POTENTIAL ORAL DISEASE DETECTION USING CELLULAR PATHOLOGY IMAGE SEGMENTATION

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Abstract-Leukoplakia and erythroplakia are terms that describe an abnormal area in the mouth or throat. Leukoplakia is a white area on the mucosa. Erythroplakia is a slightly raised, red area that bleeds easily, if scraped. The seriousness of leukoplakia or erythroplakia in each person can be accurately determined only by a biopsy, a sampling of tissue for examination under the microscope. These white or red areas may be a cancer, dysplasia or some relatively harmless condition. There are mild, moderate, and severe forms of dysplasia. These diseases are normally termed as Oral Potential Malignant Disease. These are based on how abnormal the tissue appears under the microscope and, in turn, help predict how likely the abnormality is to progress to cancer or to go away on its own or after treatment. The idea is to detect the disease type with normal scanned image. Usually it is hard to predict the disease type with normal scanned image, thus by using Contrast stretching and watershed algorithm the abnormal oral cancer cells will be easily identified using the color contrast among the normal and abnormal cell, then the disease type will be identified using Back Propagation Neural Network. The proposed system shows 90 percent accuracy.

Keywords: Contrast stretching, Erythroplakia, Leukoplakia, Watershed algorithm.

1. INTRODUCTION

The main purpose of medical image processing task is to help the clinicians to analyze the various image types at their disposal and help in the diagnosis or prognosis of diseases using different technologies, for example: x-ray, fluorescence and MRI. These different systems capture and acquire images of particular area of interest of human body, so that clinicians can analyze them and establish their diagnosis more precisely. Digital image processing for the wide medical field find its application in detection and diagnose of breast, lung and mouth cancer, brain tumor, backbone, knees and heart diseases. The important fact is that the early detection and identification of these high risk diseases reduced

A. Analysis of abnormal regions in image

So, these captured images can be analyzed using various images processing algorithms for the identification of the abnormal region. For the last few decades, the number of diagnosed abnormalities inside the oral cavity (like leukoplakia [1], erythoplakia [2], squamous cell carcinoma (SCC) [3], frictional keratosis, Oral lichen planus [4], dysplasia, etc.) has increased due to the excess of alcohol consumption, betel chewing, micronutrients deficiency and tobacco [5]. It is a challenging task for the clinicians to diagnose these abnormalities in their early phases due to the non-visibility of some diseases, located under the mucosal layer. Moreover, the mortality of diagnosed patients is very high due to late detection. Indeed, particular oral cancerous cells can spread more deeply in the tissues or spread under the mucosal surface making them impossible to cure at this stage.

Furthermore, it is difficult to detect dysplasia with naked eyes by clinician and in few cases dysplasia can lead to cancer in its later stages. One of the most important and primary/first step for the screening of the oral cancer patient is the conventional oral examination (COE), COE is highly sensitive in detecting changes of the oral cavity. However its specificity and accuracy is still low. Nowadays, along with COE, there is a variety of commercial diagnostic devices available such as: Toluidine Blue test (TB), light based detection [7]. They are used as adjunctive tools for sub-mucosal layer visualization to improve the specificity and sensitivity of OPMDs detection. With the help of these additional tests the accuracy in screening and detection of oral lesions gets higher. Although these screening devices help the clinicians in finding the abnormal areas inside the oral cavities, the analysis of the acquired images still depends on human observation to differentiate between the abnormal regions and the normal ones.

Examination of specific disease

At second step, these devices help the clinicians to examine the oral cavity, but most areas of oral cavity are not completely examine due to its shape complexity (difficulty to access) and as it depends on human visual system and clinicians expertise, the method is not objective and useful information can be missed by the clinicians. The auto fluorescent imaging device allows the clinicians to capture digital images that are stored for further analysis and following of disease evolution. Hence, digital image processing techniques can be applied in order to fasten and help the doctors in establishing their prognosis and diagnosis. To realize such a task, this paper proposes different image enhancement techniques to compensate the difficult conditions of acquisition. Indeed, as the clinicians are acquiring the images, it results to noisy, blurred (out of focus) and/or low quality images. Image enhancement techniques are usually performed to enhance particular regions of interest (ROI), as in our case to highlight and identify the area different of OPMDs.

State of Art

Oral Cancer was not known before the advent of cigarette smoking. It was not even recognized as a serious disease until there was a major death rate. Many studies have been carried out that deal with Orthopantomogram image analysis. Different Techniques are presented in their papers. Banumathi.A et.al [2] have proposed cyst detection and severity measurement of cysts using image processing techniques and neural network methods. The suspicious cyst regions are diagnosed using Radial Basis Function Network.

The severity of the cysts is calculated using circularity values and the results show the part of the cysts extracted [2]. Woonggyu Jung et al [3] proposed a technique in oral cancer detection using Optical Coherence Tomography (OCT). For the imaging depth of 2-3 mm, OCT is suitable for oral mucosa. They also detected oral cancer in 3-D volume images of normal and precancerous lesions [3]. Ranjan Rashmi Paul et al [4] proposed a detection methodology to detect oral cancer using wavelet - neural networks.

The wavelet coefficients of Transmission Electron Microscopy (TEM) images of collagen fibers from normal oral sub mucosa and Oral Sub mucous Fibrosis (OSF) tissues have been used in order to choose the feature vector which in, turn used to train the Artificial Neural Network. The trained network could classify the normal and precancerous stages after getting the image as an input [4]. Ghassan Hamarneh et al [5] have proposed the application of active contour models for the segmentation or oral lesions in medical color images acquired from the visual part of the light spectrum. The proposed work also classifies cancerous and non – cancerous lesions.

The automatic segmentation algorithm simplifies the analysis of oral lesions and can be used in clinical practice to detect potentially cancerous lesions [5]. K. V. Kulhalli et al [6] have designed a computer aided diagnostic system using Image Processing and Artificial Neural Network (ANN). Features are extracted from the histopathological image which is used to train the ANN, to identify whether it is benign and malignant [6]. Tathagata Ray et al [7] compared Hybrid Segmentation Algorithm and Region Growing Algorithm to detect the constituent layers of histological OSF. The misclassification is compared with the algorithms. The method presented provides an automatic means of segmenting histological layers [7].

2. SYSTEM OVERVIEW

The proposed work is done in coordination with the help of Image segmentation using contrast stretching algorithm. Oral cancer is a significant health problem throughout the world. It is very important to detect such types of cancer at an earlier stage than the later stage where the treatment becomes unsuccessful. Early detection helps surgeons to provide necessary therapeutic measures which also benefit the patients. In this paper, a technique is proposed to detect cancers present in mouth provided by an Orthopantomogram. A novel mathematical morphological watershed algorithm is proposed to preserve these edge details as well as prominent ones to identify tumors in dental radiographs. Applying contrast stretching on images leads to over segmentation even though it is preprocessed. With these the pattern will be recognized and it will be feed into neural network for detecting the specification of disease type. The results obtained are quite good and were tested.

Contrast stretching

Contrast stretching (often called normalization) is a simple image enhancement technique that attempts to improve the contrast in an image by `stretching' the range of intensity values it contains to span a desired range of values, e.g. the full range of pixel values that the image type concerned allows. It differs from the more sophisticated histogram equalization in that it can only apply a linear scaling function to the image pixel values. As a result the `enhancement' is less harsh.

Before the stretching can be performed it is necessary to specify the upper and lower pixel value limits over which the image is to be normalized. Often these limits will just be the minimum and maximum pixel values that the image type concerned allows. For example for 8-bit graylevel images the lower and upper limits might be 0 and 255. Call the lower and the upper limits a and b respectively. Image segmentation is an essential process for most image analysis techniques. Segmentation is done using watershed algorithm. It subdivides an image into its constituent parts. Segmentation algorithms are based on one of the two properties of intensity values, namely discontinuity and similarity.

First category is to partition an image based on abrupt changes in intensity, such as edges in an image, Second category are based on partitioning an image into regions that are similar according to a predefined criteria. Histogram, Thresholding approach falls under this category. As watershed transformation suffers from over segmentation, Marker controlled watershed segmentation is used in this work. The watershed transformation has been widely used in many fields of Image Processing, including medical image segmentation due to the number of advantages that it possesses: it is a simple, intuitive method, it is fast and can be parallelized and it produces a complete division of the image in separated regions even if the contrast is poor, thus avoiding the need for any kind of contour joining. Furthermore, several researchers have proposed techniques to embed the watershed transformation in a multi scale framework. The watershed transformation finds "catchment basins" and "watershed ridge lines" in an image by treating it as a surface where light pixels are high and dark pixels are low.

Experimental Results

The simplest sort of normalization then scans the image to find the lowest and highest pixel values currently present in the image. Then each pixel P is scaled using the following function:

$$Pout = (Pm - c)\left(\frac{b-a}{d-c}\right) + a$$

Values below 0 are set to 0 and values about 255 are set to 255. The problem with this is that a single outlying pixel with either a very high or very low value can severely affect the value of *c* or *d* and this could lead to very unrepresentative scaling.

Therefore a more robust approach is to first take a histogram of the image, and then select *c* and *d* at, say, the 5th and 95th percentile in the histogram for example, 5% of the pixel in the histogram will have values lower than *c*, and 5% of the pixels will have values higher than *d*. This prevents outliers affecting the scaling so much.

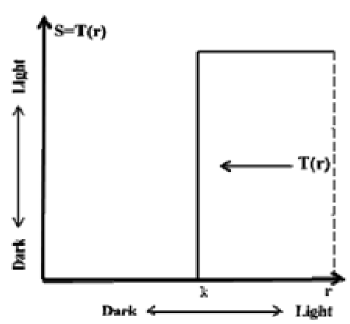

Fig 1 Threshold function of original image

Fig 1 shows the general equation for threshold image is s=0 if $r \le a$ and s= L-1, if r>a.

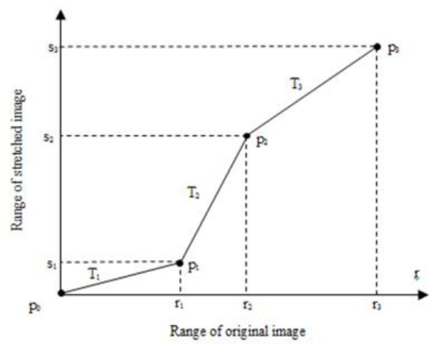

Fig 2 Contrast Stretching Graph

Fig 2 shows the image Contrast Stretching Graph for the given input image. The co ordinate r1 of point 1 is determined based on the statistical analysis shown in table 2 that will help in determining the threshold value for first region (disease parts). With this the pattern will be obtained.

This pattern will be input into the neural network for disease type prediction using Back Propagation Neural Network. An important application of neural networks is pattern recognition. Pattern recognition can be implemented by using a Back Propagation neural network that has been trained accordingly. During training, the network is trained to associate outputs with input patterns. When the network is used, it identifies the input pattern and tries to output the associated output pattern. The power of neural networks comes to life when a pattern that has no output associated with it, is given as an input. In this case, the network gives the output that corresponds to a taught input pattern that is least different from the given pattern. The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms one is Associative and other is Regularity detection. Here Regularity detection is used.

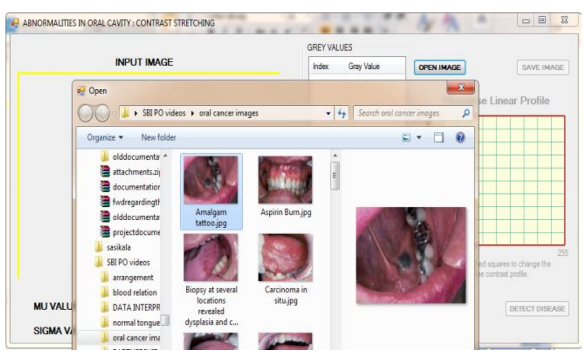

Fig. 3 Oral disease testing image

Here the units learn to respond to particular properties of the input patterns. Whereas in associative mapping the network stores the relationships among patterns, in regularity detection the response of each unit has a particular 'meaning'. This type of learning mechanism is essential for feature discovery and knowledge representation.

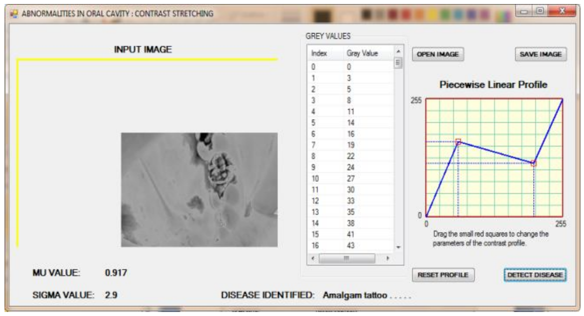

Fig.4 Oral disease prediction

Performance Evaluation of proposed system		
No of Training samples	5,000	
No of tested samples	500	
Precise Disease identification	Not determined	Wrong prediction
93.2%	2.8%	4%

Table.1 Performance evaluation table

The Cohen's kappa coefficient measure is used for analyzing the performance of proposed system. The Cohen's kappa coefficient is a statistical measure of the inter-rater agreement for qualitative items. The coefficient measure can be given by the following formula.

$$\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)}.$$

Where Pr(a) is the relative observed agreement among raters, and Pr(e) is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. κ indicates the agreed rate. The proposed system shows accuracy rate of 89%. Fig 8 shows an accuracy rate of the proposed system.

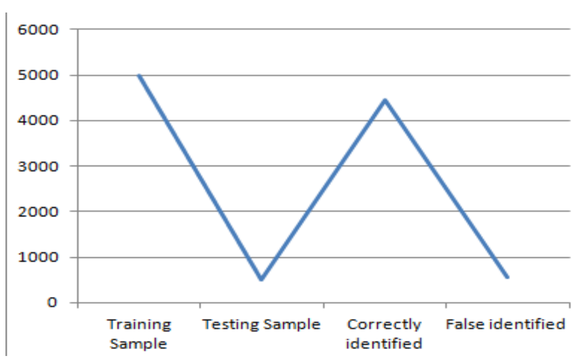

Fig. 3 Performance graph

3. CONCLUSION AND FUTURE WORK

In this proposed work, the oral image is captured and the series of operations to enhance the quality of the image and detection of tumor is performed. In this approach the quality of the image is enhanced using linear contrast stretching. After that watershed transformation is used to segment the image. Due to the problem of over segmentation, Marker controlled watershed transformation is used. After this the result image is compared with the source image to check the image quality and the tumor area. The problem here is to differentiate benign and malignant tumors. The suspected malignant tumor cases have to undergo biopsy. The accuracy obtained is 93.2%. In future it is proposed to increase more number of cases to achieve more accuracy.

Here the strength of watershed segmentation is that it produces a unique solution for a particular image, and it can be easily adapted to any kind of digital grid and extended to n-dimensional images and graphs. However, the noise in the image results in over segmentation. Lack of smoothness is the disadvantage for the watershed segmentation. Hence the accuracy of the project could be improve more by enhancing the smoothness of the watershed algorithm in segmentation.

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