Analysis of Image Segmentation Techniques for Diagnosis of Dental Caries in X-ray Images

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***Abstract*—**Early diagnosis of dental caries is essential for maintaining dental health. In this paper, method for diagnosis of dental caries is proposed using Laplacian filter, adaptive thresholding, texture analysis and Support Vector Machine (SVM) classifier. Analysis of the proposed method is compared with Otsu thresholding, watershed segmentation and active contouring method. Adaptive thresholding has comparatively better performance with 96.9% accuracy and 96.1% precision. The results are validated using statistical method, two-way ANOVA, at significant level of 5%, that shows the interaction of proposed method on performance parameter measures are significant. Hence the proposed technique could be used for detection of dental caries in automated computer assisted diagnosis system.

***Keywords*—**Computer assisted diagnosis, dental caries, dental radiography, image segmentation.

I. Introduction

MAJOR applications of digital image processing are biometric and biomedical image processing. Dental X-ray image analysis is greatly helping in dental procedures and diagnosis. Dental caries causes bacterial damage to teeth. At an early stage, caries which are located in between teeth may not be visible to human eye. In such cases, dental X-ray image analysis plays an important role in diagnosis of caries.

Dental radiographs use lower radiation dose. Occurrence of quantum, photonic, electronic and quantization noises degrade dental X-ray images [1]. The 'artefact' on X-ray image appears as light or dark spots, lines, fogging, specks etc. that are caused by motion, poor contact and so on. To improve both contrast and intensity simultaneously and to remove noise, computer aided image processing algorithms can be used [2].

Dental X-ray images consist of teeth areas with highest intensity, bone areas with average intensity and background with lowest intensity. In case of an uneven exposure, it is difficult to distinguish between tooth and bone areas [3]. Hence pre-processing of dental radiographs is essential to sharpen the boundaries of dental caries and to increase the contrast between image background and tooth. Segmentation of teeth is a significant problem due to teeth variation in shape and size, arrangement of teeth varies between one person to another [4]. Automating the process of analysis of dental radiographs is necessary to improve dental procedures.

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Reference [5] illustrates Gaussian filter and morphological top-hat and bottom hat operations to reduce noise and smoothen the dental X-ray image and then segmented using Otsu thresholding, watershed operator and morphological close operations. Reference [6] exhibits top-hat and bottom-hat morphological operators to enhance dental X-ray images, adaptive thresholding for segmentation. Reference [7] shows iterative thresholding followed by adaptive thresholding for segmentation of teeth in dental radiographs. Reference [8] proposes a variational level set segmentation approach for computer aided dental X-ray analysis. Reference [9] illustrates an enhancement method that combines homomorphic filtering, adaptive contrast stretching based homogeneity and adaptive morphological transformations. Reference [10] shows top-hat, bottom-hat morphological transformation techniques for enhancement.

Rule based computer assisted diagnostic system cannot work efficiently for caries detection because of teeth position, health condition, patient's age and living environment. Reference [11] attempts to classify dental cysts using textural based K-means classifier.

The remaining sections are categorized as follows: Proposed methodology, experimental results and discussion, and conclusion.

II. Proposed Methodology

This paper presents a methodology for dental caries detection. Binary SVM is used to classify caries or normal dental images. The system is implemented using MATLAB 2017a.

A. Experimental Dataset

The dataset used for SVM training, validation and testing, consists of 64 dental X-ray images (49 caries images and 15 normal images). The images are taken using Gendex X-ray machine with RVG (Radio VisioGraphy) sensor type sirona. The dataset was obtained from SJM Dental College, Chitradurga, India. The caries in the dental images are annotated by a dentist.

B. Pre-Processing

The dental X-ray images are converted to bmp format by using MATLAB conversion tool applications. After the conversion, the image is resized to 256 X 256 of class double. The resultant image is enhanced using Laplacian filter. Laplacian filter is a second order gradient of the image. By convolving the Laplacian mask with the image, edges of the image are highlighted and thereby low frequency components such as contrast are removed.

C. Segmentation

Image segmentation is partitioning of an image into multiple sub-regions based on the desired feature. Here, adaptive thresholding is used for segmentation. Smaller regions in the image are more likely to have approximately uniform illumination, suitable for thresholding. Hence, adaptive thresholding is applied to the image, by taking the median value of each 3 X 3 sub image as optimum threshold. The thresholded image is dilated and eroded. Then eroded image is subtracted from the dilated image to get the segmented image.

D. Feature Extraction

The segmented image is resized to 100 X 100 and fed to feature extraction stage. 22 textural features of the segmented image are extracted using Grey Level Co-Occurrence Matrix (GLCM) technique and stored in the database. The extracted features include contrast, correlation, energy, homogeneity, mean and entropy.

E. SVM Classifier

Binary SVM is used to classify normal or caries images. SVM handles both separable and non-separable problems of simple, linear as well as complex, nonlinear classification tasks. SVM uses hyperplane to define decision boundaries, which separates the classified data as normal or caries data.

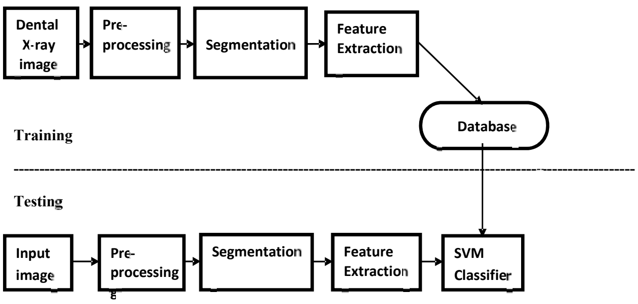

Fig. 1 Block Diagram of Proposed Architecture

Fig. 1 shows the proposed architecture for identification of dental caries. The system consists of two stages: training and testing stage. Digital dental X-rays images of the training set are passed through Laplacian filter and then segmented using adaptive thresholding. 22 textural features of the training images are extracted using GLCM and stored in the database. To detect the presence of the caries in the test image, the test image is enhanced using Laplacian filter, segmented using adaptive thresholding, and textural features are extracted and applied to SVM. By using database, SVM classifier identifies the given test image as caries or normal image.

III. Results and Discussion

The dental images are first resized to 256 X 256 size of type double and then passed through Laplacian filter for enhancement.

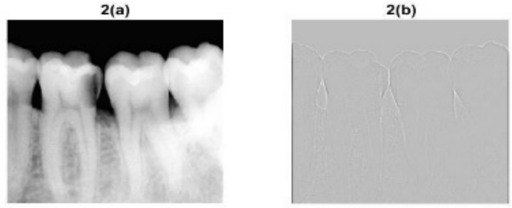

Fig. 2 Effect of enhancement on dental image (a) original image (b) enhanced image using Laplacian filter

The original image, enhanced image using Laplacian filter are shown in Figs. 2 (a) and (b), respectively. The enhanced image has edges only around tooth and caries region and remaining portion of the image is blurred. This greatly helps in extracting the features of tooth region.

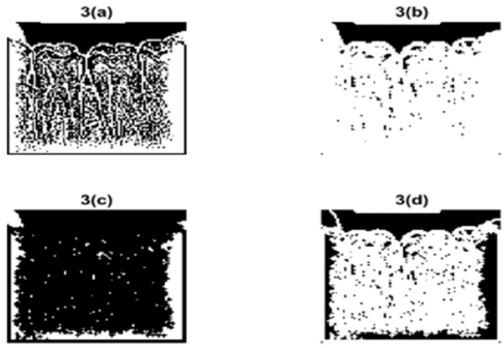

Fig. 3 Segmentation results for caries identification using texture analysis and SVM (a) segmented image (b) dilated image (c) eroded image (d) resultant image after subtracting eroded image from dilated image

Fig. 3 (a) shows the image after applying adaptive thresholding. The eroded and dilated images are shown in Figs. 3 (b) and (c), respectively. Fig. 3 (d) shows segmented image that is obtained by subtracting eroded image from dilated image. The image is resized to 100 X 100. Experimentally, it is found that the features extracted from the image of 100 x 100 give better performance than 256 x 256. Textural features of the segmented images are extracted using GLCM. Table I shows contrast, correlation, energy, entropy and homogeneity features extracted from the systems with Laplacian filter + watershed segmentation + GLCM + SVM, Laplacian filter + Otsu thresholding + GLCM + SVM, Laplacian filter + active contouring technique + GLCM + SVM and the proposed system. These features are plotted in Fig. 4.

TABLE I
Extracted Features for Different Segmentation Techniques

Methods	contrast	Correlation	energy	entropy	Homogeneity
Watershed	15.474	0.0639	0.223	-2.299	0.597
Otsu thresholding	0.363	0.3627	0.376	-1.161	0.819
Active contour	0.778	0.778	0.9	-0.336	0.963
Adaptive thresholding	6.053	6.053	0.466	-0.98	0.892

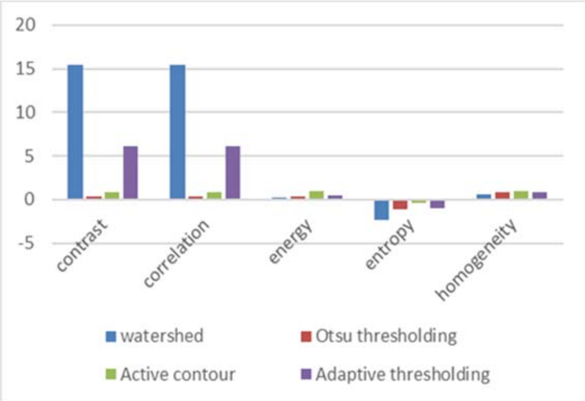

Fig. 4 Comparison of features of different segmentation techniques for dental caries identification system using Laplacian filter, GLCM and SVM

TABLE II
PERFORMANCE MEASURES FOR DIAGNOSIS OF DENTAL CARIES USING SVM CLASSIFIER AND TEXTURE ANALYSIS WITH OR WITHOUT LAPLACIAN FILTER AND WITH OR WITHOUT ADAPTIVE THRESHOLDING.

Methods	**accuracy**	**Sensitivity**	**Specificity**	**Precision**
Without enhancement + GLCM+SVM	0. 6154	0.7143	0.3125	0.7609
Laplacian filter + GLCM+SVM	0.9375	0.9184	1	1
Proposed method	0.9688	1	0.8667	0.9608

Training set consists of 35 dental X-ray images (25 caries and 10 normal images) and testing set consists of 64 dental X-ray images (50 caries and 14 normal images). The performance measures; accuracy, sensitivity, specificity, precision and F score values, are calculated for caries identification system with GLCM and SVM (without any enhancement and segmentation), Laplacian filter cascaded with GLCM and SVM (without any segmentation) and the proposed method. The results are listed in Table II. Accuracy of proposed method is giving 96.88% accuracy, sensitivity value of 1, specificity of 0.8667 and 96.08% precision. The result indicates that adaptive thresholding improves the performance of the system. Performance measures for these systems are plotted in Fig. 5.

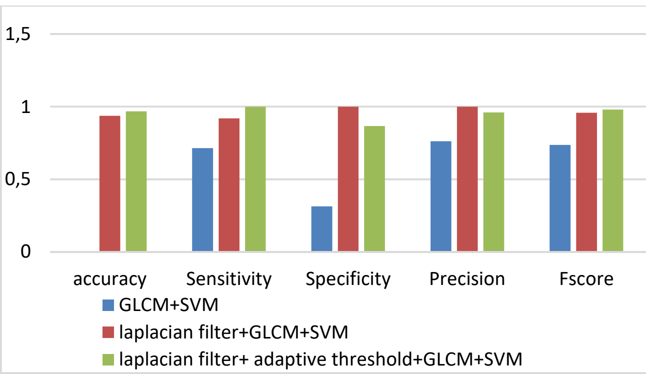

Fig. 5 Comparison of performance measures for diagnosis of dental caries using SVM and texture analysis, for different combination of enhancement and segmentation techniques

TABLE III
PERFORMANCE MEASURES FOR DIAGNOSIS OF DENTAL CARIES USING SVM CLASSIFIER AND TEXTURE ANALYSIS FOR DIFFERENT SEGMENTATION TECHNIQUES

Methods	Accuracy	Sensitivity	Specificity	Precision	F score
Laplacian+ Otsu + GLCM + SVM	0.813	0.875	0.625	0.875	0.875
Laplacian+ active contour+ GLCM+SVM	0.875	0.939	0.667	0.952	0.92
Proposed method	0.969	1	0.867	0.961	0.98
Laplacian+ watershed+ GLCM+SVM	0.938	0.918	1	1	0.957

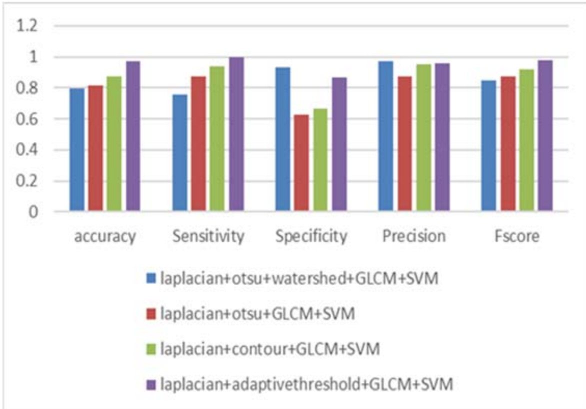

Fig. 6 Comparison of performance measures for diagnosis of dental caries using SVM and texture analysis for four different segmentation techniques

The performance measures' accuracy, sensitivity, specificity values for Laplacian + watershed segmentation + GLCM + SVM, Laplacian + Otsu thresholding + GLCM + SVM, Laplacian + active contouring + GLCM + SVM and the proposed system are listed in Table III. The comparison between the different performance measures for these systems is indicated in the form of bar chart in Fig. 6. The proposed system has achieved highest value of accuracy (96.9%), sensitivity (1) and F score (0.98). But the specificity (0.867) and precision (0.961) values are slightly inferior to the system with watershed segmentation, although the differences are not considerably significant. The result shows that adaptive thresholding technique is better than active contouring, watershed transformation and Otsu thresholding method of segmentation for diagnosis of dental caries in X-ray images.

Results shown in Table II are verified using two-way ANOVA, at significant level of 5%. Results shown in Table IV indicate that interaction of proposed method on performance measures is significant. Hence the proposed method can be used for dental caries diagnosis.

Receiver operating characteristic (ROC) curve for the proposed system shown in Fig. 7 has the area under the curve (AUC) of 0.9333. It shows that the performance of the proposed system is significant.

TABLE IV
TWO-WAY ANOVA STATISTICAL ANALYSIS RESULTS (FOR DATA IN TABLE III)

Source	SS	df	MS	F	Prob>F
Columns	0.067	4	0.017	3.83	0.0313
Rows	0.078	3	0.026	5.97	0.0099
Error	0.052	12	0.004		
Total	0.196	19			

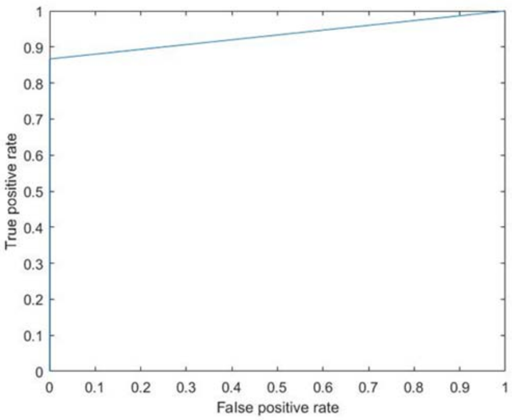

Fig. 7 ROC curve for proposed system for dental caries

IV. CONCLUSION

In this paper, an efficient texture based dental caries diagnostic system is proposed. The experimental results show that caries and normal X-ray images could be distinguished more accurately by adaptive thresholding, rather than watershed transformation, active contouring and Otsu thresholding method of segmentation. Accuracy and reliability of computer assisted dental caries diagnosis system can be improved furthermore by using a larger size dataset.

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