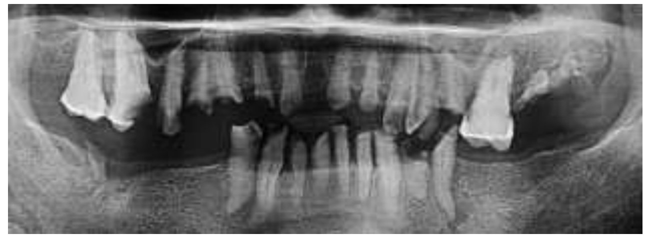

(a) (b)



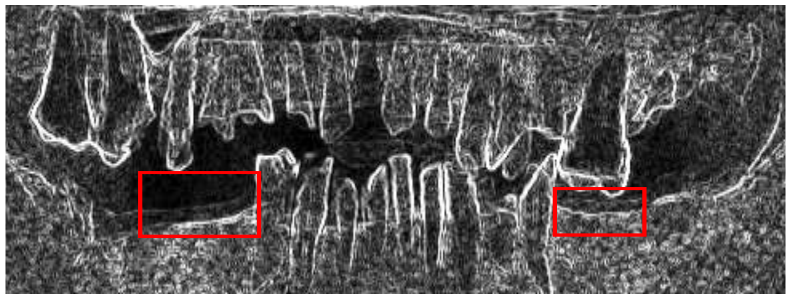
(c)

Fig.6.24 : (a) original image for **patient 4** (b) Cropped image and (c) Edge detected image for detection of chipped tooth





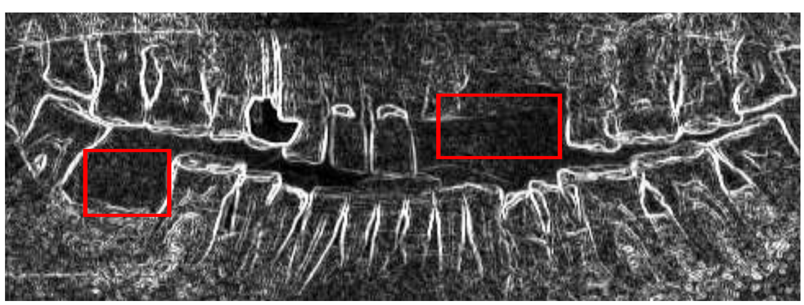
(a) (b)



(c)

Fig.6.25 : (a) original image for **patient 5** (b) Cropped image and (c) Edge detected image for detection of diastema disease

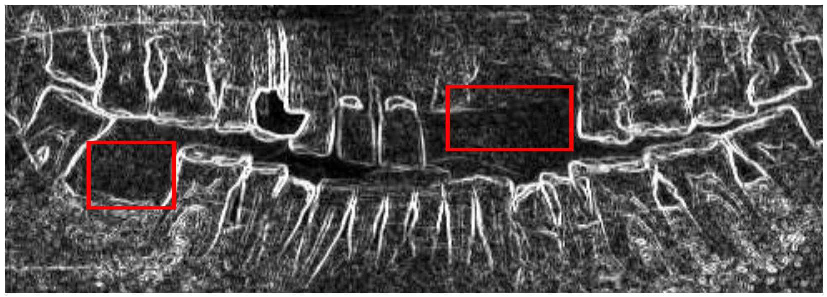
(a) (b)



(c)

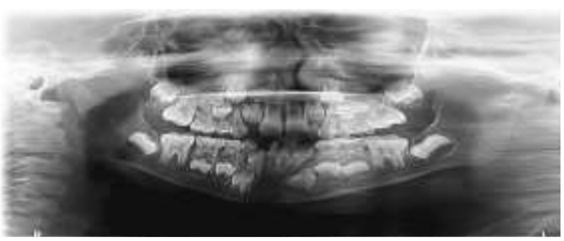
Fig.6.26 : (a) original image for **patient 6** (b) Cropped image and (c) Edge detected image for detection of diastema disease

(a) (b)

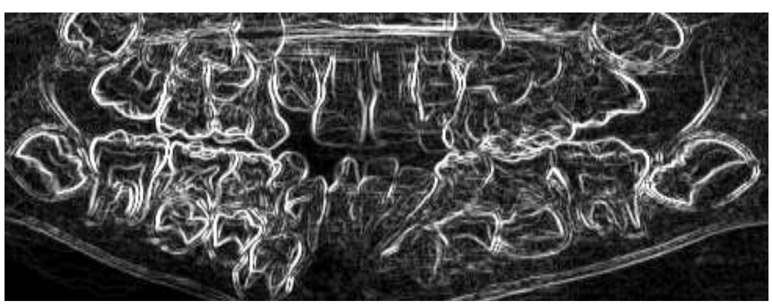


(c)

Fig.6.27 : (a) original image for **patient 7** (b) Cropped image and (c) Edge detected image for detection of diastema disease

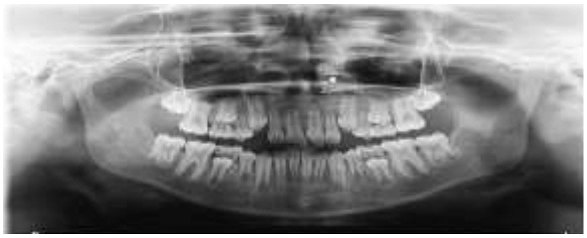


(a) (b)

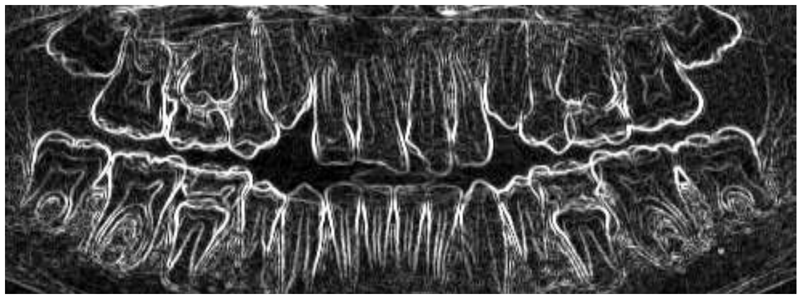


(c)

Fig.6.28 : (a) original image for **patient 8** (b) Cropped image and (c) Edge detected image for detection of Crooked teeth

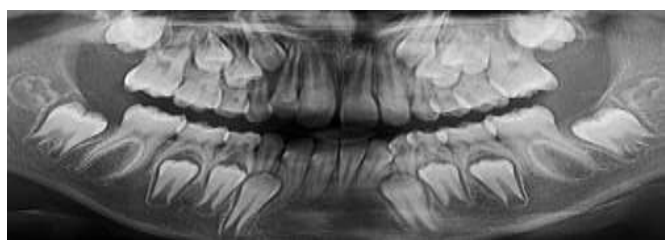
 

(a) (b)

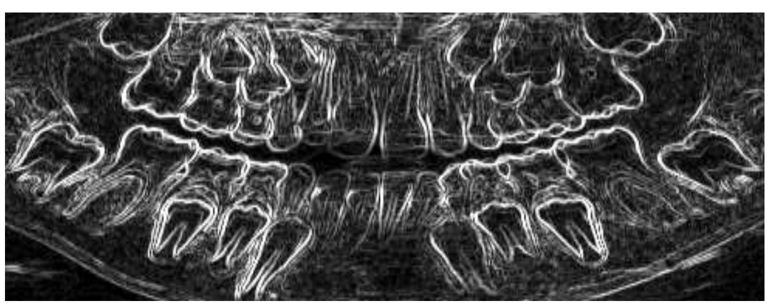


(c)

Fig.6.29 : (a) original image for **patient 9** (b) Cropped image and (c) Edge detected image for detection of Crooked teeth

(a) (b)



(c)

Fig.6.30 : (a) original image for **patient 10** (b) Cropped image and (c) Edge detected image for detection of Crooked teeth

In IT2FLS it is essential to employ sobel operators to the input images, and then use a FIS to create the vector of edges. The Sobel operator performs a 2-D spatial gradient measurement on an image. The type-2 fuzzy logic is implemented on ten different patient images The edge image that contains edge pixels are obtained for all the ten images, total number of edges is calculated for all ten images. Edge detection with IT2FLS follows the same process that in T1FLS but only difference is in applied membership function and results outcomes after the comparison .

Table. 6.3. Edge Detected pixels using IT2FLS edge detection technique.

Patient Number	**Edge detected Pixels**
P1.	125406
P2.	125963
P3.	125955
P4.	125927
P5.	125955
P6.	125385
P7.	125927
P8.	122786
P9.	125921
P10.	125113

Table 6.3 shows edge detected pixels using IT2FLS for total patients that is 10 for every patients total edge detected values are different. And from table 6.1 ,6.2 and 6.3 concluded that edge detected pixels are more in IT2FLS and discussed that by taking consideration lots of parameters of the image edge detection or any other results gets more precise. . The Sobel operator employed on a digital image in gray level computes the gradient.

6.4 Comparison of three implemented algorithms

IT2FLS gives better result than sobel and T1FLS. For the same image IT2FLS provides more and clear edges than T1FLS . In order to obtain an objective comparison among T1FLS and IT2FLS , a table has been shown that shows the total number of edges obtained from both the methods. Table 6.1,6.2 and 6.3 shows the total number of edges obtained from sobel, T1FLS and IT2FLS for all the ten images. Thus, IT2FLS is improved than T1FLS . It can be seen from the table Type-2 fuzzy logic provide more edge pixel than T1FLS of same image and edge pixels have good appearance in IT2FLS thanT1FLS. Thus, type-2 fuzzy logic gives better result than T1FLS and sobel in terms of time taken by algorithm.

Table 6.4 Comparison based on edge detected pixels

Input Images of Patients	**Algorithms**						
	Sobel edge detector					**T1FLS**	**IT2FLS**
	T = 210	T = 220	T = 230	T = 240	T = 250		
P1.	5072	4565	4118	3769	4133	25120	**125406**
P2.	5705	5052	4488	3998	4039	26342	**125963**
P3.	6085	5415	4853	4443	5678	24567	**125955**
P4.	4049	3552	3156	2788	2214	25486	**125927**
P5.	3078	2659	2307	2015	10243	29613	**125955**
P6.	2030	1749	1530	1344	6896	16017	**125385**
P7.	4026	3552	3156	2816	7710	25546	**125927**
P8.	5269	4679	4140	3740	11392	20505	**122786**
P9.	3814	3311	2903	2561	9102	20493	**125921**
P10.	4125	3623	3192	2824	4391	20552	**125113**

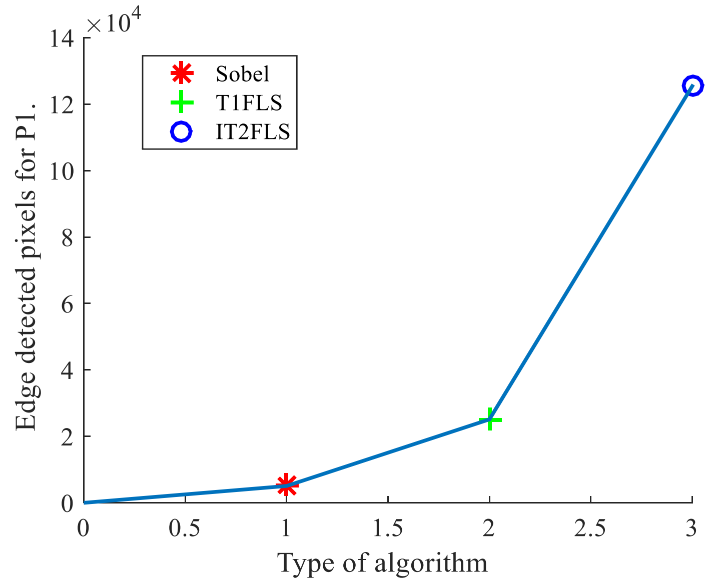
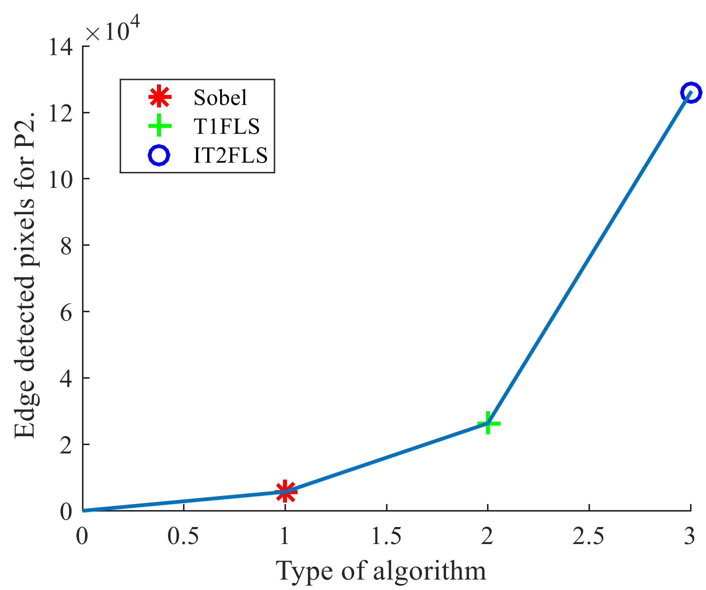
Table 6.5 Comparison based on total percentage of edge detected pixels

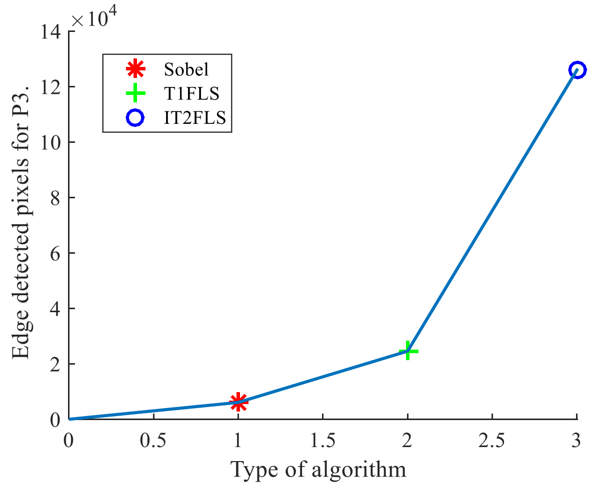
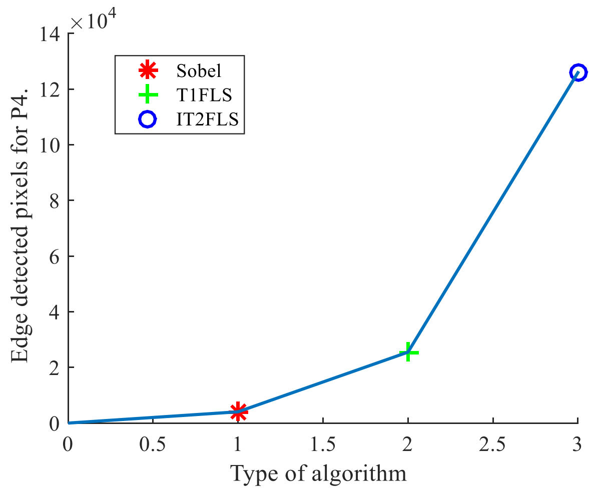
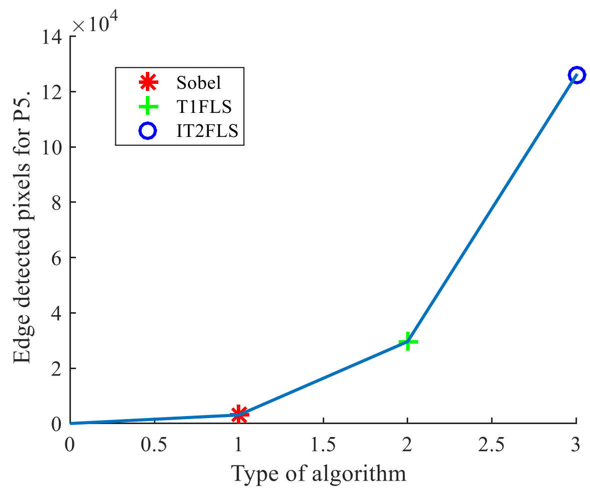
Input Images of Patients	**Sobel edge detected pixels at T=210**	**T1FLS edge detected pixels**	**IT2FLS edge detected pixels**	**Total number of pixels**	**Total %Edge detected pixels (Sobel)**	**Total %Edge detected pixels (T1FLS)**	**Total %Edge detected pixels (IT2FLS)**
P1.	5072	25120	125406	127500	3.98	19.70	**98.36**
P2.	5705	26342	125963	127500	4.47	20.66	**98.79**
P3.	6085	24567	125955	127500	4.77	19.27	**98.79**
P4.	4049	25486	125927	127500	3.18	19.99	**98.77**
P5.	3078	29613	125955	127500	2.41	23.23	**98.79**
P6.	2030	16017	125385	127500	1.59	12.56	**98.34**
P7.	4026	25546	125927	127500	3.16	20.04	**98.77**
P8.	5269	20505	122786	127500	4.13	16.08	**96.30**
P9.	3814	20493	125921	127500	2.99	16.07	**98.76**
P10.	4125	20552	125113	127500	3.24	16.12	**98.13**

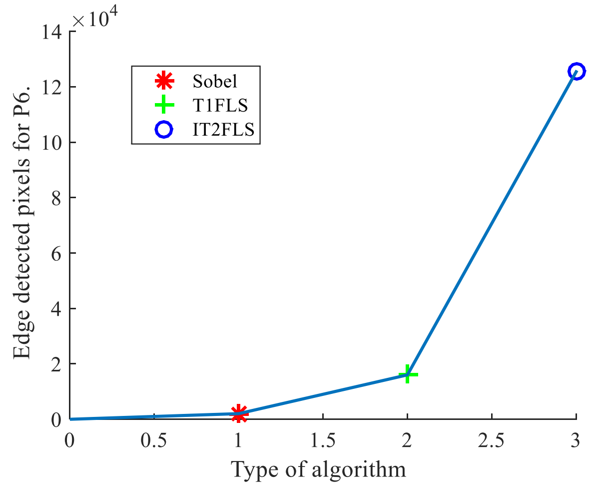
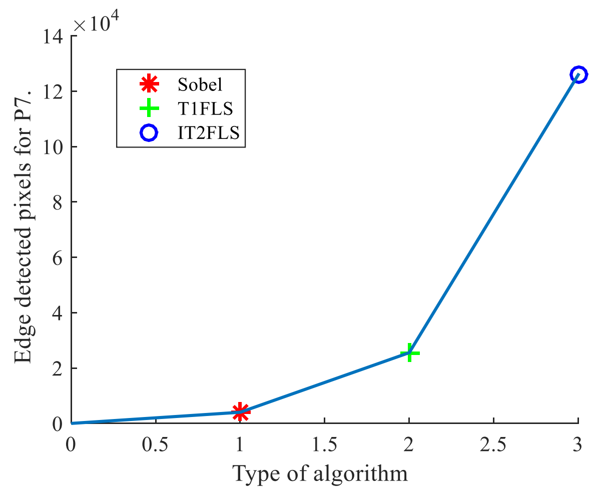
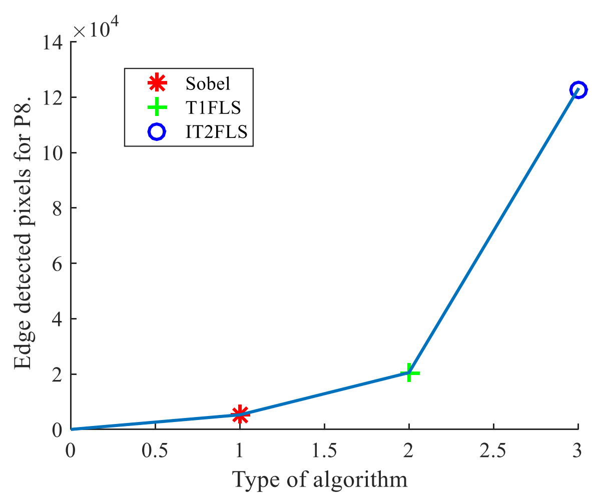
Table 6.6 Comparison based on average time taken by algorithms

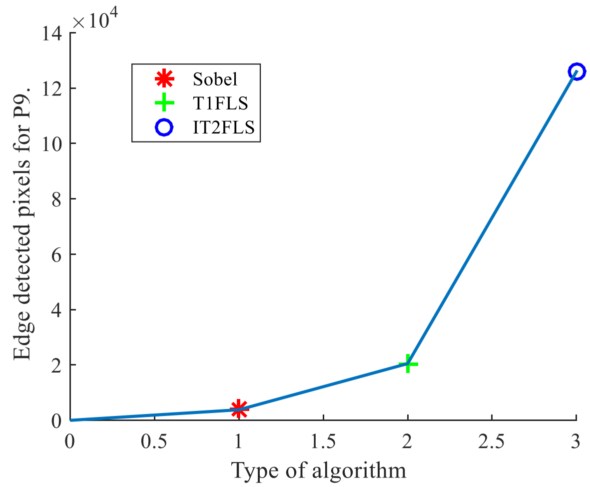
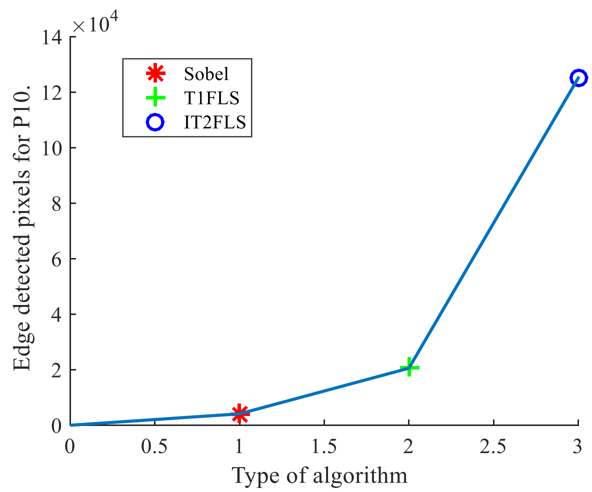
S. No.	**Name of Algorithm**	**Avg. Time taken in seconds**
1.	Sobel	100.838 sec
2.	T1FLS	109.303 sec
3.	IT2FLS	**97.841 sec**

Table 6.7 Comparison based on graphical representation

Patient No.	Graph (x-axis represents type of algorithm and y-axis represents total number of edge detected pixels)
P1.	
P2.	

P3.	 $\times 10^4$ Sobel T1FLS IT2FLS Edge detected pixels for P3. Type of algorithm
P4.	 $\times 10^4$ Sobel T1FLS IT2FLS Edge detected pixels for P4. Type of algorithm
P5.	 $\times 10^4$ Sobel T1FLS IT2FLS Edge detected pixels for P5. Type of algorithm

P6.	$\times 10^4$ Sobel T1FLS IT2FLS Edge detected pixels for P6. Type of algorithm
P7.	$\times 10^4$ Sobel T1FLS IT2FLS Edge detected pixels for P7. Type of algorithm
P8.	$\times 10^4$ Sobel T1FLS IT2FLS Edge detected pixels for P8. Type of algorithm

P9.	
P10.	

In Table 6.7 the graph for sobel, T1FLS and IT2FLS has been shown in the diagram. On the basis of these graphs, a comparison can be seen among these three methods. It can be seen from the table IT2FLS give number of edges than T1FLS for the same image. Thus, T2FLS is better than T1FLS . It can be seen from the table IT2FLS provide more edge pixel than T1FLS of same image and edge pixels have good appearance in Type-2 than Type-1.Comparision among them is also visible in table 6.7 where comparison is based on average time taken by the algorithm to detect edges from the image, which shows that less time is taken by IT2FLS for the detection of edges from the input images.

7

CONCLUSION & FUTURE SCOPE

The three different edge detection methods (Sobel, T1FLS and IT2FLS) have been implemented on dental radiographs and a comparison has been made between among these methods using two parameters that are total edge detected pixels in an images and average time taken by algorithm for detection of edge from the image. These three methods (Sobel, T1FLS and IT2FLS are very simple and small but very efficient algorithms to shorten the concepts of artificial intelligence and digital image processing. The results of these three algorithms have been shown to make the readers understand the accuracy of all the three algorithms. Thus the three algorithms applied shows to the doctor and that results are very helpful for them, for the identification of dental diseases from edge detected x-ray images. Following are the graphs based on time taken and total edge detected pixels from image by all three algorithm shows in Fig. 7.1 and 7.2

In Fig 7.1 graph shows between type of algorithm and total time taken by algorithms, where clearly visible that IT2FLS took less time comparatively. Time shown in graph is in second and for sobel edge detector average time taken for all threshold value executions. More time is taken by T1FLS that's why we switched to IT2FLS for detection of edges from the dental radiographs.

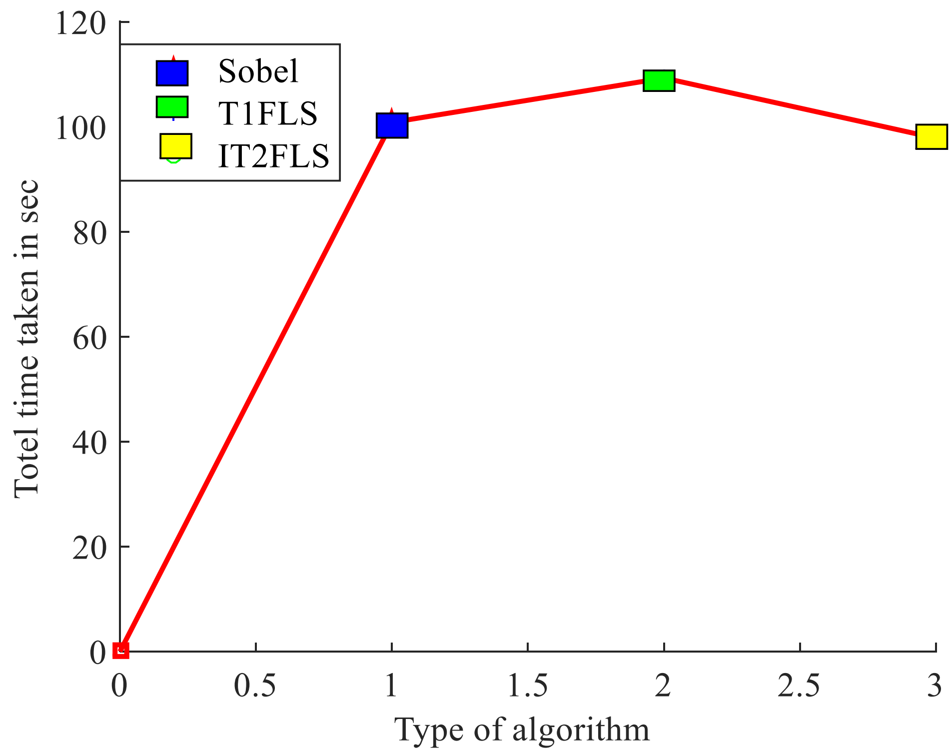


Fig.7.1: Graph between total time taken by every algorithm

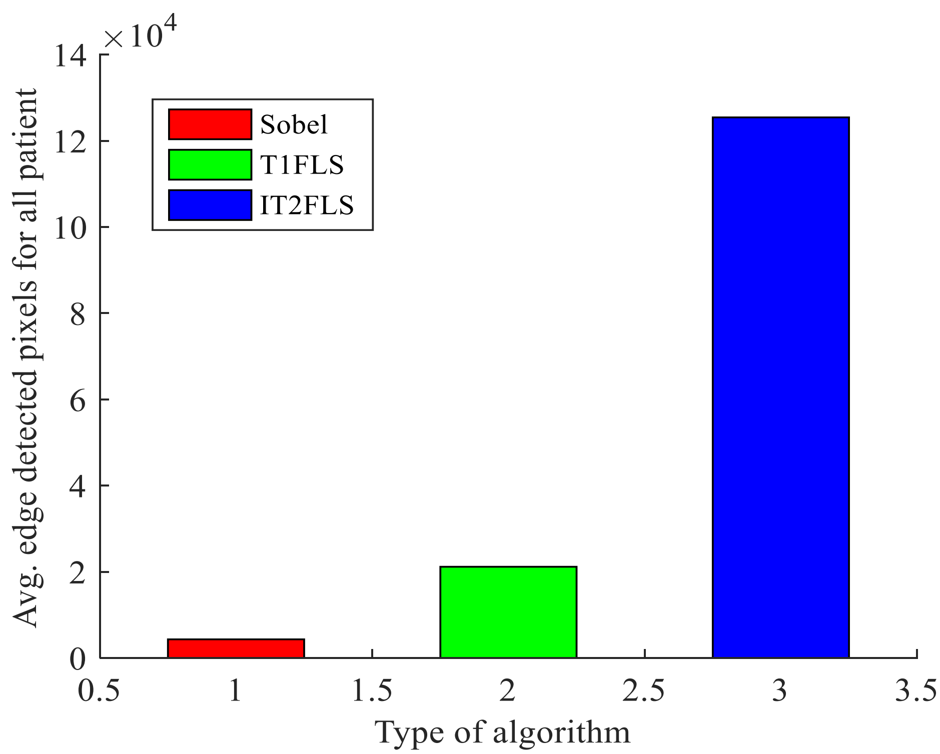


Fig.7.2: Bar graph between avg. edge detected pixels for all patients by every algorithm

In Fig 7.2 graph shows between type of algorithm and total edge pixels detected, where clearly visible that IT2FLS detected more edge pixels comparatively.

In Future Research, look forward to get more precise and improved results by using general type-2 fuzzy logic systems (GT2FLS) for detection of edges application because it deals with real time application by taking consideration all possible parameters. Additionally helpful in detecting more dental diseases from the edge detected image.

Table 7.1 Research papers

S.No	Authors	Title	Conference	Status
1.	Rosepreet Kaur Bhogal and Aayushi Agrawal	Comparative Study of Image Edge Detection Techniques (Sobel, T1FLS & IT2FLS)	International Conference on Information and Communication Technology for Competitive Strategies (ICTCS 2017) and publication in Springer LNNS series	Accepted
2.	Rosepreet Kaur Bhogal and Aayushi Agrawal	A Review - Edge Detection Techniques in Dental Images	International Conference on Intelligent Circuits and Systems (ICICS 2018)	Communicated

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