Dental Radiograph-Based Tooth Isolation Using Vertical Integral Approach for Segmentation and Connected Component Labelling for Dental Caries Detection

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Abstract. The study is based on analyzing dental radiographs for diagnostic accuracy in context of dental image based diagnostic systems. Periapical view radiographs with caries have been used for segmentation and feature extraction of teeth. The study is based on separation of affected teeth and segmentation of teeth from dental radiograph and checking each tooth for caries detection. The radiographs are obtained from the Institute of Dentistry, at Liaquat University of Medical & Health Sciences, Jamshoro. The obtained radiographs are enhanced using thresholding, erosion, dilation and then separated using vertical integral approach. The separated tooth has been checked for cavity detection, which has been done using k-means clustering. We have seen promising results for cavity detection with the detection metric of 95.45%. The results show the significance of the proposed technique, which may be used as a preprocessing technique for machine learning algorithms.

Keywords: Dental cavity, Cavity detection, cavity segmentation.

1 Introduction

According to WHO, 60–90% [1] pupils between 5-18 and almost all of adults suffer from dental cavities. However, these can be averted by retaining a constant low level of fluoride in the oral cavity. It is found that the aged between (35-44 year) are severely affected by periodontal disease. Due to this disease people may lose their teeth. Children and adults from impoverished and marginalized communities experience higher rates of oral disease. Globally, about 30% of people aged 65–74 have no natural teeth [2]. Tooth diseases may be caused due to several factors including an unhealthy diet, tobacco use, harmful alcohol use, poor oral hygiene, and social determinants. The aim of the research is to map out the diagnostic methods available for early caries lesions. The literature shows that the majority of current diagnostic techniques are highly sensitive and specific

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in detecting dentin caries. However, they do not have high specificity and sensitivity for identifying enamel caries [3]. Based on the WHO diagnostic criteria, dental caries can be identified by the presence of defects in the pits, grooves, or smooth surfaces of the tooth, along with any softening on the floor or walls of the tooth surface [4]. Many studies, including those of the DPB (Dental Practice Board, UK) have shown that up to 50% of dental radiograph images are of poor standard. Consequently, it is common for dentists to have varying interpretations of the same radiographs. This variation is not due to differing therapeutic perspectives but rather to differences in diagnosing the presence or extent of lesions on the radiographs. This diagnostic challenge arises because the human eye tends to smooth out grey shadows. As a result, radiography has limitations, including an inability to detect the initial stage of caries and an underestimation of the size of demineralized areas. The National Institute of Health (NIH) has emphasized the need to enhance the accuracy of radiographic methods for caries diagnosis.

Singh.A and Kanwal,N, [5] recommends a hybrid technique for enhancement of the dental radiographs, considering reliance on region growing segmentation and works adaptively for enhancement of the radiograph image. The seed-dependent technique yields better results when the seed is selected from darker regions compared to brighter regions.

Lehmann. et al., [6] studied that 13 programs are available for image processing and improving facilities. All programs supply grey-scale image display with interactive brightness and distinction adjustment and grey-scale inversion. Most programs sparsely embrace filters and tools for image analysis and comparison. As we see that, image processing and enhancement functions are seldom incorporated in industrial software for direct digital imaging in dental radiology.

Analoui, [7] modified attributes of an radiograph image to enable it to be adjusted for a given task and particular observer. Throughout this method, one or many attributes of the image are modified. We see that totally non-matching methods were tested to achieve desired image enhancement goals.

Grafova., et al., [8] developed an edge detection task in dental panoramic radiographs. They introduced an alternate approach for edge detection in orthopantograms (OPGs), and additionally improved the automated parameter selector for common edge detectors. The research also conjointly compares the novel approach with common edge detectors and feeds out faster outputs without compromising quality. An advanced approach for edge detection encompassing statistical methods was introduced. A set of N edge detection results was calculated from a given input image and a specific kind of edge detector. As we can see, the technique is based on edge detection in panoramic radiographs.

The above techniques lack any proposal for development and assessment of diagnostic algorithm(s), which is designed for evaluation of proximal carries in posterior teeth. The already proposed algorithms have not provided specific objective related to the indication of depth and location of carries in digital radiographic images.

2 Methodology

1500 periapical radiographs were utilized in a composition used during design phase, having cavity and noise. Thresholding was done by taking grayscale image as input and, within the simplest implementation, outputs a binary image representing the segmentation. For every picture element(pixels) within the image, a threshold was calculated. If the pixel value is below the value it's set to the background value, otherwise. it assumes as the foreground value. Image components extracted based on their relevance as of boundaries and skeleton and segmentation induced noise was removed. Dilation and erosion were used to close the holes with structuring element. A set of multi-dimensional structuring elements were applied to area of interest for morphological dilation and erosion operations as shown in Figure 1.

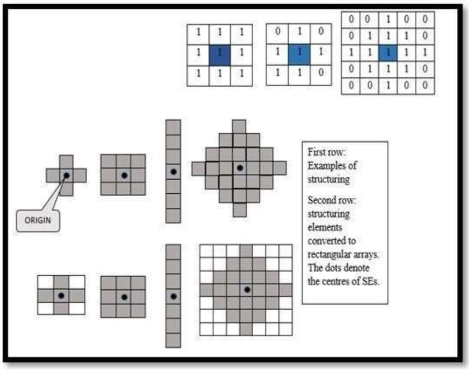

Fig. 1. Structuring Element

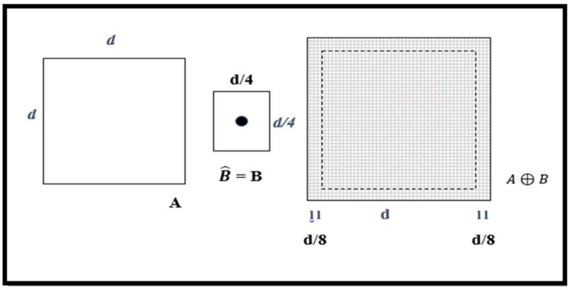

Fig. 2. (A) Set A, (B)Structuring element (C) Dilation of A by B

The resultant is converted to grayscale image. Clustering [9] is applied to the image by finding natural spectral grouping present in the data set. K-means clustering method application results in cluster centers across the data in the multidimensional space. Firstly, the seed value for the K centers is identified then the K cluster centers are calculated. Each pixel in the image is bonded to that cluster that is nearer to the center. The process is repeated until the convergence of the algorithm. The quality of the output is dependent on the seed cluster center's location. The segmentation step follows with extracting region of interest to get desired segmented tooth [9]. In our methodology, we have a tendency to area unit victimization for extraction of alveolar bone by segmentation and varied improvement techniques to boost the visual aspects of an image[10]. The segmentation involves three distinct regions: brighter areas, middle areas, darker areas. The region localization of each tooth is based on levels of intensities which differ substantially to the teeth intensities. The method involves row vector formation by adding intensities in vertical direction. Image partition is obtained based on row vector values. The resultant is a cropped image of teeth with well-defined boundary. Smoothing the resultant separated tooth has been done using, morphological operator (dilation, and to make amends for abrupt variations in the values, a Gaussian kernel is used [11].

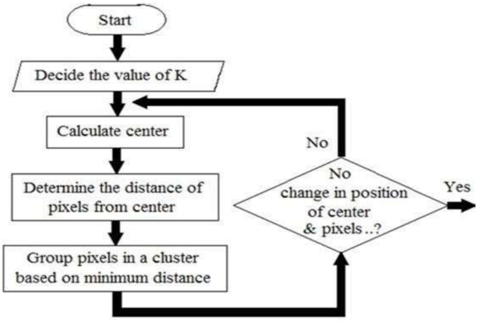

Fig. 3. K-Means Process

The next step involves finding regional properties to hunt for cavity region. The process of identifying cavities within the segmented region by connected component labeling [12] works by scanning the region pixel by pixel (from top to bottom and left to right) to identify the connected pixel regions i.e. regions sharing pixel intensity equalization [13].

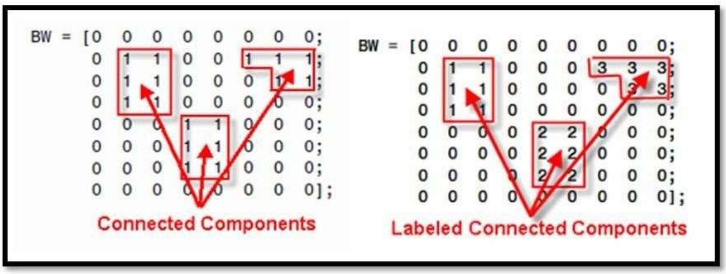

Fig. 4. Connected Component Labelling

The cavity part of the image is darker compared to the rest of image so it can easily be separated out from the rest of the image. Now boundaries of cavity in the teeth is extracted and cropped and saved in a file. Then area percentage of cavity in tooth excluding background has been calculated and displayed in the main file.

3 Results

The result shows prominently that the dental radiograph image has been enhanced and tooth has been successfully segmented as well as separated as an individual teeth image. From the figure it can be clearly seen that each tooth cavity has been detected, as per objective we have tried to implement and propose a method to detect, separate and segment the cavity effected teeth along with the intensity or depth of the cavity. This has been achieved through exploration of several image processing techniques and then selecting the best to achieve results. We have explored some of the techniques regarding digital dental radiography somehow succeeded in reducing diagnostic errors. Several mathematical algorithms were applied to develop and assess dental radiographs with better interpretation.

Fig. 5. original radiograph image processed in MATLAB, serving as the baseline for subsequent segmentation and cavity detection steps

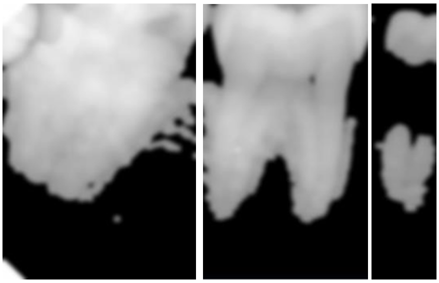

Fig. 6. Illustrates the segmented images of dental radiographs obtained using the proposed methodology. The segmentation process effectively separates individual teeth, allowing for precise detection and analysis of dental caries.

Table 1. Workspace output showcasing cavity detection results, including presence, depth in pixels, affected percentage, and total number of cavities identified.

Workspace	
Name	**Value**
Cavity True	1
Cavity Depth	441
Cavity Percentage	95.45%
Cavity Number	2

The workspace in Table 1 clearly shows that the cavity has been detected as 1 with a detection metric of 95.45%. The method also detected the number of cavities as 2 (two).

4 Discussion and conclusions

The results show the significance of the proposed technique, which may be used as a preprocessing technique for machine learning algorithms. This research paves the way for further exploration of machine learning algorithms such as CNN for automated cavity detection.

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