OPG Images Automatic Segmentation and Feature Extraction for Dental Lesion Diagnosis Purposes

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Abstract: Dental lesions which affecting jawbone can be detected using Orthopantomogram (OPG). Cysts lesions and tumors of OPG region are a major subject for health care concerned. Detection of these lesions is important for accurate diagnosis of these lesions in early stages that has a positive consequence on prediction of the disease. Cystic lesions if not detected and treated early may possibly lead to tumors. Generally, image analysis and techniques are required in order to improve the OPG image quality for the purpose of obtaining a precise dental lesion diagnosis using an efficient hybrid filtration of noise reduction via adaptive median filter (AMF) and discrete wavelet transform (DWT) and contrast enhancement process via mathematic morphology and contrast limited adaptive histogram equalization (CLAHE). Then, automatic segmentation of sequential processes for detection object with aid using Otsu's thresholding and canny filter. Thus, texture features extraction task will be accomplished from these segmented objects which are First-order statistics texture (FO), Gray level co-occurrence matrix GLCM and Gray Level Run Length Matrix (GLRLM). Such feature will lead to a better organization result for a precise diagnostic. This paper presents an algorithm for automatic segmentation of OPG images to detect suspicion abnormal segmented regions of lower jaw using OPG. The proposed algorithm consists of sequence's steps which are image enhancement, segmentation and feature extraction.

Keywords: Orthopantomogram, CLAHE, Canny filter, GLCM, GLRLM.

1. Introduction

OPG is considered as a panoramic dental X-ray scan, its main purpose is generating a double-dimensional sight of the facial constructions. Moreover, panoramic images have a significant clinical importance for the purpose of diagnosing problems that need wide coverage of the jaw [1, 2]. Generally, Cysts and tumors of maxillofacial region are considered one of the most important topics that have gained a great attention and concern of dental doctors. Additionally, diagnosing the lesions accurately in the early stages has a good and positive influence on both management and prognosis of disease correspondently. To put it another way, ignoring cystic lesions and no treating it in the early stage will mainly lead to tumors. Furthermore, Cysts and tumors that have an influence on jawbone are detected by the means of radiographic examination using OPG [1]. It has been argued that cysts can be typically exist in jaws more than the other bone as a result of their first generation which begins from different cell rests of epithelium after the arrangement of the tooth. The affection of the jaw bones is influenced largely by different cysts. Not only that, but the cyst is characterized according to its nature of the margins, extent, homogeneity of the contents has a great role in diagnosing [1, 2, 12].

Firstly, the origin of radicular cyst returns back to the most frequently occurring jawbone cysts and it is regularly of round shape or oval one [1-3]. A follicular cyst is another name given to dentigerous cyst as illustrated. Provided that the previously mentioned term considered another famous and common kind of cyst that occurs in the jaws [1]. where, it

is a cyst that can be formed around the crown of an unerupted tooth. The mainstream of follicular cysts most regularly seen in the area of low jawbone [1-3]. Obtaining a precise dental lesion diagnosis. Image segmentation is defined as a type of the methods of analyzing the image, in addition it is a technique that is proposed to extract the objects that are existed in an image for the purpose of additional analysis [23, 28]. Then, features extraction task will be accomplished in order to make the best feature of images. Such feature will lead to a better organization result for a precise diagnostic [3].



(a) A radicular cyst (b) A follicular cyst Figure 1: The most frequently occurring jawbone cysts

Figure 1. illustrates the most frequently occurring jawbone cysts. To give an illustration, tumors generally occur in the low jaw more than the upper one. It grows in a slow way, the result lesions may lead to severe irregularities of both face and jaw. Additionally, as a result of the easy grow of irregular cell infiltrates and its ability to destroy the nearby bony tissues, extensive surgical excision is needed in order to deal with such a disorder [2, 4].

Basically, image analysis and techniques are required in order to improve the OPG image quality for the purpose of

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obtaining a precise dental lesion diagnosis. Image segmentation is defined as a type of the methods of analyzing the image, in addition it is a technique that is proposed to extract the objects that are existed in an image for the purpose of additional analysis. Then, features extraction task will be accomplished in order to make the best feature of images. Such feature will lead to a better organization result for a precise diagnostic [5].

In the few recent years, many different researches have focused on the subject of medical image processing, especially diseases diagnosis using learning machines techniques, these researches studied different ways to denoised, enhanced and diagnosed diseases using X-ray medical images. Showkat H. Malik and et al [6], applied different methods of image de-noising on CT images. Notably, for the purpose of de-noise an image; Median Filter, Weighted Median Filter, Mean Filter, and Wiener Filter are investigated. Moreover, AHE procedure is developing the lower contrast CT scan image, in addition to keeping the details of images for Diagnosis. S. Muniyappan and et al [7], presented a method that depends on Contrast Limited Adaptive Histogram Equalization (CLAHE) algorithm in order to enhance the breast cancer images. Veska M. Georgieva and et al [8], presented a method for the purpose of enhancing dental X-ray image to detect caries on the basis of the place of the lesion. It includes improving the contrast by using CLAHE and morphological processing. Ingrid Nurtanio and et al [9], proposed a model for segmenting the lesions of cyst or tumor from panoramic image using active contour method. This method was applied for finding object boundaries in medical image in order to achieve segmentation and analysis purposes. B. Vijayakumari and et al [10], presented an automatic analysis technique that emphasizes the dental cyst diagnosis by the way of using the textures information. Firstly, the pre-processing is achieved then a contrast stretching method has been presented The type of cyst is recognized depending on the gray level cooccurrence matrix (GLCM) and their associated characteristics. Rajdeep Mitra and Menaka R. [11], established a technique that uses an image processing methods which contains a watershed segmentation that include GLCM texture features to detect oral cancer by analyzing the true color images. Veena Divya.K [12], have significantly presented two distinctive algorithm of images processing for the purpose of detecting the dental anomalies.

In this work, OPG image passes through sequential phases which are image conditioning, image segmentation and feature extraction phase in order segment automatically suspicious objects for further analysis and classification processes. The remaining part of the current paper is divided in to four sections: Section (II) is devoted to illustrate the phases of proposed method, Section (III) discusses the obtained results. While the last section includes the conclusions.

2. Basic Phases of Proposed Method

The goal of computerized OPG images detection systems is to achieve high sensitivity for detecting normality and

abnormality that radiologists might miss. Computer processing for OPG images typically involves image processing techniques that used in the proposed system. Accordingly, the proposed system classifies the input OPG images into normal and abnormal images, the abnormal OPG images is classifying into cysts lesions which are (radicular and follicular cysts) plus tumor. The proposed method consists of three phases are image conditioning, image segmentation and feature extraction phase for further process and classification purposes. Furthermore, the flowchart of the overall proposed method for automatic diagnosis is illustrated in the Figure 2. where, the first part of flowchart represents the preprocessing operations applied on OPG image. The second part of flowchart covers the segmentation process and feature extraction from objects. The following sections discuss in details the phases that the proposed method passed through intended for automatic segmentation for the OPG images.

2.1 Image Conditioning Phase:

Image conditioning phase includes two stages, which are image preprocessing and image enhancement. Both these stages have a vital role to prepare the input images for the next stages in order to ease the segmentation process intended for better classification. Initially, there are two operations have been considered as a preprocessing stage. Image windowing by making the all input image with the same size (HD image dimensions) so that, image truncating can be done correctly. Moreover, in order to get the region of interest (lower part of the jaw) the OPG image is truncated by 60%. The upper jaw region including sinus, is out of the scope of this study. The truncating action will sure that only the lower part of the image will be processed and be under focused.

Medically, dental lesions are frequently located at the lower jaw than the upper one as mention early.

The second operation is image enhancement stage which divided into two basic parts Noise Reduction and Contrast Enhancement, these stages dedicated for filtering and improving the quality of the medical image thus, can be used it trusty for diagnosis of diseases.

There is no doubt that one of the major issues related to the medical images are that most of them are suffered from noise and other different quality-related problems and difficulties in extracting suitable information. Therefore, it necessary to design some techniques that can enhance the image in such a way so that, it will be suitable for further processing.

Having said that the nature of intra-oral digital radiographs has a low image quality due to low dose utilization. Then again, the strategy of low dosage utilization is related to its impact on patient's health. In this way image processing techniques such as image enhancements methods are the accepted methods to improve the radiograph's image quality.

For purifying and improving the medical image quality presented for OPG images for better visual apparent includes of two basic process which are called as noise reduction and

contrast enhancement. Two efficient filters have been used in order to remove the various types of noise. The first one is an Adaptive Median Filter which is responsible for removing the salt and pepper noise in an effective manner. Not only that but there is also a tend to utilized Discrete Wavelet Transform for the purpose of disposal the other kinds of noise as a second stage, especially Gaussian noise [13]. Then there is an application of the morphology image processing for edges purifying and Contrast Limited Adaptive Histogram Equalization (CLAHE) for the purposes of contrast enhancement on the denoised images in order to obtain an appropriate visualization and compensate the influence of the process of filtration that adds some blurring to images [8,13]

Furthermore, the adaption of such approach presents a kind of hybrid filtration, in addition to the contrast enhancement for OPG images is very useful later in segmentation method.





Figure 2: Flow chart of the proposed method

2.2 Image Segmentation Phase

Image segmentation is applied as a second phase. This phase includes two main stages which are denoted as image segmentation stage and select region of interest stage. The main objective of segmentation process is to locate objects and boundaries in OPG images. Furthermore, in order to achieve the goal of segmentation, the representation of an image is being altered into something that is more meaningful

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and easier to explore. Beginning from the instance of entering the enhanced-truncated image, which is prepared from the previous phase in order to obtaining results of five extracted objects which are represented in the lower jaw region under examination. Initially, the image is converted from grayscale to binary image using Otsu's Thresholding. basically, thresholding is considered as a method that is used in order to make image with an important intensity value contrast that occurs between the background and the desired object. Nonetheless, thresholding has been used for separating the intensity values of an image by the way of splitting the pixels that are seen to be bigger than the threshold's value (T) as the main group, whereas the intensity value seems to be smaller than the value of T as a second group. So, the produced image in such a process is in the shape of binary image with a setting that is depended on a grayscale histogram. To give an illustration, the Otsu technique is considered as a method of thresholding that has been used in this work. Notably, the Otsu technique can automatically calculate the value of threshold T depending on the input image [14].

Then, two morphology processing operations (closing and opening) are used for filling gaps and remove tiny details. Later, edge detection procedure is achieved for each object with the aim of calculating the area by determines the numbers of pixels of each extracted object. Furthermore, the obtained objects are sorted in descending order (according to area). Here, a new approach is considered by neglecting the largest detected one, practically we found that the largest detected object could be frequently the neck region, which is out of our interest. Then, the next largest five objects are selected and investigated later by the next phase.

2.3 Feature Extraction Phase:

Basically, statistical texture analysis is being used for extracting the features. Moreover, these texture feature are being calculated on the basics of statistical transportation of the intensity of pixel at an identified location that is related to another pixel in the matrix of the symbolized image [15, 16].

Texture is defined as an image which is similar in shape to homogeneous or even inhomogeneous, in addition to smooth or irregular etc. The main purpose of those features is defining the amount of characteristics for a definite area of an image by the way of handling associations' basis on the spreading of gray-level of a certain area image [16].

According to the five extracted objects obtained from the prior segmentation process. The proposed system will give its decision by the aim of using a collection of texture features extraction which are (FO, GLCM and GLRLM)

It is agreed upon the fact that FO stands for the principal order statistics, whereas, the other order statistics which represent the Gray level co-occurrence matrix (GLCM). Additionally, higher-order statistics symbolized by Gray Level Run Length Matrix (GLRLM) are being used.

Furthermore, the object's area is seen as one of the important properties that are being used for extracting the feature for

the purpose of the analysis of OPG images. To that end, an object's area is being calculated according to the fore coming equation [17].

$$I = \sum_{r=0}^{N-1} \sum_{c=0}^{M-1} x(r,c)$$
 (1)

Where, I = intensity of object X. Moreover, r, c represents the number of raw and column with dimension N, M of object matrices.

2.3.1 First-order statistics texture (FO)

Generally, FO which is the abbreviated form of First order statistics texture are being statistically calculated from the image's intensity values. Without putting in consideration the relation that exists in the neighborhood of the pixel; the analysis of texture is made on histogram methodology which is being built on the concentrations of intensity values that exist on the whole image or evens a part of it. In other words, features are basically contained moments like mean, entropy, variance, skewness in addition to kurtosis [15,16].

The first-order histogram is defined as:

$$P(I) = \frac{\text{number of pixels with gray level } I}{\text{total number of pixels in the region}} \qquad (2)$$

Where, I is a variable specified as the gray levels of image area and on the basis on P(I), the Mean m_1 is built which represents as the amount of average intensity.

$$m_1 = E[I] = \sum_{l=0}^{N_g-1} IP(l)$$
(3)

Entropy identifies as the measurement of randomness. In addition, it can mathematically present by:

$$e = \sum_{l=0}^{N_g - 1} P(l) \log(P(l))$$
(4)

Where, Central Moments μ_k of *I* are given by

For K= 2,3,4, Where N_g represents the quantity of probable gray levels. The extreme that used essential moments are Variance, Skewness and Kurtosis that are given by μ_2 , μ_3 , and μ_4 correspondingly. Furthermore, the Variance refers to the measurement of the width of histogram that is being used for the purpose of measuring the variation of gray levels from the Mean. While, Skewness is considered a measurement of the histograms irregularity range around the Mean and Kurtosis has a benefit in the in measurement of the histogram's sharpness [16].

2.3.2 Second-Order Statistics (GLCM)

It worth mentioning that there is a great relation between an image's properties and the second-order statistics and those are principally assessed by the Gray level co-occurrence matrix GLCM. Furthermore, this has been used extensively in extracting texture features [12].

The measurements of FO texture are statistically being handled with the innovative image pixel. On the other side,

Volume 7 Issue 11, November 2018 <u>www.ijsr.net</u> Licensed Under Creative Commons Attribution CC BY the measurements of GLCM are taking into consideration its relation with the neighboring pixel. Another important thing is that GLCM is made up of information which includes the amount of incidence of every pair in possible gray level of pixel in the image at a period. The distinction of a GLCM p(i,j) of two pixels with gray levels i and j is made by the way of specifying a substitution vector d that happens between the pixel pairs and their relative direction θ . Generally, the angles θ are 0°, 45°, 90° and 135° can be averaged out in four directions that are characterized as horizontal, diagonal, vertical and anti-diagonal [16].

Figure 3. shows the formation of the GLCM of gray level that equal four of an image at the distance d = 1 with the direction of $0\Box$. For instance, the neighboring pair of pixel intensity 0 and pixel intensity 1 can occur two times. As a result, the GLCM is shown in Figure (3 - b) value 2 in row 0 and column 1. In a similar manner, the matrix is completed by the remained values.



Figure 3: (a) Image with 4-gray level image. (b) GLCM of distance 1 at the direction 0°.

(b)

Similarly, the measurements of texture that are extracted from GLCM can be summarized as follows [18]:

• Energy is the contrast of entropy. It has been used for the purpose of local homogeneity measurement in the image and has been given by:

$$E_{energy} = \sum_{i,j} p(i,j)^2 \qquad \dots \qquad (6)$$

(ä)

• Homogeneity refers to the measure of resemblance in gray levels that occur between neighboring pixels in an image and it returns back a value that can measure the nearness of the spreading of elements in the GLCM to the GLCM diagonal.

$$E_{homogeneity} = \sum_{i,j} \frac{p(i,j)}{1 + (i-j)^2} \dots (7)$$

• The contrast refers to the measurement of variations of intensity illumination that occurs between a pixel and its bordering pixels.

$$E_{contrast} = \sum_{i,j=0}^{N_g-1} (i-j)^2 p(i,j) \qquad \dots \dots \dots (8)$$

• Correlation is a measurement of the way in which a pixel is related to the intensity of neighboring pixels in the image.

$$E_{correlation} = \sum_{i,j=0}^{N_g-1} \frac{(i-\mu_i)(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \quad \dots \dots (9)$$

Where, μ and σ represents the mean and standard deviation respectively.

2.3.3 Gray Level Run Length Matrix (GLRLM)

Gray Level Run Length Matrix is a term that refers to a matrix which the properties of texture are able to extract for the purpose of analyzing a texture. The above mentioned texture can be realized as design of the gray intensity pixel in a specific direction from a reference pixel. Moreover, run length can be defined as the number of the neighboring pixels that are characterized by having similar gray intensity in a specific direction. That is to say, gray level that run length matrix has multiple dimensional matrix in that every single component $p(i,j|\theta)$ refers to the number of elements j with an intensity i, in direction θ . Figure (4-a) below illustrates a matrix of size 4X4 pixel image which has 4 gray levels. Whereas, Figure (4-b) shows matrix of GLRLM in a direction of 0° [$p(i,j/\theta = 0^{\circ})$]. Besides the 0° direction, GLRLM is able to be made in another direction, in other words 45 °, 90 ° or even 135 °. Providing that some types of texture properties have the ability extract from GLRL matrix, like Short Runs Emphasis (SRE), Long Runs Emphasis (LRE), Gray Level Non-uniformity (GLN), Run Percentage (RP), Run Length Non-uniformity (RLN), Low Gray Level Run Emphasis (LGRE), and High Gray Level Run Emphasis (HGRE). The previously mentioned features are defined as following [15]:

1	2	3	4	Gray level	Gray level Run le			ength (j)		
1	3	4	4	i	1	2	3	4		
3	2	2	2	1	4	0	0	0		
4	1	4	1	2	1	0	1	0		
	(C.			3	3	0	0	0		
				4	3	1	0	0		

Figure 4: (a) Matrix of image (4 x 4) pixels (b) GLRLM

(a)

$$SRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{j^2}$$
(10)

$$LRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i,j) * j^2 \qquad (11)$$

$$RP = \frac{n_r}{p(i,j) * j} \tag{13}$$

$$LGRE = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i,j)}{i^2} \qquad (15)$$

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$$HGRE = \frac{1}{n_r} \sum_{i=1}^{m} \sum_{j=1}^{n} p(i,j) * i^2) \qquad (16)$$

Where, n_r means number of run length.

10

3. Results and Discussion

The proposed method is implemented in MATLAB 2016 for automatic segmentation and feature extraction of objects from panoramic dental images where, four different datasets of OPG image are considered which are 20 Normal, 6 Radicular cysts, 6 Follicular cysts and 5 Tumor images. Initially, an OPG image will be processed by two stages which are image preprocessing and image enhancement. So that, a proper technique will be adopted for each stage depending on the best achievement accomplish comparing with others techniques. Figure 5. shows how an OPG image is prepared by applying the truncating by 60% and enhancement processes using the proposed hybrid filtration techniques for better visualization and to ease the segmentation process later.





(a) OPG input image (b) OPG image after uncating and enhancement Figure 5: OPG image before and after image conditioning

The resulting image generates from image conditioning phase passes through the next stage for segmentation processing. First of all, the region of interest (ROI) must be carefully chosen so that the segmentation can take place correctly. All ROIs' are automatically determined and then segmented from the OPG images by the segmentation algorithm in order to applying feature extraction process. Five objects are considered from each segmented image for further analysis. Figure 6. shows the steps of image segmentation after the improvement phase in order to obtain ROI objects under examination. Segmentation stage as described earlier which

includes Otsu's Thresholding besides edge detection using Canny filter are used in order to detect the edges of the objects for advance texture analysis. After edge detection processing, the area of each object is being calculated and then the objects are sorted in descending order. After ignoring the largest object, which frequently belongs to the neck region, subsequent steps are applied for obtaining the next five largest objects. Thus, creating a mask for the required objects in order to apply the logical AND operation with the input image that yields the extracted segmented object as shown in Figure 7. The five objects which obtained using the above steps in the segmentation algorithm with colored edges as demonstrated in the Figure 8. In feature extraction phase, the segmented images are analyzed depending on the statistical texture by utilizing FO, GLCM in addition to GLRLM feature measurements. A collection of features has been extracted from each class (normal, radicular, follicular and tumor). Accordingly, five features are extracted from FO in addition to the area of the object, four features extracted from GLCM and seven features extracted from GLRLM respectively with the ranges from minimum and maximum values for each of class in order to store it in feature vectors and using it later in classification process as illustrated in Tables (1-3).

4. Conclusion and Future Work

This work has presented an efficient algorithm for automatic segmentation of OPG images. This technique depends on various image processing techniques for enhancing, segmenting and extracting the features of the segmented objects from the panoramic images. Four different types are considered as datasets which are normal, radicular cysts, follicular cysts and tumor images. The methods provide good automatic segmentation results of suspicious objects for low contrast or noisy images. A combination of texture features has been extracted from each segmented objects using FO, GLCM and GLRLM where, these features after overall segmentation process know how to assist in study these objects to classify it to different type of dental lesion subsequently that helping in recognizing and treatment of jaw cysts to avoid its further growth.



Figure 6: Steps of image segmentation process for the enhanced input image. (a) Enhanced input image. (b) Applied otsu's thresholding. (c) Morphology (closing and opening) processing. (d) Edge detection using canny filter

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(c)Applying AND operation (the mask with original image) (d)Detected the object with edge coloring on the input image.

811509 306908 466773

Figure 7: Operations applied on segmented object (considering one object)



Figure 8: The detected five objects with coloring edges

Table 1: FO Extracted features with range of minimum and maximum value										
F	Ersterner	Normal		Radicular cyst		Follicular cyst		Tumor		
	Features	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	
	Mean	0.82499	45.8825	0.4839	42.1270	0.70657	49.6668	0.4699	58.910	
	Variance	77.6341	3167.57	33.4708	2345.5	54.9812	2272.29	30.457	1949.55	
	Entropy	0.1009	5.0702	0.10503	4.17009	0.12625	3.82915	0.1030	5.14283	
	Skewness	0.0113	13.2316	0.08192	12.6063	0.02517	11.4931	0.4314	12.2865	
	Kurtosis	1.1447	178.772	1.0677	224.3579	1.26001	140.766	1.2239	164.435	

Table 2: GLCM extracted features with range of minimum and maximum value

594606

411732

82690 5809475 22383

Footures	Normal		Radicular cyst		Follicular cyst		Tumor		
reatures	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.	
Contrast	0.0180	0.1734	0.0307	0.09712	0.0121	0.3359	0.0066	0.2506	
Correlation	0.7613	0.9563	0.9370	0.9636	0.7624	0.9675	0.7872	0.9648	
Energy	0.3011	0.9215	0.3634	0.4482	0.3663	0.9799	0.2709	0.9834	
Homogeneity	0.9378	0.9971	0.9882	0.9932	0.9813	0.9981	0.9595	0.9986	

Table 3: GLRLM extracted features with range of minimum and maximum value

Faaturaa	Normal		Radicular cyst		Follicular cyst		Tumor	
reatures	Min.	Max.	Min.	Max.	Min.	Max.	Min.	Max.
SRE	0.2952	0.5402	0.31793	0.54027	0.31793	0.54027	0.3179	0.5402
LRE	69.158	1135.194	97.45853	116099	97.4585	116099	97.458	116099
GLN	66.902	4538.98	864.11	11595.29	864.113	11595.2	864.11	11595.2
RP	0.027	1.118	0.0273	1.0885	0.0275	1.0885	0.0279	1.08851
RLN	97.245	3283.67	676.997	10939	676.997	10939.2	676.99	10939.2
LGRE	28.117	89.864	25.7714	88.8674	25.7714	88.8674	25.771	88.8674
HGRE	68.241	2383.531	864.113	11595.2	864.113	11595.2	864.11	11595.2

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Area

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