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An Automated Segmentation Approach using Clustering Technique for Dental Problems Impacted 3rd Molar

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***Abstract*—Segmentation refers to a subclass of enhancement methods by which a particular object, organ, or image characteristic is extracted from the image data for purposes of visualization and measurement. Segmentation is a central problem of image analysis because it is a prerequisite for most analysis methods, including image registration, shape analysis, motion detection, volume, and area estimation. Unfortunately, there is no common method or class of methods applicable to medical images based on the assumption that the objects of interest have intensity or edge characteristics that allow them to be separated from the background and noise, as well as from each other. In dentistry the wisdom tooth (3rd molar), has the lack of room to erupt, it commonly affects other teeth as they develop and become partially erupted or impacted. To diagnose the problems associated with the wisdom teeth automatically and prepare the radiograph for final analysis, a segmentation algorithm is implemented and followed by post processing stage. The proposed segmentation method aims to extract wisdom teeth using clustering techniques. This information is used further to classify wisdom teeth as impacted, partially erupted, or completely erupted based on distance from IAN.**

***Index Terms*— Image-Segmentation; Intensity-Inhomogeneity; Level Set; Root Canal Treatment (RCT); lesion.**

I. INTRODUCTION

Medical imaging is an upcoming technology and widely used in medical field for diagonsis purpose. Imaging is the representation of body parts, tissues for use in clinical diagnosis, treatment, and disease monitoring. Imaging method covers like radiology, nuclear medicine, and optical imaging. Radiological techniques give the anatomical and physiological detail of the human body at high spatial and temporal resolution. This strategies like ultrasound, CT, X-ray and MRI.

Medical radiography is a broad term that covers a few types of studies that require the representation of the inward parts of the body utilizing x-ray technique. Radiography may also help for dentist to diagnose, plan treatments, and monitor both treatments and lesion development. It is used to diagnose or treat patients by recording images of the inward structure of the body to assess the absence of disease and structural damage.

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Dental x-rays usage as a standard diagnostic procedure is well established in the profession. X-ray imaging is easy, convenient, and easy to read once the observer is trained.
The dental radiograph is broadly divided in four major categories namely Panoramic, Bitewing, Occlusal and Periapical. The periapical dental radiograph is very important for dentist as it give the ability to see between and inside the tooth. It is considered to the crucial diagnostic for the early detection of abnormal changes in gums and root area of the tooth. The periapical dental radiograph helps in representing the entire tooth from crown to root. It further helps in identification of lesions or carries beyond the root area attach to the jaw as shown in figure 1. The main objective of image segmentation is to partition an image into useful segment based on the context of the application such as periapical dental radiograph.


(a) Bitewing dental radiograph


(b) Periapical dental radiograph


(c) Occlusal dental radiograph


(d) Panoramic dental radiograph

Figure 1Various types of dental radiographs {Courtesy: Dr. Ronak Panchal}

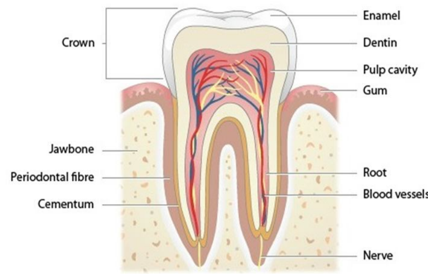


Figure 2 Classification of lesion detection {Courtesy: Dr. Ronak Panchal}

Several image processing techniques have been used for the purpose of identification of tooth abnormalities in the form of caries or lesions. Perception and prediction by medical practitioners is an important for detection of medical abnormalities in dental radiograph. Accuracy and precision based lesion detection is the need of the hour for further processing or treatment of dental disease. In a primary stage, lesion detection is the most important thing to find. Proper lesion detection using segmentation has become the need of the hour. Lesion detection is any abnormal damage or change in the tissues of tooth usually caused by the disease. There are various parts of a tooth namely enamel, dentine, pulp, gum or root. Lesion can attack the tooth from any one of this parts. Carries can be categorised under incipient caries, overt caries and advanced(deep) caries. The part of the tooth that is typically unmistakable over the gum is known as the crown and the part that is connected to the gum is known as the root as shown in figure 2.

Enamel - It is one of the hardest substances in the body. It is highly mineralized a cellular tissue and carries act upon it through a chemical process brought on by the acidic environment produced by bacteria. The early manifestation of the caries process is a small patch of softened enamel at the tooth surface, often hidden from sight in the grooves of teeth or in between the teeth.

Dentine - The destruction spreads into the softer, sensitive part of the tooth beneath the dentine that called overt caries. Overtime until the bacteria physically penetrates the dentine.
Pulp - It contains the blood vessel the nerves. It is also connective tissue inside the provides the tooth blood and nutrients.
The dental specialist has moved toward diagnosing and treating dental lesion construct generally with respect to radiographs. In any case, precise and target strategies for radiographic caries determination are ineffectively investigated. The point of this challenge is to investigate possible automated method of recognition of lesion in periapical dental radiograph.
This paper presents a review on lesion detection. In section 2, we present a brief liturature survey based on segmentation and feature extraction of periapical dental radiograph. Section 3 comprise of various techniques commonly used by domain experts for further analyzing the tooth and lesion detection. A soft computing approach for lesion detection is suggested in Section 4. Section 5 present the conclusion of review paper.

II. Problem Definition

Pedro *et al.*with his research work proposed image segmentation technique for panoramic dental x-ray images [1]. The approach is divided in four major steps. The first one is shape model generation where images are trained based on PCA parameters and their respected models are created. The second step is image preprocessing where acquired image goes through quad tree mask generation as well as Otsu thresholding for avoiding teeth overlapping with the help of first step boundaries of individual tooth are extracted and analyze. Using search mean shape best fit analysis tooth is further segmented. With the help morphometric data extraction technique along with snake model teeth measurement are done. The main drawback of this paper was overlapping between teeth which are not being able to get identified using step two.

Po *et al*. in this paper, author took 60 bitewing image for tooth isolation [2]. They isolated individual single tooth and compared there method with Nomir Abdel–mottaleb's method. Their approach is fully automatic tooth isolation of bitewing dental x-ray. With the help of gray scale integral projection upper and lower jaws are separated along with angle adjustment to handle skewed images with least information lost. An adaptive windowing scheme for locating gap valley is introduced for improving accuracy.

The above same author Abdolvahab *et al.* reviewed image segmentation technique like edge detection, level set method, region growing method, active contour method and clustering. Various abnormalities in dental radiograph lead to varying segmentation techniques. A single technique is not applicable for all categories of dental radiograph. Hence regularization of this technique based on abnormalities is still need of the hour [3]. In his next paper [4] he proposed a new technique named morphological region based initial contour (MRBIC). In it, local initial contour selection for the level set method was taken into consideration. Binarization has been applied using variable thresholding values for the preprocessing purpose. Thresholding method is used to remove background area from the foreground. The approximated threshold value will prevent wrong selection of initial contours and also the segmentation process would become faster.

Moving further authors concentrated their research in the domain of human identification using k-means clustering [5]. They performed the automatic k-means clustering method for segmentation after image enhancement. They chose k=5 as the data image clusters for some irregular teeth such as filled, dental cavity or tooth with dental caries. The above authors Abdolvahab *et al.*[6] in their next paper tried the identification of the irregularities in tooth based on filled, dental cavity or a tooth with dental caries. They extracted features multiple of dental x-ray images using texture statistic technique like GLCM (Gray-level co-occurrence matrix). In both papers, texture features were extracted such as contrast, correlation, entropy, homogeneity and energy.

Solmaz *et al.* took 9 teeth including 183 proximal surfaces image database for designing the software [7]. Teeth were separated from each other by using root area in alveolar bone. Fuzzy c means clustering was applied to the images to cluster or segment tooth. A Comparative study of ICC (intraclass correlation coefficient (ICC)) and bland–Altman plot was done to identify a single tooth from a given image and further its histological analysis was done.

III. MATERIALS & METHODS

Analysis of digital dental radiograph plays a key role in oral dentistry and is widely used for detection of dental diseases. Extraction of tooth or teeth or other important regions play yet important role in identification and diagnosis of diseases. Machine learning techniques, specifically clustering techniques, have contributed actively for preparing model and using it for segmentation. Some popular clustering techniques like K–means, Fuzzy C–Means (FCM), and other advance clustering techniques have been investigated in this chapter for segmentation of dental radiographs.

A. K–Means Clustering for Image Segmentation

This algorithm is applied in following steps: Let X= $\{x_1, x_2....x_n\}$ is the set of data points and V=$\{v_1,v_2....v_n\}$ is the set of centres as shown in table I.

TABLE I: - ALGORITHM OF K MEAN CLUSTERING

Steps	
1	Choose arbitrarily k objects from K as the initial cluster centers
2	Calculate the Euclidean distance between each data point and cluster centers.
3	Assign the data point to the cluster centre whose distance from the cluster center is minimum of all the cluster centers.
4	Recalculate the new cluster centers using $V_i = \left(\frac{1}{c_i}\right)\sum_{j=1}^{c_i} x_i$ …… (3.2)
5	Recalculate the distance between each data point and newly obtained cluster centers.
6	If no data point was reassigned then stop,otherwise repeat from step 3.

B. Fuzzy C–Means clustering for segmentation of Dental Radiographs

The algorithm for performing segmentation of radiograph using fuzzy C–Means clustering is presented in Table 2. The steps of this algorithm are also produced in the form of block diagram and presented in section 4.

TABLE II. ALGORITHM OF FUZZY C MEAN CLUSTERING

Steps:	
1	Initiate U= [$\boldsymbol{u_{ij}}$] matrix, U (0) and the data point x_i= (1,2…N)
2	At k–step calculate the center's vectors *C(k)=[$\mathbf{c_j}$] with U(k).* $c_j = \frac{\sum_{i=1}^{N} u_{ij} * x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$ …. (3.5)
3	Update U(k), U(k+1) $u_{ij} = \frac{1}{\sum \left(\frac{\lVert x_i - c_j \rVert}{\lVert x_i - c_k \rVert} \right)^{\frac{2}{m-1}}}$ …. (3.6)
4	If $\lVert U^{(k+1)} - U^{(k)} \rVert < \epsilon$ then stop, otherwise return to step 2.

C. Kernel Fuzzy C–Means Clustering

The Kernel Fuzzy C– Means (KFCM) calculation adds part data to the customary Fuzzy C–Means calculation and it conquers the drawback that FCM calculation can't deal with the little contrasts between bunches as shown in Table III.

TABLE III. ALGORITHM OF KERNEL FUZZY C MEAN CLUSTERING

Steps:	
1	Fix c, t_{max}, Initiate U= [u_{ij}] matrix, U (0).
2	For t=1, 2 …. t_{max}. Update all prototypes v_i as $v_i = \frac{\sum_{k=1}^{n} u_{ik}^{m} k(x_k, v_i)}{\sum_{k=1}^{n} u_{ik}^{m} k(x_k, v_i)}$ …. (3.15)
3	Update all memberships value. U (t), U(t+1) $u_{ik} = \frac{(1 - k(x_k V_j))^{-1/m-1}}{\sum_{j=1}^{c} (1 - k(x_k, V_j))^{-1/m-1}}$ …. (3.16)
4	Stop condition If $\lVert U(t+\mathbf{1}) - U(t) \rVert < \epsilon$.

IV. COMPARITIVE ANALYSIS OF CLUSTERING TECHNIQUES

A. K MEAN CLUSTERING FOR IMAGE SEGMENTATION

Based on the discussed algorithm various digital dental radiographs were applied with K–Means clustering technique. The steps of this algorithm are shown in Table 4. The results obtained based on application of algorithm are shown in Figure 4. Each column represents steps wise result of different radiographs. The process of application of radiograph segmentation is also shown graphically in Figure 3.

TABLE IV. ALGORTIHM K–MEANS CLUSTERING FOR SEGMENTATION OF DENTAL RADIOGRAPH

Steps:–	
1	Take any input dental radiograph image from the given dataset.
2	Apply the shaping effect (variation on the radius & amount strength on the shaping effect) in the given input image.
3	Apply K–Means segmentation technique to find the cluster index and cluster centre.
4	After K–Means clustering, the image index is labelled by the cluster index.
5	We apply the Harris Corner detection in image labelled by the cluster index for detecting corner feature.
6	After segmentation image is classified by the three clusters.
7	Results of segmentation are shown in Figure 3.

The individual column represents the three different clusters namely cluster 1, 2 and 3 being formed for the purpose of classification in Figure 4 (d1 – d5), (e1 – e5) and (f1 – f5) respectively. In Figure 4, five different radiographs of varied dental problems are considered, and result are displayed for the purpose of analysing the clustering technique and its effect for the purpose of understanding the outcome. The first column represents the original radiograph in Figure 4(a1 – a5). Next column represents the sharpened radiographs after pre–processing in Figure 4 (b1 – b5). Third column represents the result of segmentation on sharpened radiographs in Figure 4 (c1 – c5).

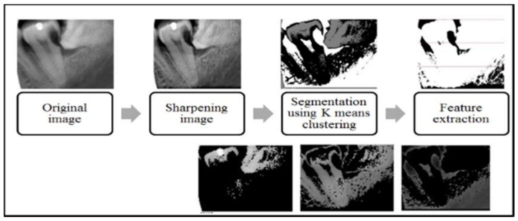


Figure 3 Block diagram of Dental radiograph segmentation using K–Means Clustering

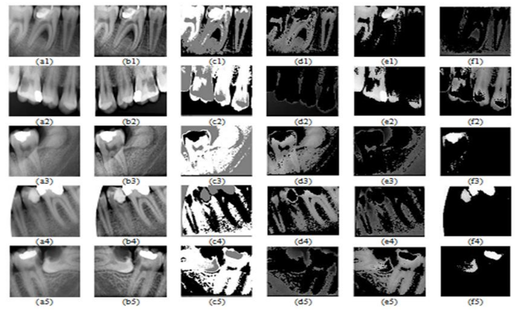


Figure 4 K–means clustering technique for Segmentation and clustering

The performance parameters as discussed in section 1 are analysed on available radiographic images. Based on the defined parameters for measurement, the confusion matrix for one of the radiographic images and ROI of one of ground truth image (obtained with one expert) is shown in Table 5.1. According to the confusion matrix shown in Table 5.1 and Table 5.2, the accuracy, precision, error rate and specificity of our segmented result based on ROI of ground truth set 1 and ground truth set 2 are presented in Table 6 respectively.

TABLE V. CONFUSION MATRIX OF A SAMPLE RADIOGRAPH IMAGE COMPARED WITH ROI OF GROUND TRUTH SET 1(5.1) & SET 2(5.2)

Table 5.1					Table 5.2				
	Predicted Class					*Predicted Class*			
Actual class		*YES*	*NO*	*TOTAL*	*Actual class*		*YES*	*NO*	*TOTAL*
	YES	5439	1472	6911		*YES*	5439	1502	6941
	NO	1509	61133	62642		*NO*	1290	61133	62423
	TOTAL	6948	62605	69553		*TOTAL*	6729	62635	69364

TABLE VI. PERFORMANCE PARAMETERS FOR ROI INDICATED IN GROUND TRUTH IMAGE SET 1 & 2 USING K–MEANS CLUSTERING

Image No.	Ground truth set 1					Ground truth set 2				
	Accuracy	*Precision*	*Error Rate*	*Recall*	*Specificity*	*Accuracy*	*Precision*	*Error Rate*	*Recall*	*Specificity*
1	91.54	65.91	1.17	67.09	99.38	92.43	85.05	00.26	95.30	99.79
2	94.34	91.3	1	92.2	99.43	93.59	85.73	01.71	86.60	99.05
3	98.39	68.87	2.3	69.46	98.78	98.27	67.70	02.34	69.32	98.73
4	96.88	90.46	1.18	90.26	99.37	97.02	57.71	07.33	60.26	95.76
5	91.83	63.39	6.54	64.37	96.32	92.01	49.64	04.59	50.87	97.53
Avg. 723 images	**97.83**	**79.54**	**2.16**	**2.16**	**98.77**	**96.40**	**68.71**	**3.59**	**67.67**	**98.14**

The bar chart summarising the evaluation measures of K–Means technique w.r.t. ROI of ground truth image set–1 and set–2 is shown in Figure 5.

B. Fuzzy C Mean Clustering Technioque Forsegmentation of Dental Radiograph

The algorithm for performing segmentation of radiograph using fuzzy C–Means clustering is presented in Table 7. The steps of this algorithm are also produced in the form of block diagram and presented in Figure 6. Based on the discussed algorithm various digital dental radiographs were applied with FCM clustering technique.

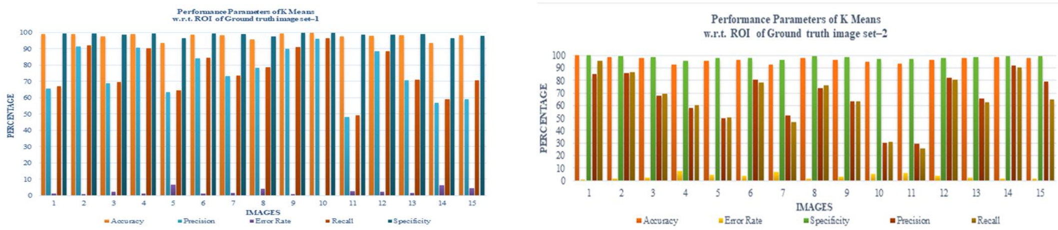


Figure 5 Parametric Evaluation measures of K–Means w.r.t. ROI of ground truth image set – 1 & set – 2

The steps of this algorithm are shown in Table 7. The results obtained based on application of algorithm are shown in Figure 7. Each column represents steps wise result of different radiographs. In Figure 7, five different radiographs of varied dental problems are considered, and result are displayed for the purpose of analysing the FCM clustering technique and its effect for the purpose of understanding the outcome. The first column of Figure 7 represents the original radiograph from (a1 – a5). Next column of Figure 7 represents the segmented radiograph using FCM from (b1 – b5). Third column of Figure 7 represents the result of corner detection on segmented radiographs from (c1 – c5).

TABLE VII. ALGORITHM FUZZY C–MEANS CLUSTERING FOR SEGMENTATION OF DENTAL RADIOGRAPH

Steps: –	
1	Take any input dental radiograph image from the given dataset.
2	Using FCM segment the radiograph image in following manner ➢ Choose random centroid at least two ➢ Compute membership matrix according to Equation (3.6) ➢ Calculate the 'c' cluster centers according to Equation (3.5)
3	The radiograph image index is labelled by the cluster index.
4	We apply Harris Corner detection in image labelled by the cluster index for detecting corner feature.
5	On the corner detected images apply dilated gradient masking technique for the purpose of separation of cyst from the radiograph.
6	Apply gray level thresholding to the gradient masked image and the radiograph image is then divided to three parts as shown in figure 6.
7	The final output radiograph is then superimposed on original image to separate the cyst from the given radiograph.

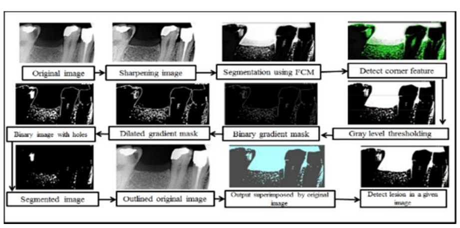


Figure 6 Block diagram of Segmenting Dental Radiograph image using FCM Clustering

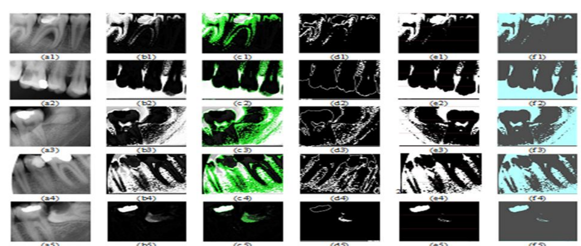


Figure 7 FCM clustering for Segmentation

Fourth column represents the dilated gradient masked radiographs. Next column of Figure 7 represents the gray level thresholded radiograph from (d1 – d5). At last, the resultant radiograph is superimposed on original radiograph to identify the cyst in Figure 7 from (e1 – e5). The performance parameters as discussed earlier are analysed on available radiographic images. Based on the defined parameters for measurement, the confusion matrix for one of the radiographic images and ROI of ground truth set 1 as shown in Table 8.

TABLE VIII. CONFUSION MATRIX OF A SAMPLE IMAGE FOR ROI OF GROUND TRUTH SET 1 & 2

Table 8.1					Table 8.2				
	Predicted Class					*Predicted Class*			
		YES	*NO*	*TOTAL*			*YES*	*NO*	*TOTAL*
Actual class	*YES*	5439	1472	6911	*Actual class*	*YES*	5439	1502	6941
	NO	1509	61133	62642		*NO*	1290	61133	62423
	TOTAL	6948	62605	69553		*TOTAL*	6729	62635	69364

TABLE IX. PERFORMANCE PARAMETERS FOR ROI INDICATED OF GROUND TRUTH SET 1 & 2 USING FCM CLUSTERING TECHNIQUE

Image No.	Ground truth set 1					Ground truth set 2				
	Accuracy	*Precision*	*Error Rate*	*Recall*	*Specificity*	*Accuracy*	*Precision*	*Error Rate*	*Recall*	*Specificity*
1	97.1	67.81	1.11	66.89	99.18	96.89	84.89	0.29	97.21	99.68
2	95.61	91.25	1.12	91.1	99.41	94.16	85.61	1.52	87.17	99.03
3	99.04	69.87	2.28	69.16	98.79	98.79	68.61	2.36	69.46	97.83
4	96.11	54.89	6.31	58.15	96.31	95.76	56.68	6.35	60.86	96.75
5	91.01	89.91	1.16	89.88	99.47	91.84	49.54	4.39	51.25	96.58
Avg. 723 images	**97.21**	**79.46**	**1.85**	**81.97**	**97.98**	**97.45**	**68.15**	**2.48**	**64.65**	**98.74**

The bar chart summarising the evaluation measures of FCM technique w.r.t. ROI of ground truth set 1 and set 2 is shown in Figure 8.

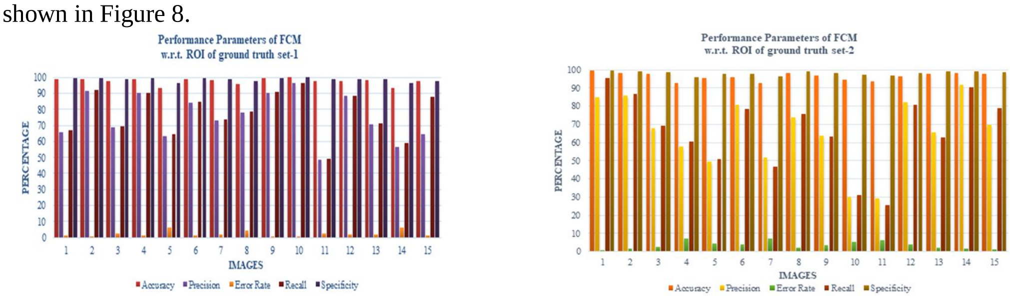


Figure 8 Parametric Evaluation measures of FCM w.r.t. ROI of ground truth set 1 & set 2

C. Kernel Fuzzy C Mean Clustering for Dental Radiograph

Based on Table 10 various digital dental radiographs were applied with KFCM clustering technique and results so obtained are shown in Figure 10. Each column represents steps wise result of each patient as discussed in the block diagram 9. In Figure 10, five different radiographs of varied dental problems are considered, and result are displayed for the purpose of analysing the KFCM clustering technique and its effect for the purpose of understanding the outcome.

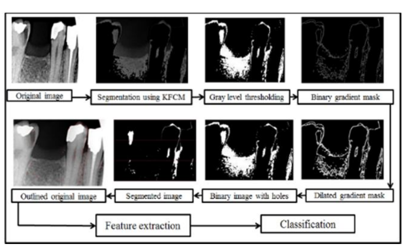


Figure 9 Block diagram of Segmentation and Classification using Kernel FCM Clustering

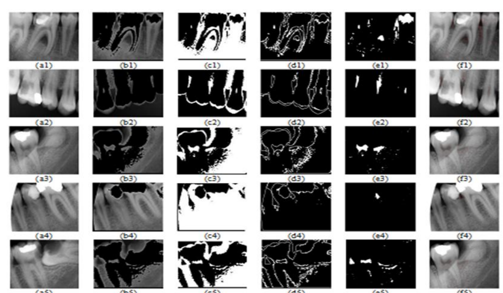


Figure 10 KFCM clustering technique for Segmentation

TABLE X. ALGORITHM KERNEL FUZZY C–MEANS FOR SEGMENTATION AND CLUSTERING OF DENTAL RADIOGRAPH

Steps:	
1	Choose the kernels for the input dental radiograph image.
2	Using KFCM segment the radiograph by following steps Evaluate the membership of pixels Compute the successive centers Repeat the steps iteratively until no new cluster centers are found
3	Apply gray level thresholding on segmented radiograph.
4	Then apply binary gradient mask on thresholded radiograph.
5	Later on, to highlight the sharp edges dilated gradient mask is being used.
6	Now the radiograph is Binarized and then again segmented to highlight the cyst in the outlined original radiograph. As shown in Figure 9.

The first column of Figure 10 represents the original radiograph from (a1 – a5). Second column of Figure 10 represents the segmented radiograph using KFCM from (b1 – b5). Next column of Figure 10 represents the gray level thresholded radiograph from (c1 – c5). Fourth column of Figure 10 represents the dilated gradient masked radiographs from (d1 – d5). Next column of Figure 10 represents the segmented radiographs from ((e1 – e5). Last column of Figure 10 represents the radiograph outlined with red line showing the cyst from (f1 – f5). The performance parameters as discussed earlier are analysed on available radiographic images. Based on the defined parameters for measurement, the confusion matrix for one of the radiographic images and ROI of ground truth set 1 as shown in Table XI.

TABLE XI. CONFUSION MATRIX OF A SAMPLE RADIOGRAPH IMAGE COMPARED WITH ROI FORM ITS GROUND TRUTH SET 1 & 2

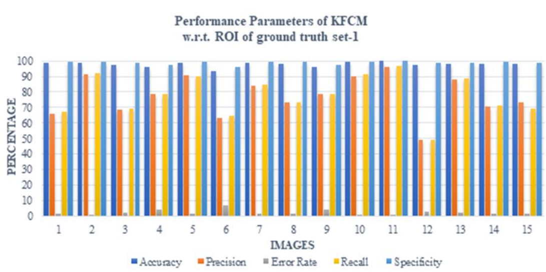
Table 11.1					Table 11.2				
	Predicted Class					*Predicted Class*			
		YES	*NO*	*TOTAL*			*YES*	*NO*	*TOTAL*
Actual class	*YES*	5439	1462	6901	*Actual class*	*YES*	5439	1532	6971
	NO	1509	61133	62642		*NO*	1487	61133	62620
	TOTAL	6948	62595	69543		*TOTAL*	6926	62665	69591

According to the confusion matrix shown in Table 11.1 and Table 11.2 the accuracy, precision, error rate and specificity of our segmented result based on ROI of ground truth set 1 and ROI of ground truth set 2 is presented in Table XII.

TABLE XII. PERFORMANCE PARAMETERS FOR ROI INDICATED IN GROUND TRUTH SET 1 & 2 USING KFCM CLUSTERING

Image No.	**Ground truth set 1**					**Ground truth set 2**				
	Accuracy	*Precision*	*Error Rate*	*Recall*	*Specificity*	*Accuracy*	*Precision*	*Error Rate*	*Recall*	*Specificity*
1	94.53	65.91	1.17	67.09	99.38	95.67	85.05	0.26	95.30	99.79
2	95.83	91.3	1	92.2	99.43	96.12	85.73	1.71	86.60	99.05
3	98.64	68.87	2.3	69.46	98.78	98.89	67.70	2.34	69.32	98.73
4	97.33	78.28	4.27	78.81	97.59	97.88	57.71	7.33	60.26	95.76
5	92.27	90.46	1.18	90.26	99.37	93.4	49.64	4.59	50.87	97.53
Avg. 723 images	**98.50**	**81.08**	**1.79**	**80.81**	**99.01**	**98.97**	**69.71**	**2.01**	**66.64**	**98.97**

The bar chart summarising the evaluation measures of KFCM technique w.r.t. ROI of ground truth set 1 and ROI of ground truth set 2 is shown in Figure 11.



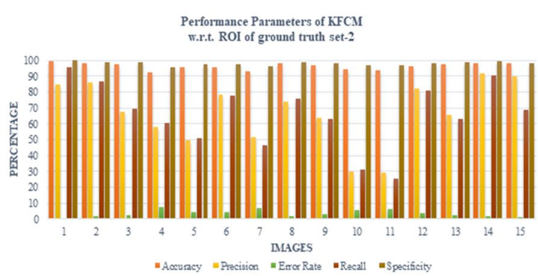


Figure 11 Parametric Evaluation measures of KFCM w.r.t. ROI of ground truth set 1 & set 2

V. RESULT AND DISCUSSION

In this paper we have evaluated three clustering methods, namely K–Means, Fuzzy C–Means and Kernel based Fuzzy C–Means for dental segmentation of dental radiograph. FCM is used for more than one clustering and KFCM K–Means, FCM and KFCM is used for non–mapping clustering. Moreover, KFCM overcomes the demerit of FCM technique. Validation of segmentation is not the prime requirement for diagnosing the problem in radiograph, rather the accuracy, precision, recall, error rate, specificity and most importantly reduction in computational speed of segmentation, as well as decrease in amount of manual interaction are major parameters to be considered. All the algorithms were evaluated on 723 database images and simulation results of all RVG images comprising of different dental problems. The results obtained were also validated with same medical practitioner, the results are found to be useful during their practice.

Our final purpose was to investigate the role of computational machine learning based clustering techniques for the segmentation and analysis of decayed region in dental radiographs. Two popular clustering methods, namely, K–Means and Fuzzy C–Means were investigated, and results were compared with the ground truth. Finally, a Kernel based Fuzzy C–Means method was investigated and found to be better and robust compared to earlier two clustering methods on radiographs having different diseases.

A comparative table comprising of accuracy of all three methods are described in Table 13. It clearly reflects that KFCM method provides proper segmentation and high accurate results in identification of dental decays. The bar chart summarizing the comparative accuracy measurement w.r.t ground truth set -1 and 2 is also shown in Figure 12.

TABLE XIII. ACCURACY PERFORMANCE FOR ROI INDICATED IN GROUND TRUTH SET–1 AND 2 USING THREE CLUSTERING METHODS

Image No.	Ground truth set 1			Ground truth set 2		
	Accuracy (KFCM)	Accuracy (K-Means)	Accuracy (FCM)	Accuracy (KFCM)	Accuracy (K-Means)	Accuracy (FCM)
1	94.53	91.54	97.10	95.67	92.43	96.89
2	95.83	94.39	95.61	96.12	93.59	94.16
3	98.64	98.39	99.04	98.89	98.27	98.79
4	97.33	96.88	96.11	97.88	97.02	95.76
5	92.27	91.83	91.01	93.40	92.01	91.89
Avg. 723 images	**98.50**	**95.89**	**96.89**	**98.97**	**96.40**	**97.40**

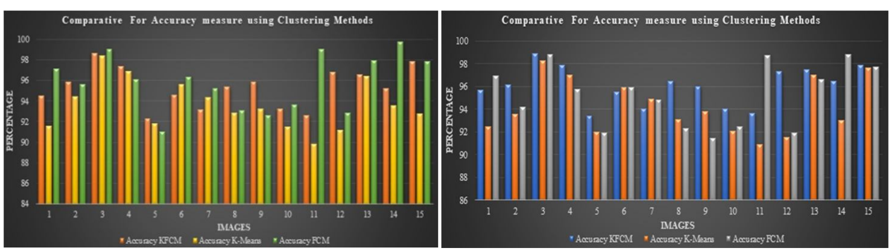


Figure 12 Comparison of Accuracy among various clustering techniques w.r.t ROI of ground truth set-1 & set – 2

The motivation for the realization of this work is exploiting the methods of image processing as well as machine learning in the domain of applied medical sciences. The state of art review highlighted that there are no significant contributions made for dental disease identifications and diagnosis. Hence, the proposed approaches can serve as an add–on help during their pre and post diagnostic identifications and treatment. The results of the methods were also validated with the practitioners who shared their dental radiograph images and ground truth information. As per interaction with the practitioners, the results obtained are satisfactory and can provide add–on help during their practices.

VI. CONCLUSION

In this paper, an automated segmentation method based on Clustering techniques for segmenting region of interest from a dental radiographic image is presented. The results produced by the proposed method was compared with the ground truth results obtained with two domain experts. Based on the evaluation mesures, the proposed method is found to be quite effective in identification of interested region. The proposed method can be useful for assistance to the dental medical practioners during their endodontic treatment of the tooth. The method can further be evaluated regirously and can also be integrated in any computer based diagnostic tool.

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